Revenue Collapses and the Consumption of Small Business Owners in the Early Stages of the COVID-19 Pandemic*

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Abstract

Using detailed transaction-level data from financial accounts, this paper shows that the revenues of small businesses and the consumption spending of their owners both decline by roughly 40% following the declaration of the national emergency in March 2020. However, through May 2020, the vast majority of this average decline in revenues is due to national factors rather than to variation in *local* infection rates or policies. Further, there is only a modest propensity for business owners to cut consumption in response to their individual business losses: Comparing owners in the same county but whose businesses operate in industries differentially impacted by local infections and state-level policies, we show that each dollar of revenue loss leads to a 1.6 cent decline in the consumption of the owner at this early stage of the pandemic. This limited pass-through appears to be explained by three factors: (1) the liquidity of households and businesses entering the crisis – consumption is twice as responsive for small business owners who operate with low liquidity; (2) emergency Federal programs – median account balances in both business and checking accounts decline in March but rebound in April and May when the transfer programs begin; (3) pandemic induced declines in the ability to spend on consumption – spending on travel, restaurants or personal services dropped dramatically.

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The small business sector plays an important role for the economy as a whole, typically accounting for two-thirds of net job growth and 44 percent of U.S. economic activity (SBA, 2019). The Covid-19 pandemic has brought unprecedented challenges for small businesses and their owners due to the collapse in demand, supply chain disruptions, and production slowdowns associated with unsafe work environments. Small businesses typically contract earlier and more severely than large firms when the economy slows down (Davis et al., 1996), partly because they operate with lower overhead and fixed costs. Not only does this seem to be true in this pandemic downturn, but the owners of small businesses may bear the brunt of these contractions. While there is little research measuring the exposure of small businesses owners to their firms' performance, small business owners are not well diversified. They typically hold much of their wealth in their own businesses and depend on their businesses for their labor incomes (81 percent of small businesses are nonemployer businesses, FRBNY, 2019). Thus, a significant concern in the pandemic, reflected in the Coronavirus Aid, Relief, and Economic Security Act (CARES) Act of 2020, is the damage to the small business sector and the standard of living of its owners.

Using de-identified data on the checking and credit-card accounts of small businesses and households from JP Morgan Chase (JPMC) bank account records, we document how the revenues of small businesses and the consumption of their owners has been impacted by local infection rates and policy responses during the early stages of the pandemic. We use transaction-level information to construct a weekly panel dataset on the revenues, expenses, and profits of small businesses linked with the consumption of their owners from January 2019 to the end of May 2020. Unlike other datasets covering small businesses, our sample of businesses has significant coverage of non-employer businesses.

We first document that the COVID-19 pandemic had an enormous impact on small businesses and their owners in March, April and May 2020. Average revenues decline by more than forty percent in the weeks following the declaration of the national emergency (March 13, 2020), and show little to no evidence of recovery over the next few weeks. Consumption spending of small business owners declines by a similar amount – more than forty percent on average – but then partially rebounds two months into the pandemic. This decline in revenues is in line with prior studies that also document a dramatic decline in small business employment (Bartik et al., 2020; Chetty et al., 2020) and finances (Farrell et al., 2020b) during this early phase of the pandemic. Average expenses track revenues closely, suggesting that businesses downsized immediately in response to a sudden drop in revenues. We also find substantial exit of small businesses in February and March (just over 2.5% of businesses per month), but a lower rate of exit in April and May (just over 1%). The highest incidence of business closures occurs for full-service restaurants, residential remodeling, beauty salons, and trucking.

The large declines in both business performance and owner consumption over the few weeks following the national emergency are similar across businesses of different size, maintaining different levels of liquidity ex ante, and for employer versus non-employer businesses. But we find that the average declines in revenues are much larger for businesses in non-essential industries (roughly 50%) than for those in essential industries (roughly 30%).[1] We also find some differences in partial recovery in April and May. The average revenue decline for the smallest businesses start recovering as early as three weeks into the pandemic, whereas the revenue drop for larger small businesses persists until the end of our sample (end of May).[2]

Second we show that the collapse of small business revenues and the consumption of their owners is predominantly explained by nationwide factors, and that only a small part of the collapse is related to county-level variation new infection rates or state-level variation in policies such as shelter in place (SIP) orders. Following the declaration of the national emergency, both new infection rates and state-level policies differ significantly across counties and states and have low correlation with each other. Regressing outcomes onto infection rates and SIP orders and including weekly time fixed effects to control for national factors, we find that local infections and SIP orders have only modest direct effects on small businesses and their owners. Specifically, an increase in new infections by two standard deviations leads to a 1.5 percent decline in business revenues. The introduction

[1]Essential business are classified according to the CISA guideline and verified via news searches. There is little difference in exit rates in essential vs. non-essential industries.

[2]This finding is consistent with Bartlett III and Morse (2020) who find that microbusinesses show greater revenue resiliency relative to bigger small businesses.

of a SIP order leads to a 2.5% incremental decline in business revenues and a 4.4% decline in owner consumption. The sum of these two effects amount to only ten percent of the average observed decline in small business revenues. Thus, most of the decline in both revenues and consumption, while surely caused by the pandemic, is not directly related to either local infection rates or SIP orders.

However, new infection rates have large effects in the few places where they are especially high. At this early stage of the pandemic, the standard deviation of county-level new infection rates is low because only a few counties have significant infection rates. Across the areas with the highest and the lowest infection rates in the same week, local infections lead to a 11 percentage point difference in weekly revenues. These results are not driven by our use of SIP orders as a summary of anti-pandemic policies. Our findings are similar if we instead use the first principal component of a broad set of Non-Pharmaceutical Interventions (NPIs) instead of analyzing just the imposition of SIP orders.[3] Our finding that NPIs had modest effects where they are imposed is consistent with Correia et al. (2020), which finds that cities that had stricter NPI policies do not perform worse than those with less stringent policies during the 1918 Flu pandemic, although we find more modest effects of the local disease incidence while that paper finds that the main source of differences in economic disruption was the pandemic itself.

Our final and most novel result is that the decline in a small business's revenues has only had a small direct effect on the consumption spending of its owner in these first couple of months of the pandemic. The challenge in identifying the magnitude of the consumption response to revenue declines is that the pandemic affects household consumption decisions not only through the drop in business revenues but also directly through the local prevalence of the disease and the local restrictions on mobility and consumer-facing businesses. For example, business owners in hard hit areas might see a drop in revenues but also reduce spending endogenously due to the infection risk when leaving the house. For wage-earning households, Cox et al. (2020) finds a reduction in

[3] Specifically, we construct a composite measure of NPI strictness that reflects a state's NPI strictness relative to other states using a principal component analysis. We find that a one standard deviation increase in NPI strictness reduces business revenues, expenses, and owner's consumption by 2 to 3 percentage points. The magnitude of this effect is similar to that of SIPs.

spending on average in the initial months of the pandemic across many types of households, indicating that the drop in household spending extended to those whose income was not directly affected by the pandemic.

We estimate the propensity of owners to reduce consumption in response to revenue declines using a two-stage least squares strategy that compares businesses in the the same county and week that experience relatively more and relatively less severe revenue losses in response to local infections and SIP orders because they are in different industries. That is, our identification strategy relies on the idea that the direct effect of local factors on the consumption of business owners is driven by local conditions that affects households independently of their own business revenues. Therefore, we include county x time effects in our regression to control for this endogenous variation in consumption. Further, because consumption and revenues are co-determined for any given business, we use the interactions between 4-digit NAICS industry indicators and local infections and SIP orders to generate revenue changes that are plausibly orthogonal to any remaining endogenous variation in consumption. The changes in revenues for the five least affected industries since the onset of the national emergency ranges from zero to a 20% increase, while the changes in revenues for the five most affected industries are as large as a 90% decline.

Our estimates show that for every dollar decline in business revenues, expenses, or profits, the owner of that business decreases consumption spending by only 1.6 to 4 cents. While this average pass-through effect is relatively modest, during the national emergency it still amounts to a significant impact on household spending due to the large average drop in revenues. The implied dollar effect of the consumption drop driven by business revenue losses is as large as the typical variation in weekly consumption observed prior to the onset of the national emergency. Another way of framing the magnitude of the pass-through effect in dollar terms is to compare average changes in revenues for the least and the most affected sectors. We find that the consumption decline driven by business revenue losses is as large as 15% of the overall consumption drop for the most affected sectors.

There are several potential explanations for the low average pass-through of revenue losses into the consumption of business owners in the early phases of the pandemic. First, it is possible that businesses and households went into the pandemic with enough liquidity, debt capacity, or other sources of household income to buffer some of the initial revenue collapse. Consistent with an important role for ex ante liquidity, we find that the pass-through of revenues to consumption is twice as large for owners of businesses who enter the crisis with low liquidity.

Second, hard hit business owners may stabilize their consumption using the substantial fiscal support provided by the federal government. Consistent with an important role for the CARES Act, average and median balances in both business and personal accounts rise in April and May. The average *personal* account balance of owners of businesses in the most affected industries falls in March but fully recovers in April and rises in May. The average *business* account balance for businesses in the most affected industries drops in March, and again but by less in April, but then partially recovers in May.

Third, the pandemic imposes significant restrictions on everyone's ability to spend, which may make the common, lower level of consumption relatively insensitive to individual-business revenue declines. While we have no direct evidence on this channel, we find disproportionate declines in spending on goods and services that are luxuries or that require close personal contact, such as travel, eating out, or personal services.

In sum, in the early stages of the pandemic, the large average (40%) drop in the consumption of small business owners appears to be largely divorced from the specific performance of their individual business and mainly driven by the national crisis. The low direct effects appear to be due to pandemic related restrictions on consumption outside the house, the owners' own preparedness for bad times, and to the governments large fiscal responses in the early stages of the pandemic. The pass-through of business losses into owner's consumption may well rise over time as liquidity and government funds are exhausted and the pandemic continues.

Related literature Several recent papers have conducted surveys of small businesses and their owners in the early phases of the pandemic and find mass layoffs, temporary closures, and downsizing of businesses. Bartik et al. (2020) finds that 43% of businesses were temporarily closed by the end of March, 2020, and estimates from the U.S. Census

Small Business Pulse Survey show that only 25% of firms had enough cash on hand to cover 3 months of operations at the end of May (U.S. Census, 2020). Bartlett III and Morse (2020) finds that larger small businesses experienced 14% higher revenue declines than smaller small businesses, and Humphries et al. (2020) reports that 60% of small businesses had laid off at least one worker by the end of April. Alekseev et al. (2020) documents that increased household responsibilities, such as taking care of children and self-isolating household members, affected business owners' ability to focus on work during the crisis. Studies that make use of administrative data document a sudden, 12.7% drop in median business cash balances at the onset of the pandemic (Farrell et al., 2020b) and substantial heterogeneity in the speed of recovery by owner's race or by income profiles of the neighborhood in which businesses operate, with African-American businesses recovering at a slower rate than White-owned businesses (Fairlie, 2020) and business located in less affluent areas experiencing smaller revenue losses than those located with more affluent areas (Chetty et al., 2020).[4] Our study complements these studies by providing well-identified estimates of the effect of local infections and NPIs on small business revenues and expenses and by quantifying the extent to which disruptions to business revenues impacted the living standards of their owners.

Our work contributes to the consumption literature that estimate the marginal propensity to consume out of transitory income shocks.[5] Recent studies that examine household spending dynamics during COVID-19 find that households across all income distribution initially cut spending in the early phases of the pandemic and that spending has rebounded most rapidly for low income households (Cox et al., 2020; Baker et al., 2020). Our paper is the first paper to study how the living standards of small business owners are impacted by their own business performance.

[4] Fairlie (2020) documents that African-American business owners experiencing a drop of 26% in business activity from pre-COVID-19 levels compared to only 11% drop for White business owners by May, 2020. Farrell et al. (2020a) similarly finds that cash balances of White-owned restaurants doubled in May compared to only 38% increase for Black-owned restaurants.

[5] These studies estimate the extent to which households can smooth transitory variation in income generated by, for example, randomized timing of disbursement of economic stimulus (Parker et al., 2013; Broda and Parker, 2014), arrival of tax refunds (Baugh et al., 2020), household liquidity shock (Gross and Souleles, 2002), and unemployment insurance (Ganong and Noel, 2019).

The remainder of the paper proceeds as follows. We describe the data used in this study in Section 1, including our sample construction procedures and the definition of primary outcomes considered in the study. Section 2 presents descriptive evidence of how small businesses performed and owners' consumption evolved in the early months of the pandemic. We present our main findings on the effect of infections and NPIs in Section 3. In Section 4, we describe our estimation strategy for quantifying the causal effect of revenue losses on owners' consumption and present the pass-through estimates. Section 5 discusses potential explanations behind the modest average pass-through effect of business revenue losses. Section 6 concludes.

1 Data

Our analysis makes use of de-identified financial accounts data provided by JPMorgan Chase Institute (JPMCI). We use transaction-level data from both small business accounts and personal accounts to construct a panel dataset on the revenues, expenses, and profits of small businesses linked with the consumption of their owners. Our final dataset provides weekly business outcomes and household consumption for 380,532 businesses and 333,128 business owners between January and May, 2020.

1.1 Samples

We start by constructing a data set of the universe of small business checking accounts. We define a small business to be a collection of small business checking accounts linked to the same signer of the account.

The *all businesses* sample. We apply several screening criteria to identify active businesses that primarily use financial accounts provided by JPMC to manage their business finances. First, we exclude businesses that have more than two business checking accounts and those with multiple location or industry assignment. We next apply several account activity filters to ensure that the set of firms we consider are actively operating businesses prior to the pandemic. We limit the sample to firms with "open" business checking account status for at least twelve consecutive calendar months. We also require that a checking account has at least three transactions per month for at least ten months in 2019 (i.e., our baseline period). Finally, we require a business to have an "open" account status for at least one month in 2020 in order. This reduces our sample of 3.44 million small businesses to 1.8 million businesses with active accounts as of the beginning of 2020. This sample is henceforth referred to as the *all businesses* sample.

The *business owners* sample. From this all businesses sample, we next create a subsample of accounts for which we can match at least one of the owners of the small business to a personal account at the same large financial institution. We construct a *business owners* sample of paired small-business accounts and personal accounts where each observation represents a small-business matched with the personal accounts of one of its owners. Specifically, we start from the all businesses sample and apply several additional screening criteria to ensure that the set of owner households we consider also use financial services provided by JPMC to manage their personal finance. Specifically, we require that a business owner has an active personal checking account (or accounts) that is "open" for at least twelve consecutive months and has at least 3 transactions during *all* months in 2019. Relative to the business account activity filter that we impose – i.e., at least 3 transactions for 10 months in 2019– we require personal accounts to have activity in all months. This is because business account activity tends to be more volatile due to variation in cash flows, whereas personal accounts are not subject to the same concern. This procedure leads to a sample of 363,428 small business-owner pairs.

Further subsamples We categorize observations in the business owners sample by type of businesses along the following dimensions: employer versus non-employer, essential versus non-essential, small versus big, and low versus high liquidity.

A business is categorized as employer if it has payroll expenses for at least 6 months in 2019. In our sample, 15% are employer firms. We next identify essential and non-essential businesses based on their 4-digit North American Industry Classification System

(NAICS) sub-sector. Specifically, we categorize businesses that operate in sectors classified as "critical workforce" by the Department of Homeland Security (HLS)'s advisory list as *essential* businesses. We make a few exceptions to this list.[6] Namely, we categorize several sub-sectors in the food and agriculture industry, such as bakeries, caterers, or full-service restaurants, as *non-essential* because they are heavily affected by stay-at-home restrictions even if food and agriculture sectors were considered to be essential and technically not closed. According to this measure, roughly 60% are essential businesses.

We use two measures of firm size. In our descriptive statistics, we define firm size based on its average weekly revenues during 2019. Businesses with average weekly revenue below the first tercile are classified as *smaller*, and those with weekly revenues greater than the third tercile are classified as *larger*. For later estimation (in section 4), we define firm size based on the within-industry distribution of annual revenue in 2019. Since our estimation exploits differential industry exposure to local NPIs and infection rates, using within-industry distribution is a better measure of relative size. Businesses with 2019 revenue below the median for their industry are classified as *small*, and those above the median for their industry are classified as *large*.

Business liquidity is computed as the ratio of average cash balances at the end of each month in 2019 to average monthly expenses in 2019. We then multiply this figure by thirty to express liquidity as the number of days of operating expenses that a business could pay out of its cash balances were its revenues to stop. Businesses are classified based on the within-industry distribution. Businesses in the bottom quarter of the distribution of cash buffer days within its NAICS4 sub-sector are classified as *low liquidity*, those in the top quarter are classified as *high liquidity*.

Supplemental Data. We supplement this administrative financial accounts data with county-level infections data from the New York Times (New York Times, 2020) and state-level non-pharmaceutical interventions from Keystone Strategy (Keystone, 2020).

[6]This list is intended to help local officials to make informed decisions, so individual jurisdictions may differ in their own requirements of essential versus non-essential distinctions. It is nonetheless a good proxy for whether a business is considered to be essential at the local level.

1.2 Measurement of Business and Owner Outcomes

Our main outcomes of interest are weekly business revenues, expenses, and profits, and household consumption.

Business outcomes of firms To construct operating revenues for each small business, we first compute total credit transactions (i.e., inflows) into business checking accounts for each firm and week. We next identify financial transactions or non-business income that are unlikely to represent operating revenues received from providing goods and services, and subtract these amounts from total inflows.

$$\textit{Operating Revenue} = \text{Total Inflows} - \text{Financial Inflows} - \text{Non-business income} \quad (1)$$

Financial inflows include any inter-personal transfers, fee reversals, or miscellaneous account activities such as SWEEP inflows, or loans from financial institutions. Non-business income includes government transfers, such as unemployment insurance, tax refunds, or veterans benefits, income from gig platforms, or other interest income.

To construct operating expenses, we categorize all debit transactions (i.e., outflows) on business checking, debit card, and credit card accounts for each firm and week.[7]

$$\begin{gathered}\textit{Operating Expense} = \text{Fuel} + \text{Equipment} + \text{Groceries} + \text{Materials} + \text{Retail}+ \\ \text{Retail Durable} + \text{Wholesale} + \text{Entertainment} + \text{Food} + \text{Insurance} + \text{MiscBizExpense}+ \\ \text{Services} + \text{Travel} + \text{Payroll} + \text{Tax} + \text{Debt Payment} + \text{Utilities}+ \\ \text{Cash Withdrawal} + \text{Check} + \text{Uncategorized} \qquad (2)\end{gathered}$$

Spending categories are identified using a combination of transaction tags provided by JPMCI, such as the Merchant Category Code (for spending on cards), identity of a transaction counterparty, or the channel of payment. We are able to classify detailed categories of business expenses, but not of operating revenues because counterparty identity for credit

[7] Deposit account transactions refer to non-debit checking account transactions, while debit transactions refer to those using debit cards.

transactions is often redacted to preserve anonymity of the business.

We code both operating revenues and expenses as continuing zeros following account closures. This approach eliminates a possible survivorship bias that could spuriously make business outcomes appear better due to dropping exiting firms that perform the worst through the pandemic.

We define *Profit* as the difference between revenues and expenses, and *Profit Margin* as profit divided by average operating revenue in 2019.

Finally, we code *Exit* as a binary variable that equals one if the small business closes or has closed its accounts, and equals zero otherwise. If a business has two deposit accounts, both accounts must be closed to be coded as having exited. This method of measuring exit likely underestimates true exit rates, and exit may be measured with delay because firms may be inactive for some time before closing an account. Since we do not consider this dormancy period as exit, the effects that we estimate on exit are likely to be conservative estimates for true exit through May 2020.

Household consumption of owners We construct business owner households' consumption by categorizing all debit transactions on the owners' personal deposit accounts, debit card, and credit card accounts:

$$\begin{gathered}\textit{Consumption} = \text{Fuel} + \text{Groceries} + \text{Pharmacy} + \text{Retail} + \text{Retail Durable}+ \\ \text{Auto Repair} + \text{Insurance} + \text{Medical} + \text{Entertainment} + \text{FoodAway} + \text{Personal Svcs}+ \\ \text{Professional Svcs} + \text{Other Svcs} + \text{Travel} + \text{Rent} + \text{Gov't} + \text{Utilities}+ \\ \text{Cash Withdrawal} + \text{Check} + \text{Uncategorized} \qquad (3)\end{gathered}$$

For credit card spending, we follow Ganong and Noel (2019), and measure spending as of the time when the goods and services are purchased, rather than when the card bill is paid. In addition to household consumption, we categorize and track household debt payments as they are major household expenses. We supplement business and household outcomes with demographic information of businesses and their owners, such as owner's gender and age, business industry, incorporation type, and location.

Relative to other account-level analyses, one advantage of our use of linked small-business and personal accounts is that we observe some business expenses in personal account and some personal expenses in business accounts and can re-classify them. That is, there are instances where it appears that the business owner uses their business accounts for transactions that are clearly for personal use (e.g., child care, medical expenses, hair salon, etc). We exclude these transactions from operating expenses and re-categorize them as household spending. Similarly, when we observe business spending (e.g., payroll, business insurance, etc) from personal accounts, we re-categorize them as operating expense.

One disadvantage of account level data in general is that we cannot capture business activities or household spending patterns if a business or household has financial accounts with other financial services company. However, given that the sample of households we study have both of their business and personal checking accounts provided by JPMC to manage their finances, combined with our activity filters, we believe that the account activity that we can track in our data capture the majority, if not all, of their business and personal finances.

Scaled outcome variables To compare businesses of different sizes, we normalize our outcome variables (except profits) using two alternative scaling factors. The first scaling factor is the weekly average of the outcome in 2019. We denote variables scaled with this factor by the superscript *avg* (for 2019 average). So for business or owner i in week t we have:

$$Y_{i,t}^{avg} = \frac{Y_{i,t}}{\overline{Y}_{i,2019}} \tag{4}$$

where $\overline{Y}_{i,2019} = \frac{1}{52} \sum_{s \in 2019} Y_{i,s}$ and $Y_{i,s}$ represents operating revenue, operating expenses, or consumption. This first normalization has the advantage of adjusting by a constant factor for each firm-household pair and so measuring changes in outcome relative to a constant baseline.

The second scaling factor is the centered 9-week average of the same outcome a year ago.

We denote variables scale with this factor by the superscript *sa* (for seasonal adjustment), as in

$$Y^{sa}_{i,t} = \frac{Y_{i,t}}{\overline{Y}_{i,(t-56,t-48)}} \tag{5}$$

where $\overline{Y}_{i,(t-56,t-48)} = \frac{1}{9}\sum_{s=t-56}^{s=t-48} Y_{i,s}$. The second normalization factor has the advantage of adjusting for seasonal fluctuations, so that one is comparing the firm-household outcome to a similar period in the previous year. We take the 9-week average so that the scale factor does not add volatility to the outcome variable from the weekly volatility during 2019.

Unlike revenues, expenses, or consumption which is each scaled by its own weekly average in 2019, we transform profits (i.e., $Revenue_{i,t} - Expense_{i,t}$) into a profit margin measure, or percentage of sales turned into profits, by normalizing profits by weekly average or centered-9 week average of operating revenue a year ago. All of the scaled and unscaled outcome variables are winsorized at the 2*nd* and 98*th* percentile.

1.3 Descriptive Statistics

Businesses in the business owners sample are smaller – both on average and across the distribution – relative to those in the all businesses sample, as shown in Panels A (all businesses sample) and F (business owners sample) of Table 1. Panels B through E show the distributions of revenues, expenses, and profits for subsamples of the all businesses sample. Average revenues and expenses track each other closely for all types of businesses with the exception of smaller small businesses (Panel D), which has higher average weekly expenses than revenues. Employer businesses (Panel C) tend to be larger and are similar in size to large small businesses (those in the top tercile of weekly revenues in 2019, Panel E). Across all business types, a median firm does not break even (median profits are negative), and median weekly expenses exceed median weekly revenues by 70. Our measure of weekly consumption represents about 20% of business revenues and expenses (Table 1 Panel F).

At the bottom of Table 1, we show that businesses in the all businesses sample are concentrated in 5 industries, in which more than half of all businesses in the sample operate. A large share of businesses (more than 70%) are pass-through entities, and less than 30% of all businesses are known to be female-owned.

How do the characteristics of the small businesses that use our financial institution compare to the national distribution? Table 2 compares our data to external benchmarks. Roughly 85% of businesses sampled in our data are nonemployer businesses, similar to 81% in the U.S. overall. Thus, a key advantage of our data is better coverage of nonemployer businesses realtive to traditional data sources (Alekseev et al., 2020). However, relative to the benchmark, our sample under-represents businesses that existed for more than 10 years and over-represents businesses that operate in professional services, real estate, and transportation sectors. Among nonemployer businesses, our sample of firms tend to be bigger in terms of annual receipts relative to the nationwide distribution.

1.4 Measurement of Infections and NPIs

To estimate the effect of local disease prevalence on business performance and owner's consumption, we obtain measures of new infections from New York Times (2020). We aggregate new cases in every county from the daily to the weekly level, and divide by ex ante population to obtain the weekly rate of new infections per $1,000$ residents at the county level:

$$D_{c(i),t} = \frac{\text{New Cases}_{c,t}}{\text{Population}_c} \times 1000 \tag{6}$$

where c indexes counties and $c(i)$ denotes the county in which business i is located. For studying exit rates, we cumulate this variable across weeks: $D^{Cum}_{c(i),t} = \sum_{s=0}^{t} D_{c(i),t}$. It is important to note that the infection rates that we use in this study do not accurately measure the true infection rates due to limited testing capability and efforts as well as other factors. However, the rates that we use reflect the available public information about the prevalence of the disease, and so these measures are more appropriate than would be the true rates for measuring the effect of local infection rates on business outcomes and owners' consumption. However, the effects we measure are obviously the effects of reported rather than actual infection rates. We obtain measures of NPI policies at the state level from Keystone (2020).

2 Average business and owner outcomes

This section shows that the performance of small businesses performed and the consumption of their owners declined dramatically in the early months of the pandemic. Following this analysis, Section 3 studies the relative roles of national vs. local infection rates and state-level policies in these severe declines. Section 4 then measures the extent to which owners' living standards are affected by their own business' revenue losses and how this differs across businesses.

Consistent with other studies, our data show sharp declines in all measures of economic activity following declaration of the COVID-19 national emergency (March 13, 2020). Figure 1 displays the average weekly dollar amounts (not scaled) of business revenue, expense, profit, and owner's consumption for our business owners sample. Figure 2 plots the average percent change in seasonally adjusted outcomes (our second scaling factor) for this same sample, relative to the average during the two months before the national emergency. Revenues, expenses, and consumption drop by more than 40% two weeks into the national emergency and remain low for six weeks until the end of May when they partly rebound. Business expenses track revenues closely, indicating that businesses on average downsized their operations. Profits fall steadily over the period by about $200 per week relative to their pre-pandemic average and by about 10% of revenues relative to their pre-pandemic average. Finally, the consumption of small business owners declines along with business revenues. Thehe two series track each other in the weeks that follow; when business revenue increases, owner consumption increases.While the set of businesses in the business owners sample tend to be smaller than those in our all businesses sample, we find that the experiences in the two samples are very similar. Appendix Figures A.1 and A.2 repeat Figures 1 and 2 for a random subset of all businesses and shows a very similar pattern to that of our business owners sample and very similar magnitudes in percent.

Figure 3 shows average changes in business revenues for different types of small businesses. Panel A shows that essential businesses experienced a $35 - 40\%$ decline in revenues two weeks into a national emergency while non-essential businesses see a much larger decline of closer to 60%. This gap is consistent with the fact that non-essential businesses were both more impacted by consumers and workers reacting to the disease and subject to more restrictions on operations by local government orders. This gap in performance between essential and non-essential businesses also remains roughly constant as both types of businesses rebound slightly. Panel B shows that larger small businesses experienced bigger revenue declines relative to smaller small businesses. Differences between employer and nonemployer businesses and between businesses that operate with high and low levels of liquidity are much smaller (Panels C and D).

The pattern of changes in expenses by type of business is very similar to that of revenues (Appendix Figure A.3). The pattern of changes in consumption by business type is also similar except for some differences for owners of businesses with different levels of liquidity (Appendix Figure A.4).[8]

These declines in business revenues, expenses, and profits are unlikely to be driven by business exits (i.e., closure of business account(s)) because exit does not increase following the declaration of the national emergency when revenues fall. Panel A of figure 4 shows the number of business closures in 2020 by month and panel B reports the cumulative number of business closures in 2020 in our business owners sample.[9] Among exiting firms, a significant number of firms exited in February even before the national emergency was declared. The incidence of business closure peaks in our sample in March. Full-service restaurants, residential remodeling, beauty salons, and trucking industries are among the

[8]Both types of businesses have similar drops in consumption in the first month after national emergency is declared, however, consumption recovers more rapidly for owner households that operate businesses with lower liquidity. To the extent that low liquidity businesses represent owner households with lower income, this result is consistent with existing studies that document faster spending recoveries for low-income households (Cox et al., 2020).

[9]While 8% of businesses in the all businesses sample exit by the end of May, only 2% of all small businesses in the business owners sample exit.

sectors with the highest incidence of business closures.[10]

Both businesses and owner households make what appear to be significant inter- and intra-temporal spending adjustments in the early months of the pandemic. Figures 5 and 6 plot the average weekly dollar amounts of expenses on detailed spending categories for businesses and their owners using the expense measures described in section 1.2. We find that both businesses and households increase spending on fuel and groceries in the week prior to the national emergency and that they sharply cut back spending on travel, food (i.e., restaurants, bars, bakeries, etc), entertainment, and personal services immediately after the national emergency is declared, similar to the household stocking up behavior documented in Baker et al. (forthcoming).

Businesses increase spending on durable retail and materials, and the level of spending on these categories remain elevated after the national emergency is declared relative to the pre-pandemic average. This spending pattern may be due to businesses in some industries, such as chemical product or detergent manufacturing firms, scaling up their operation due to increased demand and/or businesses increasing spending on personal protective equipment to ensure safe working conditions. Interestingly, the average weekly spending on groceries remain elevated for both businesses and households in weeks following the national emergency. This provides suggestive evidence that business owners' business and personal finances may be integrated to some extent. This fungibility across financial accounts raises the possibility that our estimates in Section 4 of the revenue to income pass-through may be underestimates.

Overall, the account-level data show that small businesses experienced slightly more than a 40% decline in revenues and expenses following the declaration of the national emergency, and that the owners of these business also reduced consumption by a similar magnitude. Consumption, but not revenues or profits, recovers just under half this decline during April and May. The next section builds on these descriptive facts by quantifying the extent to which local infection rates and state-level NPI policies affected small business

[10]See Appendix Figure A.5 which displays the top ten industries with the highest incidence of business closures during our sample period. This figure also shows that businesses in the essential industries are as likely to exit as those in nonessential industries.

and owner outcomes.

3 The Effects of Infections and State-level Policies

This section shows that both business outcomes and owner consumption declined dramatically as local infection rates increased and states enacted policies to slow the disease. In a simple regression framework without controls (besides business-owner fixed effects), infections and non-pharmaceutical interventions (NPIs) explain almost the entire decline in business outcomes and consumption. However, comparing across businesses in different counties and states, the direct effect of both infections and state policy responses are modest. Where infections rates were high, infections had significantly larger effects than NPIs on business outcomes and owner consumption.

3.1 Effects of Covid-19 Infections and Shelter in Place Orders

While states introduced a wide range of NPIs in response to rising infection cases, in this subsection we focus on the effects of shelter in place (SIP) orders and a composite measure of NPI strictness. Among NPIs, SIP orders are one of the most common and most strict measures. SIP orders impose direct restrictions both on the ability of many businesses to operate and on the ability of people to consume many types of goods and services. Panel A of Appendix Figure 7 shows the share of states with SIP orders imposed by week and that there is substantial variation in the imposition of SIP orders across states.[11]

There is also substantial heterogeneity in both timing and incidence of infection rates across different counties. Figure 8 shows the evolution of infection rates per $1,000$ for three counties that represent low, medium, and high growth regions. Panel A shows new cases and panel B shows cumulative cases per $1,000$. The example counties with low (Colorado, TX) and medium (Dakota, MN) caseloads use the left axis because their new infection rates per $1,000$ people are so much lower than the counties with the higher rates, for which we use the example of New York, plotted using the right axis. Not only do the

[11](Panel A of Figure A.6 shows the number of states imposing and lifting these order respectively.

new infection rates have very different levels, but also quite different timing. Figure 9 displays the average infection rate across all counties over time (in percent). The average county-level infection rates was 0.48 cases per thousand residents at the peak of our sample period, and at most 87% of the states have enacted SIP.

To quantify the impact of infections and SIP orders on businesses and their owners' consumption, we estimate variants of

$$Y_{i,t} = \alpha_i + \beta_1 D_{c(i),t} + \beta_2 1[\text{SIP}_{s(i),t}] + \mathbb{X}_{i,t} + \epsilon_{i,t} \tag{7}$$

where $Y_{i,t}$ denote our outcomes of interest (as defined in Section 1.2) and our main explanatory variables, $D_{c(i),t}$ and $1[\text{SIP}_{s(i),t}]$, denote infection rates per $1,000$ residents and an indicator for whether a state has SIP order in effect. See Section 1.4 for details on variable definition. We include firm fixed effects, α_i, in all specifications to account for time-invariant, unobserved differences across firms. We include different sets of fixed effects, denoted by $\mathbb{X}_{i,t}$ to compare firms in the same week, in the same industry, and/or of the same size. The results are reported in Table 3. The first four columns report the results of estimating equation (7) with dependent variables normalized by prior year average, $Y^{avg}_{i,t}$, and the last four columns report the results with seasonally adjusted dependent variables normalized by centered-9-week average of the respective outcomes a year ago, $Y^{sa}_{i,t}$. Reported coefficients are multiplied by 100 for readability and can be interpreted as changes in percentage points.

In columns 1 and 5 of Table 3, we first present coefficient estimates when excluding fixed effects for week (and for business type) so that these results measure not only the effect of local infections\SIPs, but also of the effect of the rise in average infections\SIPs nationally and as well as anything else correlated over time with these national averages during the onset of the pandemic. Each new case per $1,000$ residents is associated with a 0.8 or 1.2 percentage point decline in weekly business revenues while the imposition of a SIP order leads to 16 or 30 percent decline in revenues (where 'percent' is percent of average 2019 weekly revenues or the nine-week average of revenues centered around the same week in 2019). The estimated impacts of infections across all outcomes in Columns 1 and 5 of Table 3 imply that the local and national increases in the infections rates and SIP orders together explain in this broad sense almost the entire decline in business outcomes and owner's consumption.

The remaining columns of Table 3 show that the effect of local infections and SIP orders controlling for what is occurring nationally is modest, and accounts for only a small share of the large declines that Section 2 documents. Columns 2 and 6 of Table 3 include week fixed effects in $\mathbb{X}_{i,t}$, and columns 3, 4, 7, and 8 also include interactions of these week effects with categorical variables for industries or with categorical variables for firms size terciles. Each new case per $1,000$ residents in a week leads to a 0.4 to 0.6 percent decrease in revenues in that week, and a SIP order leads to a 2.3 to 2.6 percent decline in revenues, both relative to 2019. To put this number in context, the standard deviation of the infection rate following the national emergency is 1.21, so that a two standard deviations increase in the infection rate leads to a 1.2 ($\approx$ 2.42 cases per thousand $\times 0.5$) percent decline in revenues, or roughly half the effect of a SIP order. Because the infection rate is so highly skewed early in the pandemic, a slightly more informative way to compare the impact of infection rates and SIP orders is to compare areas with high and the low infection rates in the same week. For example, when New York County, NY peaked at 22.5 cases per thousand, many counties had no new cases. The local infection rate reduced average business revenues in New York County by 11 ($\approx (22.5 - 0) \times 0.5$) percentage points of 2019 revenues while local infections caused no revenue reductions in a county with no local infections. This impact is substantially larger than the roughly 2.5 percent decline due to a SIP order. Thus, early in the pandemic in the typical county, the effect of a SIP order has a much larger impact on business outcomes and consumption than the low infection rate, however in areas with high infection rates, the infection rates drive much larger declines in revenues.

Panels B through C of Table 3 that local infection rates and SIP orders both have slightly larger effects on expenses than on revenues, and as a result, local infections and SIP orders have slightly positive effects on our measure of profit margins.[12] These findings suggest that local infections and SIP orders cause businesses to cut back expenses more than

[12] As shown in Appendix Figure A.7, the average profit margin declines over time during the pandemic.

revenues, by using up inventory, postponing bill payments, or "eating" capital, potentially at significant future cost.

As shown in Panel D of Table 3, local infections also have stronger effects on the consumption of small business owners than on their revenues, decreasing consumption by 0.5 to 0.8 percent of 2019 consumption per new case per thousand residents. Similarly, state-level SIPs have much stronger effects on consumption than on revenues, decreasing consumption by 3.1 to 4.4. percent. We find that local infections have little effects on exit rates and that SIP also do not lead to higher exit rates once we account for time effects during the early stages of the pandemic (Panel E).

These estimated effects remain stable and robust across different specifications that include time $\times$ industry or time $\times$ size bin fixed effects. We note that we find similar effects for revenues, expenses, and profit margins in the all businesses sample, not just for businesses that we can match to their owners (See Appendix Table A.1). Finally, it is possible that infection rates of SIP orders have persistent effects, but we find no additional effect of cumulative cases in a county or weeks over which SIPs have been imposed in a state. Thus, as we discuss further at the end of Section 3.2, local infections and SIPs are roughly sufficient statistics for the impact of local disease outcomes and policy responses on business outcomes at this early point in the pandemic (and perhaps partly because both infection rates and NPIs are persistent processes).

Figure 10 summarizes these findings. In Panels A, B, and D, the black, solid lines with circles plot average revenues, expenses, and consumption as a percent of 2019 averages relative to their pre-national emergency averages. In panel C this line plots profit margins relative to their pre-pandemic average. From these lines we subtract the average effect of local infections and SIP orders, that is the average of: $Y_{i,t} - \hat{\beta}_1 D_{c(i),t} - \hat{\beta}_2 1[\text{SIP}_{s(i),t}] - \mathbb{X}_{i,t}$. The gap between the actual changes in business outcomes (black line) and average changes net of the effect of local differences (red or blue lines) show the combined effect of infections and SIP orders. The blue, dashed line with $\times$'s subtracts the effect estimated when time effects are included in equation (7) and the red, dashed lines with triangles subtracts the effects estimated without time effects in equation (7) (i.e., excluding $\mathbb{X}_{i,t}$). The gap between the actual average changes in outcomes and the average changes after subtracting the effect of local differences (i.e., the gap between the black and red lines) is large, indicating that the effect of infections, SIP orders, and nationwide factors explain most of the entire decline in business outcomes and owner's consumption. When we remove the effect of the national average of the infection rates and SIP orders and any correlated factors, the gap between the actual changes in business outcomes and the average changes net of the effect of local differences (i.e., the gap between the black and blue lines) is dramatically smaller, indicating that local infections and SIP orders explain only a small part of the average decline.

3.2 Effects of Infections and NPI tightness

In this subsection, we construct a summary measure of NPIs and show that the conclusions of the previous subsection – that both local infections and NPIs had modest effects – still hold for this alternative measure of state policies. Figure 7 shows that many states adopted multiple NPI policies at the same time.[13] Since packaged policies can reinforce and complement one another, correlated policies and heterogeneity in policy duration across states complicate the measurement of NPI effects.

We address this challenge by conducting principal-component analysis (PCA) and construct a simple "NPI strictness" measure that captures the intensity of state-specific packaged NPI policies relative to other states. We perform principle components analysis on the NPIs listed in Figures 7 during the period after the national emergency is declared. Appendix Table A.4 reports the detailed PCA results. We focus on the first principal component, which we call *Strictness*, which explains 76% of variance and weighs positively on all restrictions. We estimate the impact of infections and NPI tightness on businesses outcomes and owner's consumption using the following specification

$$Y_{i,t} = \alpha + \alpha_i + \beta_1 D_{c(i),t} + \beta_2 \text{Strictness}_{s(i),t} + \mathbb{X}_{i,t} + \epsilon_{i,t} \tag{8}$$

[13] Appendix Figure A.6 presents this information in terms of when various policies are imposed and lifted. Appendix Figure A.8 shows that SIP is highly correlated with various other NPI policies.

which is analogous to equation (7).

We find that NPI strictness has effects on business and owner outcomes that are very similar to the modest effects that we found for SIP orders. And the use of NPI strictness in place of SIP does not alter any of our conclusions about the modest effect of infections. Table 4 reports the effect of infection rates on outcomes (simply the estimated β_1) and the effect of NPI strictness per standard deviation increase in NPI strictness (the estimated β_2 times the standard deviation of the first NPI factor). Reported coefficients are multiplied by 100 for readability and can be interpreted as changes in percentage point. A one standard deviation increase in NPI strictness reduces business revenues, expenses, and owner's consumption by 2 or 3 percentage points when we account for time effects. Appendix Table A.6 reports the effect of NPI tightness without controlling for local infections. The magnitude is similar to the specification controlling for infections.

Finally, we return to the possibility that infection rates of SIP orders have persistent effects and that our estimates are perhaps missing substantial delayed effect of local conditions. This is surely an important possibility in the summer and fall of 2020, but our analysis can only cover the early stages of the pandemic. In our sample, covering the effect of infections and policies through the end of May, we find no role for persistent effects of local conditions.[14]

In sum, we find only modest effects of local infection rates and SIP policies on business revenues and owner consumption, suggesting that business disruptions are primarily attributable to national factors unrelated to local infections. Further, there is a low correlation between county-level infections and state-level policies, so we can reasonably estimate the contribution of each separately. Our finding of a weak effect of SIP policies is consistent with Correia et al. (2020) who find that cities that had stricter NPI policies do not perform worse than those with less stringent policies and that the main source of economic disruption was the pandemic itself rather than NPIs during the 1918 Flu pandemic. But we also find that local disease incidence also plays only a small role in differences in local outcomes.

[14] Appendix Table A.5 reports the effect of current and past infections on SIP (panel A) and on NPI tightness (panel B).

4 The Effect of Revenue Losses on Owner Consumption

Our analyses so far show that local infection rates and state-level policies have negative but modest direct effects on the performance of small businesses and on the consumption of their owners in the early stages of the pandemic. Instead the largest part of the drop in outcomes is explained by national factors. This section shows that the causal effect of individual business's revenue declines on the owner's consumption is also quite modest in the early stages of the pandemic. The vast majority of the documented decline in consumption of business owners is likely due to the restrictions on the ability to consume from infections and NPIs, a general increases in uncertainty and wealth losses not directly related to differences in revenue losses across industries, and government transfers following the CARES Act.

4.1 The Effect of Business Revenues on Owner Consumption

Before turning to regression analysis, we simply compare the average changes in business revenues and owners' consumption for the least and most affected NAICS 4-digit industries as measured by their average change in revenues since the onset of the national emergency. The least affected industries include beer, wine, and liquor stores; nursing care facilities; funeral homes and cemeteries; toilet preparation and detergent manufacturing; and chemical product manufacturing firms. The most affected industries include vending machine operators; taxi or limo service; consumer goods rental; travel/tour agencies; and drinking places.

In this simple comparison, there is almost no difference in the consumption of the owners of the least affected industries and the consumption of the owners of the most affected industries despite large revenue differences. Average revenues for the least affected industries actually increases by roughly 20% while average revenue for the most affected industries declines by nearly 90% following the declaration of the national emergency. Yet as Figure 11 shows, there is little difference in average consumption. The Figure plots revenues in blue against owners' consumption in red for the five least affected industries (solid lines), and five most affected industries (dashed lines).[15] If business's revenue losses were significantly passed through to owner's consumption, we would expect to see a larger drop in consumption for worse performing industries. However, the consumption changes are similar across industries suggesting that business losses did not cause much decline in owner consumption early in the pandemic.

This comparison does not provide a clean measure of the extent to which owners are able to insure their consumption against firm-specific revenue losses because both household and businesses are affected by the pandemic.[16] Specifically, this simple relationship does not account for differences in the location of different industries which would imply different consumption declines due to local infection rates and NPIs and possibly make this figure misleading.[17] To rule out this possibility and to quantify the consumption effect of revenue losses, we turn to regression analysis that controls for local conditions.[18]

To measure the owner's consumption decline that is *caused* by the decline in the performance of that owner's business, we compare the consumption of owners of businesses that are located in the same county but that operate in sectors that are differentially affected by local infection rates and state-level SIP orders. Our identifying assumption is that industry-specific exposure to infections and policies are not correlated with differences in the consumption of business owners other than through differential business performance,

[15] Appendix Figure A.9 also plots average revenues and consumption for the bottom and the middle three industry performance deciles and show similar patterns. Appendix Figures A.10 and A.11 plot changes in revenues and consumption for each of these individual sectors.

[16] For example, (Chernozhukov et al., 2020) analyze consumers' voluntary precautions in response to new information and policies out of fear of being infected, and Cox et al. (2020) show that wage-earning households, most of whom work for large businesses, also reduced spending on average in the initial months of the pandemic.

[17] That is, suppose that some of the least affected industries are in the areas with the highest infections (e.g. finance in Boston) where consumption dropped the most. And some of the most affected industries are concentrated in areas that are otherwise the least affected (e.g. potato farmers and meat packers which were located in low infection and NPI areas). Such differences in location would generate a negative relationship between industry declines in revenues and the consumption of the owners, as the owners of the least affected industries would have their consumption driven down the most by high local infection rates and tight NPIs directly. This correlation works in the opposite direction of the direct effect of business revenues on owner consumption.

[18] We confirm that running a simple naive OLS regression of consumption on revenues leads to attenuation bias relative to our IV estimates. Appendix Table A.7 reports naive estimates. One potential explanation for this attenuation bias is if business owners that operate under-performing businesses systematically hold higher consumption buffer relative to high-performing businesses.

within a county in a particular week. The intuition for this approach is that some industries, like restaurants are hit harder by local conditions than others, like chemical product manufacturing businesses. This industry variation generates revenue losses in response to local conditions that are plausibly orthogonal to the effect of local conditions directly on the business owner's consumption which is similar for the owners of both types of businesses. This variation is also unrelated to any individual-specific or business-specific changes in revenues driven by owners preferences or consumption needs.

Specifically, we instrument business revenues, expenses, and profits with industry-specific exposure to local infection rate and state-level NPIs. The exclusion restriction is that the only channel through which infections and NPIs can differentially affect the consumption of the owners across businesses is through differential exposure of the owner's business industry to infections and NPIs. We estimate the following two stage least squares regression:

$$Y_{i,t} = \alpha_i + \sum_j \beta_j^{FS} 1_{[j=j(i)]} NPI_{s(i),t} + \sum_j \delta_j^{FS} 1_{[j=j(i)]} D_{c(i),t} + \gamma_{c(i),t} + \epsilon_{i,t} \tag{9}$$

$$C_{i,t} = \alpha_i + \beta^{IV} \widehat{Y_{i,t}} + \gamma_{c(i),t} + \eta_{i,t} \tag{10}$$

where the two key variables in equation (9) are interactions of NAICS 4 industry indicators with state-level NPIs and with county-level infection rates respectively. These terms measure the industry-specific effect of local infections and state level policies on business outcomes. The term $\gamma_{c(i),t}$ represents week $\times$ county fixed effects which control for differences in the average effect of infections and NPI on revenues through all channels and for the different locations of different industries. The second-stage, equation (10) includes the same fixed effects and so identifies the effect of revenue declines on owner consumption only from the differences across industries in the response of business revenues to the local disease incidence and state-level policies, within a given county and in a given week. We restrict the sample to NAICS 4 sub-sectors with at least 30 firms. Our first-stage endogenous variables, $Y_{i,t}$, include normalized business revenues, expenses, and profit margin, and the second-stage outcome is normalized consumption of the owner household, $C_{i,t}$.

The marginal propensity to cut consumption in response to business losses at this stage of the pandemic is modest. Table 5 shows the results of estimating equation (9) and (10) with $Y_{i,t}$ and $C_{i,t}$ measured in levels (dollars) so as to directly measure the marginal propensity to cut consumption in response to business losses. In the Table, the odd columns only use variation by industry due to SIP or NPI strictness and the even columns use both variation by industry due to infections and SIP/NPI strictness as the excluded instruments. The first two columns in each panel A and B use SIP, and the last two columns in each panel use NPI tightness as the NPI measure. Panel A includes county $\times$ time fixed effects and panel B includes only state $\times$ time fixed effects. Outcomes are in dollars (level) and all specifications include firm-household pair fixed effects. The main lesson of the table is that for each dollar reduction in business revenues or expenses in a week, consumption declines by between 1.2 and 2.2 cents. The third row shows that a dollar reduction in profits lead to reduction in consumption of 3.4 to 4.1 cents.

To put these estimates in perspective, the average drop in revenues after the national emergency was declared (relative to its pre-pandemic average) is about $-\$925$. Therefore, the implied consumption drop due to revenue losses is $-925\times$ (roughly) $0.016 \approx -\$15$ per week. This corresponds to roughly 8% of average weekly consumption drop relative to its pre-pandemic average. This decline is modest relative to an average decline in consumption of roughly \$400. However, the average weekly variation in consumption is around \$9.4 in normal times, so that the decline in consumption of small business owners that is directly due to their business losses during the pandemic is as large as the typical weekly variation in consumption in normal times.[19]

One concern with the results in Table 5 is that business differ dramatically in size and large businesses might have many owners over which dollar losses are spread. To address this concern, we estimate equations (9) and (10) with our scaled measures of business

[19]Note that Figure 11 shows almost no difference in the decline of consumption between the most and least affected industries, which highlights the importance of comparing outcomes within counties. The industries in the least (most) affected industries are disproportionately located in counties where the consumption drops are the largest (smallest). Thus, the decline in consumption between owners of businesses in the least and most affected industries is similar because of the offsetting effects of a small pass-through of revenue drops into consumption (larger for the most affected) and the differential impact of their locations (larger for the least affected).

outcomes. This specification estimates the percent reduction in owner consumption for each percent decline in own-business outcomes (or for decline in profits as a percent of revenues).We report the complete set of results of this analysis in Appendix Table A.8. We find a similar but slightly smaller sensitivity of consumption to own-business revenues as for the levels specification reported in Table 5. A one percent reduction in revenues due to differential industry exposure leads to reduction in consumption by 0.1 to 0.2 percent. This implies that the average revenue decline of roughly 40% causes a decline in consumption of 4 to 8 percent, or \$37 to \$74 per week for the average small business owner.

4.2 The Consumption Sensitivity to Revenues Across Business Types

In this section we show that some business owners are less able to insure against revenue losses than others. Specifically, we estimate differences in the consumption impact of revenues along four dimensions of business type: employer vs. non-employer businesses; low vs. high ex ante liquidity; small vs. large businesses; and pass-though entities vs. C-corporations. As described in Section 1, we measure liquidity by the ratio of 2019 average account balances to typical spending, or 'cash buffer days,' and firm size by 2019 average weekly revenues. For this analysis, we use the within-industry distribution of business liquidity and size to define the subgroup because there are large difference across industries in the size of businesses and in how much liquidity they hold. [20]

Panels A and B of Table 6 show that the consumption of owners of non-employer businesses is more sensitive to revenue losses than is the consumption of owners of businesses with employees. In general, Table 6 reports β^{IV} from equations (9) and (10) by subgroup in the same pattern as Table 5. Panels A and B show that for a dollar reduction in revenue, owners of businesses with employees reduce their consumption by 1.1 cents, but this causal effect is twice as large (2.4 cents) for owners of non-employer businesses.

Panels C and D of Table 6 show that owners of businesses with low liquidity are more sensitive to revenue losses than those with high liquidity. Owner of businesses with low

[20] Appendix Figure A.12 shows the distribution of the 25th, 50th, and 75th percentiles of within-industry distributions of liquidity and size. The differences across industries are large.

reduce their consumption by 2.4 cents per dollar decline in revenue, while owners of businesses with high liquidity reduce their consumption by roughly half as much, 1.4 cents per dollar decline in revenue.

Panels E and F of Table 6 show that owners of smaller businesses have a greater sensitivity to revenue losses than owners of larger small businesses. This categorization is distinct from but similar to the categorization of employer vs. non-employer. Smaller owners of small small businesses reduce consumption by 6 cents per dollar revenue decline while owners of larger small businesses cut back consumption by only 1.3 cents per dollar decline.

As with our main results, we confirm that the substantive conclusions are very similar when equations (9) and (10) are estimated using scaled business outcomes and scaled consumption. Consistent with dollar effects, we find that owners of businesses with low liquidity exhibit higher consumption responses to revenue losses than owners of businesses with high liquidity (Appendix Table A.9).

Finally, Table 7 shows the sensitivity of the consumption of owners by incorporation status. We find that living standards of owners of pass-through entities are more sensitive to business losses relative to C-corporations. A dollar reduction in revenue leads consumption to drop by 1.8 cents for pass-through entities (i.e., sole proprietors and S-corporations) but only by 1 cent for C-corporations.

In sum, while on average the owners of many small businesses experienced only limited pass-through of business revenue losses into consumption in the early part of the pandemic, the owners of some businesses have seen more substantial declines in their consumption spending. In particular, for a businesses with low liquidity, roughly 15% of the average consumption drop of the owner can be attributable to revenue losses, while only 4.5% are be attributable for high liquidity business owner households.[21]

[21] We calculate these shares by multiplying the respective MPCs of high vs. low liquidity businesses by the largest average weekly drop in revenues. Specifically, the largest average weekly drop in revenues (consumption) relative to the pre-pandemic level was -$1,371 (-$226) for owners with low liquidity whereas it was -$868 (-$265) for those with high liquidity businesses. Multiplying their respective MPCs, we get consumption declines of -$33 for low and -$12 for high liquidity households. Expressed as a share of their average weekly declines in consumption, they correspond to roughly 15% (33/226) for low liquidity and 4.5% (12/265) for high liquidity businesses.

5 Explanations for the Modest Impact of Revenue Losses on Business Owners' Consumption

There are three potential explanations behind the low average pass-through of revenue losses to the living standards of business owner households in the early phases of the pandemic. First, it is possible that businesses have sufficient ex ante liquidity, debt capacity, or other sources of household income, so that the owners can keep consumption stable through temporary revenue losses. Second, hard hit business owners may be able to stabilize their consumption using the substantial fiscal support provided by the federal government. Third, the pandemic imposes significant restrictions on everyone's ability ability to spend, which may make the common, lower level of consumption relatively insensitive to individual-business revenue declines. Our evidence is consistent with all of these explanations.

First, liquidity matters. Consumption responses to revenue declines are twice as large for small business owners who enter the crisis with low liquidity relative to those with high liquidity. This heterogeneity implies that ex ante liquidity plays an important role for owner's ability to smooth consumption and that business owners on average had sufficient financial means to weather revenue declines.

Second, our data have indirect evidence that owners are insuring consumption against revenue losses using funds provided by Federal relief payments to households and short-term grants and loans to small businesses. The Coronavirus Aid, Relief, and Economic Security Act (CARES Act) included the Economic Impact Payments and Federal Pandemic Unemployment Compensation (FPUC) for households.[22], CARES also included the Paycheck Protection Program (PPP) and the expansion of Small Business Administration's Economic Injury Disaster Loans program for small businesses.

Figure 12 shows that both businesses and households begin to build up significant financial buffer in their business and personal checking accounts during the time period

[22] In addition to increasing UI generosity, the FPUC expanded unemployment insurance (UI) eligibility criteria to include business owners and self-employed individuals who would traditionally not be eligible to receive UI benefits.

when a large share of EIP payments were sent out (on April 15), and when the first-round (April 3) and second-round (April 27) of PPP started. By the end of May, median businesses and owners, respectively, have 10% and 18% higher balances in their business and personal checking accounts relative to January, 2020. Figure 13 also provides suggestive evidence that the stimulus measures might be minimizing the direct impact of revenue losses on owner's consumption. This figure plots median changes in business owner's business and personal account balances relative to January for the businesses and owners of businesses that are in the most and least affected industries (the same set of industries shown in Figure 11). The most affected businesses experience a 15% decline balances in March followed by another 5% decline in April, but then balances recover half their losses in May. The balances of the personal accounts of the owners of the most affected industries decline by 10% in March but then fully recover (on average) in April, consistent with the arrival of the Economic Impact Payments in household accounts.

Finally, our results are also consistent with the interpretation that the pandemic restricted owner's consumption even for businesses that were less hard hit. Although we have no direct evidence on this channel, we see that especially spending on luxury consumption categories and those that require people to leave the house, such as travel, eating out, or personal services, dropped dramatically after the declaration of the national emergency.

6 Conclusion

This paper documents that small businesses and their owners experienced unprecedented disruptions of up to 40% drop in weekly revenues, expenses, and consumption in the early phases of the pandemic. We find that the majority of this decline was due to nationwide factors and that local infections and state-level policies like shelter in place orders and NPI strictness had only moderate additional direct effects on business outcomes and owners' consumption. Quantitatively, an increase in the new infection rate of two standard deviations leads to a 1.5 percentage point declines in business revenues, and the imposition of a shelter in place order leads to a 2.6 percentage point decline in business revenues.

Using differential industry exposure to NPIs and infection rates, we find only a modest impact of small business losses on their owners consumption in the early stages of the pandemic. Because of the large declines in revenue, the observed consumption decline *driven* by revenue losses is still non-trivial, roughly as large as the typical weekly variation in consumption in normal times and about 8% of the average drop in weekly consumption. We also find that living standards of business owners that operate with low levels of liquidity are particularly sensitive to changes in business performance.

There are several reasons to expect the pass-through of business losses into owner's consumption to rise over time as the pandemic unfolds. As discussed in Section 5, businesses and owners started the pandemic with some liquidity, and on average their funds were replenished by fiscal stimulus measures. However, since these programs are temporary in nature, the pass-through of business losses into owner's living standards may grow substantially as businesses and owners use up liquidity.

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Table 1: Descriptive statistics of weekly outcomes in 2019 ($)

Notes: This table reports weekly business and household outcomes in 2019 in dollars. Outcomes are winsorized at the 2^{nd} and 98^{th} percentile. Columns 1 and 2 report the sample mean and standard deviation. Columns 3 to 5 report the pseudo-distribution presented as means of 10 observations in the p^{th} percentiles. Columns 6 and 7 report the number of firms and households in the sample. Panel A reports statistics using the all businesses sample. Panels B and C report those using only nonemployer and employer sample. A firm is considered to be an employer firm if a business had payroll expenses for at least 6 months in 2019. Panels D and E sample small and large firms. Firm size is determined by 2019 average weekly revenues– firms with less than the first tercile of average revenue ($787) are "small" and those with greater than the third tercile ($3,572) are "large". Panel F uses the business owners sample, which serves as the main analysis. Business and owner characteristics are reported below Panel F, and uses the all businesses sample.

	Mean	SD	p20	p50	p80	N firms	N HHs
	Winsorized						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				A. All Sample			
Revenue	5,722	14,088	0	345	5,831	1,799,935	---
Expense	5,781	12,580	38	1,068	6,577	1,799,935	---
Profit	-58	8,801	-2,204	-70	1,371	1,799,935	---
				B. Nonemployer			
Revenue	3,867	10,801	0	125	3,785	1,531,922	---
Expense	3,925	9,504	12	757	4,330	1,531,922	---
Profit	-74	7,228	-1,696	-57	1,000	1,531,922	---
				C. Employer			
Revenue	16,324	23,108	0	5,893	27,743	268,013	---
Expense	16,392	20,352	1,518	7,588	27,813	268,013	---
Profit	33	14,885	-8,274	-452	6,800	268,013	---
				D. Small			
Revenue	289	968	0	0	300	599,979	---
Expense	1,027	3,505	0	200	1,103	599,979	---
Profit	-674	2,711	-864	-75	0	599,979	---
				E. Large			
Revenue	15,033	21,188	0	6,458	23,524	599,978	---
Expense	14,093	18,411	1,279	6,701	21,959	599,978	---
Profit	833	14,274	-6,878	-57	7,637	599,978	---
				F. Owner Subsample			
Revenue	4,370	10,220	0	252	4,918	363,682	333,434
Expense	4,612	9,569	30	910	5,605	363,682	333,434
Profit	-203	6,495	-1,895	-60	1,131	363,682	333,434
Consumption	993	1,508	79	458	1,414	363,682	333,434
				G. Business and Owner Characteristics			
Business Age	6.9	6.9	1.8	5.1	10.1	1,799,935	--
Owner Age	47.1	12.9	35.0	46.0	59.0	--	333,434

Industry	N Firms	Sh (%)	Business Location	N Firms	Sh (%)
Professional Services	282,690	15.7	California	350,872	19.5
Real Estate and Leasing	212,489	11.8	New York	324,829	18.0
Other Services	211,961	11.8	Texas	228,899	12.7
Construction	164,675	9.1	Florida	160,455	8.9
Health Care and Social Asst.	136,392	7.6	Illinois	153,704	8.5

Business Ownership	N Firms	Sh (%)	Owner Gender	N HHs	Sh (%)
S-Corp	373,985	20.8	M	158,112	47.4
Sole Prop	373,104	20.7	F	99,309	29.8
LLC - Member Managed	371,762	20.7	Missing	76,013	22.8
C-Corp	216,242	12.0			
LLC - Manager Managed	167,460	9.3			

Table 2: Sample Representativeness

Notes: This table compares the representativeness of the sample used in this study to various U.S. Census external benchmarks. Column 1 reports nationwide shares. Columns 2 and 3 report the same statistics using the 2019 all businesses and the business owners samples. See section 1.1 for details on the construction of the all businesses and the business owners samples. Panel A compares the share of employer and nonemployer firms. The population statistic is from 2017 Statistics of U.S. Business (SUSB, 2017). We classify establishments with less than 5 employees in the SUSB data or those with no payroll expenses in our data to be nonemployer firm. Panel B compares the share of firms by firm age. We exclude new firms (age =0) to make the population statistic more aligned with our sample criteria because we require firms to have existed for at least a year to be included in our sample. The population statistic for firm age is from 2016 Business Dynamics Statistics (BDS, 2016). Panel C compares annual receipts in dollars for nonemployer firms using 2018 Nonemployer Statistics (NES, 2018). To make our sample comparable to NES, we also restrict our sample to nonemployer firms. Panel D compares industry shares using 2017 SUSB.

	Population	Sample	
	Nationwide Share (%)	All Business Share (%)	Owner Sample Share (%)
	(1)	(2)	(3)
A. Employer vs. Nonemployer			
Nonemployer	81.00	85.11	85.82
Employer	19.00	14.89	14.18
B. Firm age (excluding new firms)			
1	7.36	15.09	16.09
2	6.34	11.75	12.61
3	5.63	9.37	9.89
4	5.16	7.95	8.24
5	4.63	7.30	7.45
6 ~ 10	20.17	29.50	31.05
11 ~ 15	50.70	19.04	14.66
C. Annual Receipts in dollars (nonemployer only)			
< \$5,000	24.48	11.32	14.28
\$5,000-\$9,999	15.54	5.12	5.80
\$10,000 - \$24,999	23.70	11.90	12.42
\$25,000 - \$49,999	14.30	14.04	13.97
\$50,000 - \$99,999	10.36	17.09	16.88
\$100,000 - \$249,999	7.81	20.13	19.19
\$250,000 - \$499,999	2.52	9.81	8.78
> \$500,000	1.29	10.60	8.68
D. Industry			
Agriculture, Forestry, Fishing/Hunting	0.37	0.62	0.52
Mining, Quarrying, and Oil/Gas Extraction	0.31	0.28	0.23
Utilities	0.10	0.11	0.10
Construction	11.57	10.76	10.79
Manufacturing	4.09	3.10	2.87
Wholesale Trade	4.92	3.69	3.37
Retail Trade	10.68	7.78	8.10
Transportation and Warehousing	3.05	5.62	6.20
Information	1.31	2.26	2.65
Finance and Insurance	3.93	2.06	1.90
Real Estate and Rental and Leasing	5.10	13.26	10.99
Professional, Scientific, and Technical Svcs	13.38	15.81	16.39
Management of Companies and Enterprises	0.44	0.51	0.34
Administrative and Waste Manag.	5.74	6.02	6.47
Educational Services	1.54	1.81	1.95
Health Care and Social Assistance	10.80	7.58	7.47
Arts, Entertainment, and Recreation	2.15	2.84	3.43
Accommodation and Food Services	8.90	4.01	4.22
Other Services (excl. Public Administration)	11.49	11.78	11.96
Industries not classified	0.13	0.13	0.11

Table 3: Effects of Shelter in Place (SIP) controlling for Infections (%)

Notes: This table reports estimates of local infections and shelter in place (SIP) on business outcomes and consumption of the owners. For panels A through D, the first row of each panel reports the effect of each new case per 1,000 residents and the second row reports the effect of SIP. The first row of panel E reports the effect of cumulative infections per 1,000 and that of cumulative number of weeks that SIP has been in effect. Columns 1 through 4 report estimates using outcomes normalized 2019 weekly average, and the estimated coefficients can be interpreted as change as percent of 2019 weekly average. Columns 5 through 8 report estimates using seasonally-adjusted outcomes, and the coefficients can be interpreted as change as percent of 2019 9-week centered average. All regressions include firm and household pair fixed effects. Columns 2 and 6 include time effects, columns 3 and 7 include time $\times$ NAICS 2-digit industry effects, and columns 4 and 8 include time $\times$ size bin effects to flexibly control for time-varying factors related to industry and firm size. Size bins are as defined in Table 1. Coefficients are multiplied by 100 and represented in a percent unit. Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	Increase as percent of 2019 weekly average				Increase as percent of 2019 9-week centered average			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				A. Revenues				
New cases	-.803***	-.480***	-.438***	-.415***	-1.23***	-.583***	-.545***	-.509***
	(.03)	(.031)	(.031)	(.031)	(.053)	(.054)	(.054)	(.054)
Shelter in place	-15.7***	-2.44***	-2.33***	-2.42***	-30.70***	-2.58***	-2.64***	-2.56***
	(.113)	(.213)	(.213)	(.213)	(.199)	(.374)	(.375)	(.374)
				B. Expenses				
New cases	-1.10***	-.839***	-.806***	-.808***	-1.405***	-.819***	-.790***	-.791***
	(.024)	(.024)	(.024)	(.024)	(.04)	(.04)	(.041)	(.041)
Shelter in place	-13.09***	-3.16***	-2.94***	-3.15***	-25.20***	-3.73***	-3.70***	-3.70***
	(.09)	(.169)	(.169)	(.169)	(.15)	(.282)	(.283)	(.282)
				C. Profit				
New cases	.095**	.224***	.247***	.265***	.100*	.208***	.248***	.277***
	(.038)	(.039)	(.039)	(.039)	(.053)	(.054)	(.055)	(.054)
Shelter in place	-5.95***	.937***	.810***	.953***	-5.24***	1.19***	1.09***	1.21***
	(.144)	(.272)	(.273)	(.272)	(.2)	(.378)	(.378)	(.378)
				D. Consumption				
New cases	-.824***	-.547***	-.514***	-.541***	-1.375***	-.831***	-.788***	-.815***
	(.024)	(.024)	(.024)	(.024)	(.039)	(.04)	(.04)	(.04)
Shelter in place	-14.27***	-3.26***	-3.12***	-3.24***	-25.15***	-4.41***	-4.29***	-4.39***
	(.089)	(.168)	(.168)	(.168)	(.149)	(.279)	(.28)	(.279)
				E. Exit				
Cumulative cases	-.005***	-.005***	-.005***	-.005***	-.005***	-.005***	-.005***	-.005***
	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)
Shelter in place	.183***	-.019***	-.022***	-.019***	.183***	-.019***	-.022***	-.019***
	(.001)	(.003)	(.003)	(.003)	(.001)	(.003)	(.003)	(.003)
Number of Obs	6,930,012	6,930,012	6,930,012	6,930,012	6,259,378	6,259,378	6,259,378	6,259,378
Firm-Household FE	X	X	X	X	X	X	X	X
Time FE		X				X		
Time x Industry FE			X				X	
Time x Size Bin FE				X				X

Table 4: Effects of Non-Pharmaceutical Intervention (NPI) Strictness and Infections (%)

Notes: This table reports estimates of infections and NPI strictness on business outcomes and consumption of the owners. The first rows of panels A through D report the effect of each new case per 1,000 residents, and the first row of panel E reports the effect of cumulative infections per 1,000 residents. The second row of each panel reports the effect of NPI strictness per standard deviation increase in NPI strictness. NPI strictness is the first principal component in a principal component analysis of state-level NPIs and captures the intensity of state-specific packaged NPI policies relative to other states. The first component explains 76% of variance and weighs positively on all restrictions. Columns 1 through 4 report estimates using outcomes normalized 2019 weekly average, and the estimated coefficients can be interpreted as change as percent of 2019 weekly average. Columns 5 through 8 report estimates using seasonally-adjusted outcomes, and the coefficients can be interpreted as change as percent of 2019 9-week centered average. All regressions include firm and household pair fixed effects. Columns 2 and 6 include time effects, columns 3 and 7 include time $\times$ NAICS 2-digit industry effects, and columns 4 and 8 include time $\times$ firm size bin effects to flexibly control for time-varying factors related to industry and firm size. Size bins are as defined in Table 1. Coefficients are multiplied by 100 and represented in a percent unit. Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	Increase as percent of 2019 weekly average				Increase as percent of 2019 9-week centered average			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				A. Revenues				
New cases	-.599***	-.494***	-.451***	-.429***	-.715***	-.597***	-.559***	-.524***
	(.03)	(.031)	(.031)	(.031)	(.053)	(.054)	(.054)	(.054)
NPI Strictness	-8.5***	-2.15***	-.548***	-.523***	-17.26***	-2.86***	-.748***	-.694***
	(.054)	(.207)	(.056)	(.05)	(.095)	(.364)	(.099)	(.087)
				B. Expenses				
New cases	-1.01***	-.858***	-.824***	-.827***	-1.162***	-.841***	-.813***	-.813***
	(.024)	(.024)	(.024)	(.024)	(.04)	(.04)	(.041)	(.041)
NPI Strictness	-6.73***	-2.67***	-.681***	-.645***	-13.25***	-3.51***	-.93***	-.86***
	(.043)	(.165)	(.045)	(.039)	(.071)	(.274)	(.074)	(.066)
				C. Profit				
New cases	.262***	.231***	.254***	.272***	.272***	.217***	.257***	.286***
	(.038)	(.039)	(.039)	(.039)	(.053)	(.054)	(.055)	(.054)
NPI Strictness	-3.69***	.854***	.234***	.204***	-3.38***	1.0***	.28***	.24***
	(.069)	(.265)	(.072)	(.063)	(.095)	(.367)	(.099)	(.088)
				D. Consumption				
New cases	-.702***	-.566***	-.533***	-.559***	-1.126***	-.855***	-.812***	-.840***
	(.024)	(.024)	(.024)	(.024)	(.039)	(.04)	(.04)	(.04)
NPI Strictness	-7.41***	-2.43***	-.63***	-.59***	-13.24***	-3.47***	-.92***	-.83***
	(.042)	(.163)	(.044)	(.039)	(.07)	(.272)	(.074)	(.065)
				E. Exit				
Cumulative cases	.001***	-.005***	-.005***	-.005***	.001***	-.005***	-.005***	-.005***
	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)
NPI Strictness	.537***	.018**	.005**	.003	.537***	.018**	.005**	.003
	(.002)	(.009)	(.002)	(.002)	(.002)	(.009)	(.002)	(.002)
Number of Obs	6,928,131	6,928,131	6,928,131	6,928,131	6,257,500	6,257,500	6,257,500	6,257,500
Firm-Household FE	X	X	X	X	X	X	X	X
Time FE		X				X		
Time x Industry FE			X				X	
Time x Size Bin FE				X				X

Table 5: Marginal Propensity to Consume out of Business Outcomes

Notes: This table reports 2SLS-IV estimates of the owner households' consumption response per dollar change in business revenue, expense, and profit margin using equation (10). Columns 1 and 2 use variation by industry due to SIP or SIP and infections and Columns 3 and 4 use that due to NPI strictness or NPI strictness and infections as the excluded instruments. NPI strictness is as defined in Table 4. Outcomes are in dollars (level), and all regressions include firm and household pair fixed effects and time × county fixed effects. Therefore, the estimated coefficients can be interpreted as consumption declines (in dollar unit) per each dollar reduction in business outcomes. Firms that operate in sub-industries with less than 30 firms are dropped from the estimation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	Variation by industry due to		Variation by Industry due to	
Endogenous Variable	SIP (1)	SIP and infections (2)	NPI strictness (3)	NPI strictness and infections (4)
Revenue	.015***	.011***	.016***	.012***
	(.001)	(.001)	(.001)	(.001)
Expense	.020***	.013***	.022***	.014***
	(.001)	(.001)	(.001)	(.001)
Profit Margin	.036***	.034***	.041***	.039***
	(.004)	(.003)	(.004)	(.003)
Number of Obs	7,531,326	7,188,993	7,531,326	7,188,993
Firm-Household FE	X	X	X	X
Time x County FE	X	X	X	X

Table 6: Marginal Propensity to Consume out of Business by Subgroup

Notes: This table reports 2SLS-IV estimates of the owner households' consumption response per dollar change in business revenue, expense, and profit margin using equation (10) by business type. Odd numbered columns in each panel use variation by industry due to SIP or NPI strictness and even numbered columns in each panel use that due to SIP and infections or NPI strictness and infections as the excluded instruments. NPI strictness is as defined in Table 4. Outcomes are in dollars (level), and all regressions include firm and household pair fixed effects and time $\times$ county fixed effects. Therefore, the estimated coefficients can be interpreted as consumption declines (in dollar unit) per each dollar reduction in business outcomes. Panels A and B reports estimates using subsamples of nonemployer and employer firms. Panels C and D reports estimates using subsamples of low and high liquidity firms. Panels E and F report estimates using subsamples of small and large firms. Liquidity is computed as the ratio of 2019 average monthly cash balances to expenses multiplied by 30 and can be interpreted as a firm's average cash buffer days, or the number of days of operating expenses that a business could pay out of its cash balances were its revenues to stop. "Low (high) liquidity" sample includes firms with lower (higher) than the first (third) quartile of cash buffer days within its sub-industry (NAICS 4-digit). "Small" ("Large") firms includes those with lower (higher) than median annual sales in 2019 within its sub-industry. Firms that operate in sub-industries with less than 30 firms are dropped from the estimation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Endogenous Variable	Variation by Industry due to SIP (1)	Variation by Industry due to SIP & Infections (2)	Variation by Industry due to NPI strictness (3)	Variation by Industry due to NPI strictness & Infections (4)	Variation by Industry due to SIP (5)	Variation by Industry due to SIP & Infections (6)	Variation by Industry due to NPI strictness (7)	Variation by Industry due to NPI strictness & Infections (8)
	A. Nonemployer				B. Employer			
Revenue	.019***	.012***	.021***	.014***	.010***	.009***	.011***	.010***
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Expense	.022***	.013***	.024***	.015***	.016***	.011***	.017***	.012***
	(.002)	(.002)	(.002)	(.002)	(.002)	(.001)	(.001)	(.001)
Profit	.052***	.033***	.064***	.042***	.013***	.026***	.017***	.028***
	(.006)	(.005)	(.006)	(.005)	(.005)	(.004)	(.004)	(.004)
Number of Obs	6,406,312	6,115,116	6,406,312	6,115,116	1,103,674	1,053,507	1,103,674	1,053,507
	C. Low Liquidity				D. High Liquidity			
Revenue	.024***	.017***	.024***	.017***	.013***	.008***	.014***	.010***
	(.002)	(.001)	(.002)	(.001)	(.002)	(.002)	(.002)	(.002)
Expense	.025***	.016***	.025***	.017***	.026***	.012***	.027***	.014***
	(.002)	(.002)	(.002)	(.002)	(.003)	(.003)	(.003)	(.003)
Profit	.074***	.045***	.070***	.043***	.001	.010**	.007	.016***
	(.009)	(.006)	(.008)	(.006)	(.006)	(.005)	(.006)	(.005)
Number of Obs	1,883,508	1,797,894	1,883,508	1,797,894	1,865,204	1,780,422	1,865,204	1,780,422
	E. Small				F. Big			
Revenue	.056***	.039***	.064***	.046***	.012***	.009***	.013***	.010***
	(.005)	(.005)	(.005)	(.005)	(.001)	(.001)	(.001)	(.001)
Expense	.054***	.036***	.064***	.044***	.016***	.010***	.017***	.012***
	(.005)	(.005)	(.005)	(.005)	(.001)	(.001)	(.001)	(.001)
Profit	.061***	.046***	.061***	.047***	.033***	.033***	.036***	.036***
	(.015)	(.011)	(.014)	(.011)	(.003)	(.003)	(.003)	(.003)
Number of Obs	3,720,530	3,551,415	3,720,530	3,551,415	3,788,268	3,616,074	3,788,268	3,616,074
Firm-Household FE	X	X	X	X	X	X	X	X
Time x County FE	X	X	X	X	X	X	X	X

Table 7: Marginal Propensity to Consume out of Business by Incorporation Status

Notes: This table reports 2SLS-IV estimates of the owner households' consumption response per dollar change in business revenue, expense, and profit margin using equation (10) by business incorporation status. Panel A reports estimates using a sample of pass-through (sole proprietors and S-corporations) entities and panel B reports estimates using a sample of C-corporations. Columns 1 and 3 use variation by industry due to SIP and Columns 3 and 4 use that due to SIP and infections. Outcomes are in dollars (level), and all regressions include firm and household pair fixed effects and time × county fixed effects. Therefore, the estimated coefficients can be interpreted as consumption declines (in dollar unit) per each dollar reduction in business outcomes. Firms that operate in sub-industries with less than 30 firms are dropped from the estimation. Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	Variation by Industry due to				Variation by Industry due to			
Endogenous Variable	SIP (1)		SIP & Infections (2)		SIP (3)		SIP & Infections (4)	
	A. Pass-through				B. C-corp			
Revenue	.017	***	.013	***	.010	***	.006	***
	(.001)		(.001)		(.002)		(.002)	
Expense	.023	***	.014	***	.017	***	.010	***
	(.002)		(.002)		(.003)		(.002)	
Profit	.026	***	.040	***	-.012		.001	
	(.006)		(.005)		(.008)		(.006)	
Number of Obs	3,388,066		3,234,063		892,606		852,033	
Firm-Household FE	X		X		X		X	
Time x County FE	X		X		X		X	

Figure 1: Average business and household outcomes in 2020

Notes: This figure shows average weekly dollar levels of business revenues, expenses, profits, and household consumption from the week starting December 30th, 2019 to the week starting May 25th, 2020. Dotted vertical lines denote the week of national emergency, which was declared the week starting March 9th, 2020. Blue horizontal lines denote the average of respective outcomes between January 13, 2020 to February 9, 2020 (i.e., two months before the week of national emergency).

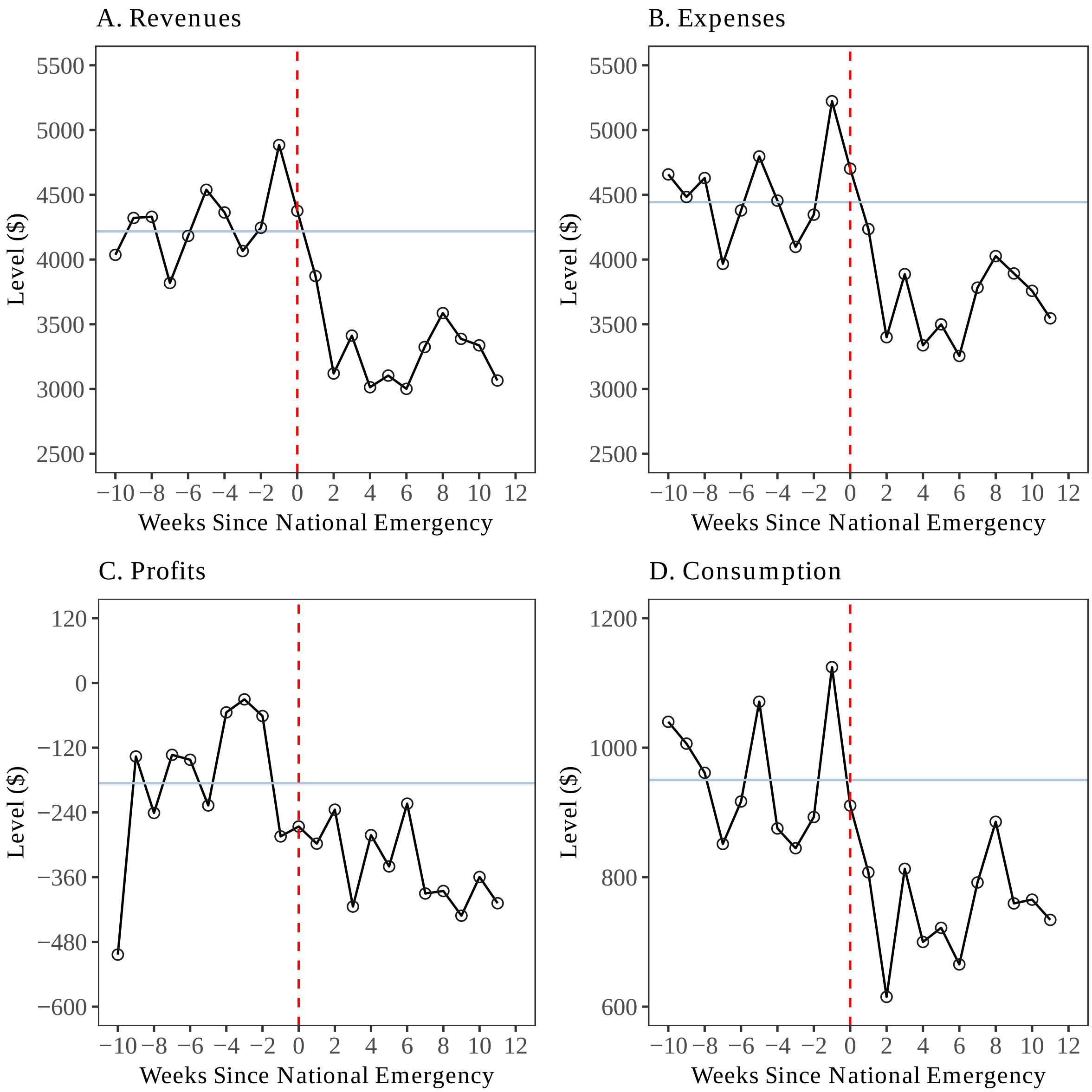


Figure 2: Average percent change in business and owner outcomes relative to 2019

Notes: This figure shows average weekly changes in business revenues, expenses, profits, and household consumption from the week starting December 30th, 2019 to the week starting May 25th, 2020. Outcomes are normalized by the centered 9-week average from a year ago, and the change is defined as a percent change from its own average between January 13, 2020 and February 9, 2020 (i.e., two months before the week of national emergency). Dotted vertical lines denote the week of national emergency, which was declared the week starting March 9th, 2020.

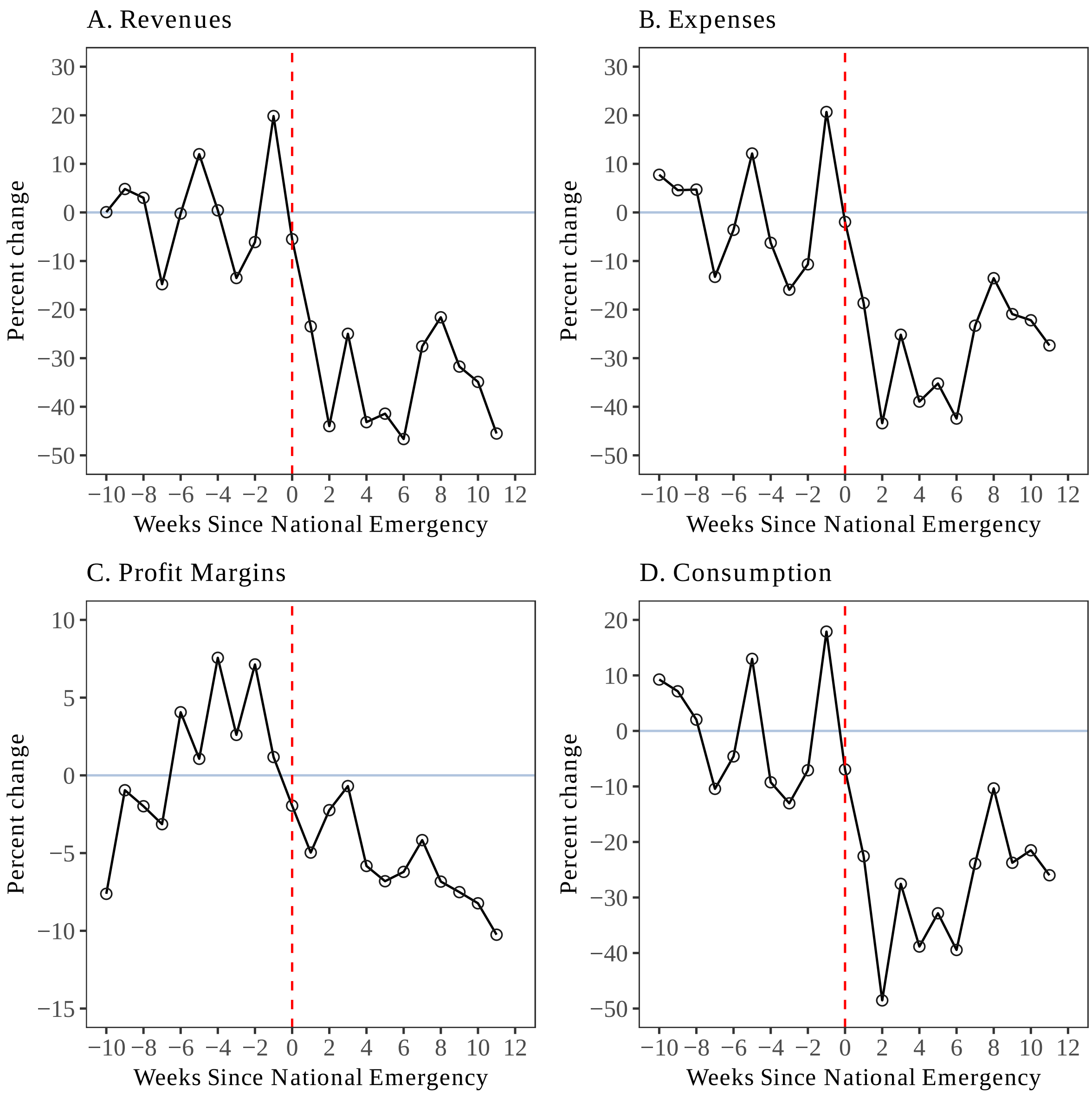


Figure 3: Average changes in business revenues in 2020 by subgroup

Notes: This figure shows average weekly changes in business revenues from the week starting December 30th, 2019 to the week starting May 25th, 2020. Outcomes are normalized by the centered 9-week average from a year ago, and the change is defined as a percent change from its own average between January 13, 2020 and February 9, 2020 (i.e., two months before the week of national emergency). Dotted vertical lines denote the week of national emergency, which was declared the week starting March 9th, 2020. Panel A plots weekly changes in revenues for essential and non-essential businesses; Panel B for small and large businesses; Panel C by employer and non-employer firms; and panel D by low vs. high liquidity firms. Essential industry categorization based on the advisory list provided by the Department of Homeland Security (HLS). "Small" ("Large") firms includes those with lower (higher) than median annual sales in 2019 within its NAICS 4-digit sub-industry. A firm is considered to be an employer firm if a business had payroll expenses for at least 6 months in 2019. Low (high) liquidity sample includes firms with lower (higher) than the first (third) quartile of cash buffer days within its sub-industry.

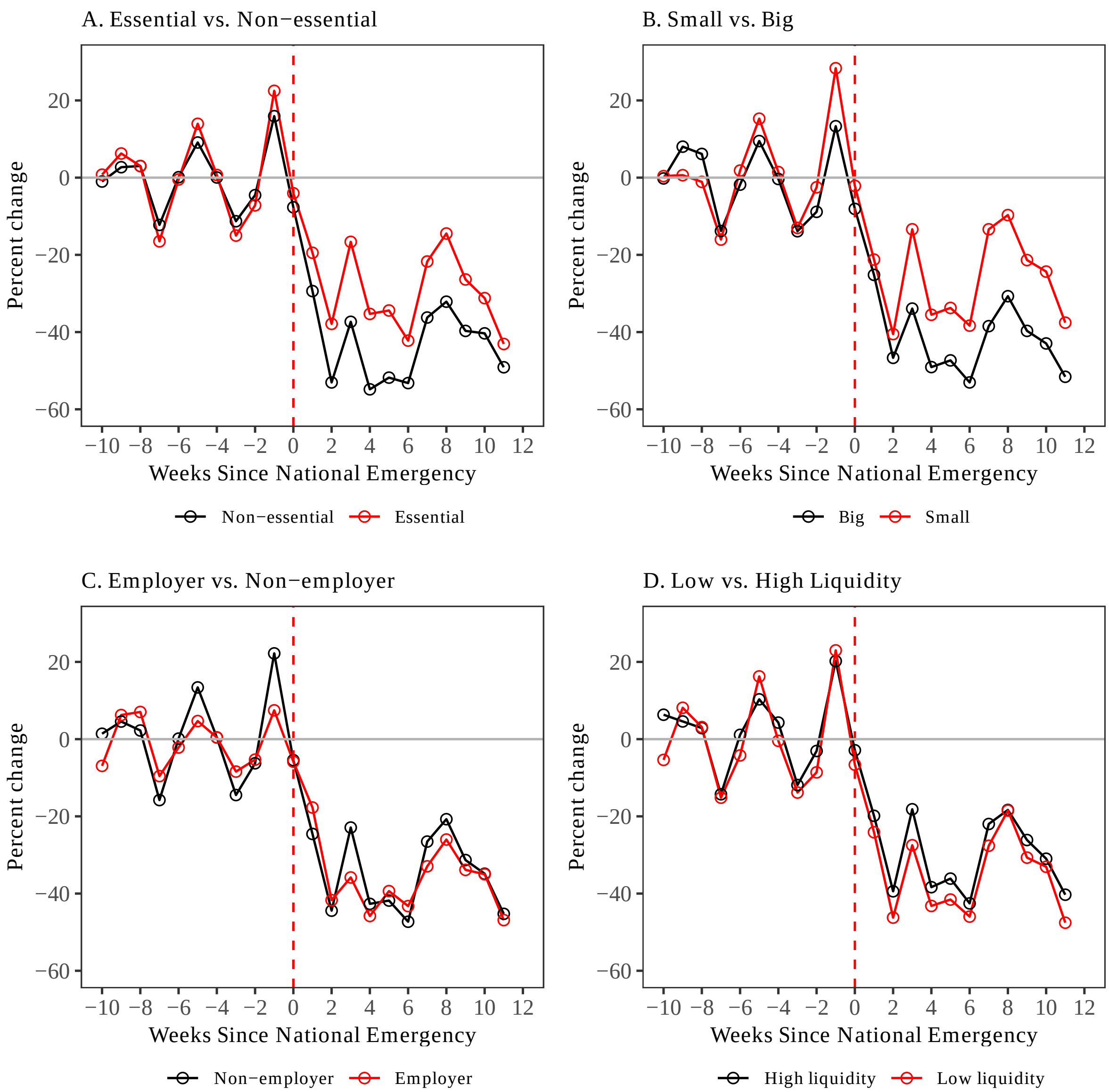
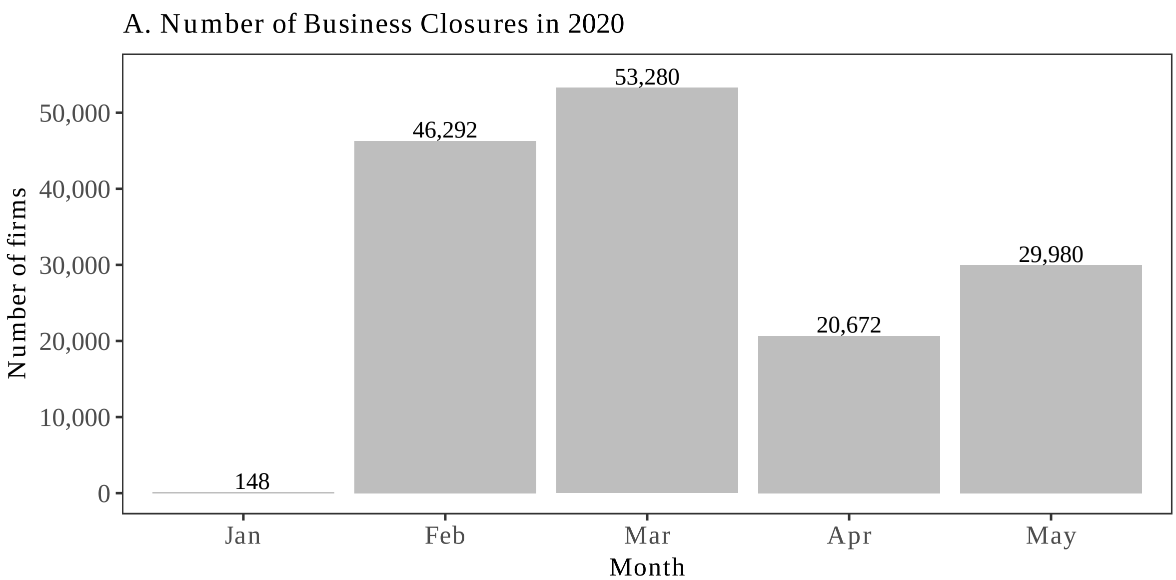


Figure 4: Business closures in 2020

Notes: This figure shows the number of business closures in the all businesses sample in 2020 by month. This sample includes 1.8mil businesses that were active in 2019 and have an open account for at least one month in 2020. Panel A shows the number of business closures by month, and panel B shows the cumulative number of business closures. Exit is defined as the closure of a business checking account. If a business has two business checking accounts, both accounts must be closed to be coded as exit.



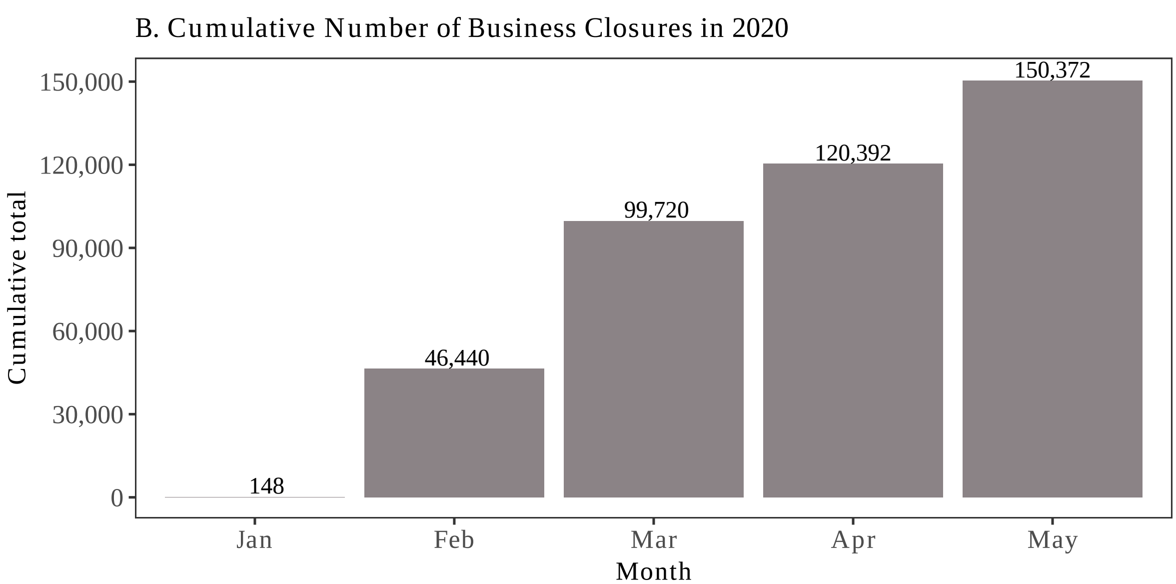


Figure 5: Average business expenses in 2020 across spending categories

Notes: This figure plots detailed categories of average weekly dollar levels of business expenses in 2020. See section 1.2 for details on business expense categorization. "Goods" expenses are plotted in black. "Services" are plotted in blue. "Other major expenses" are plotted in red. Uncategorizable cash, check, or wire transfer expenses are plotted in green. Dotted vertical lines denote the week of national emergency, which was declared the week starting March 9th, 2020.

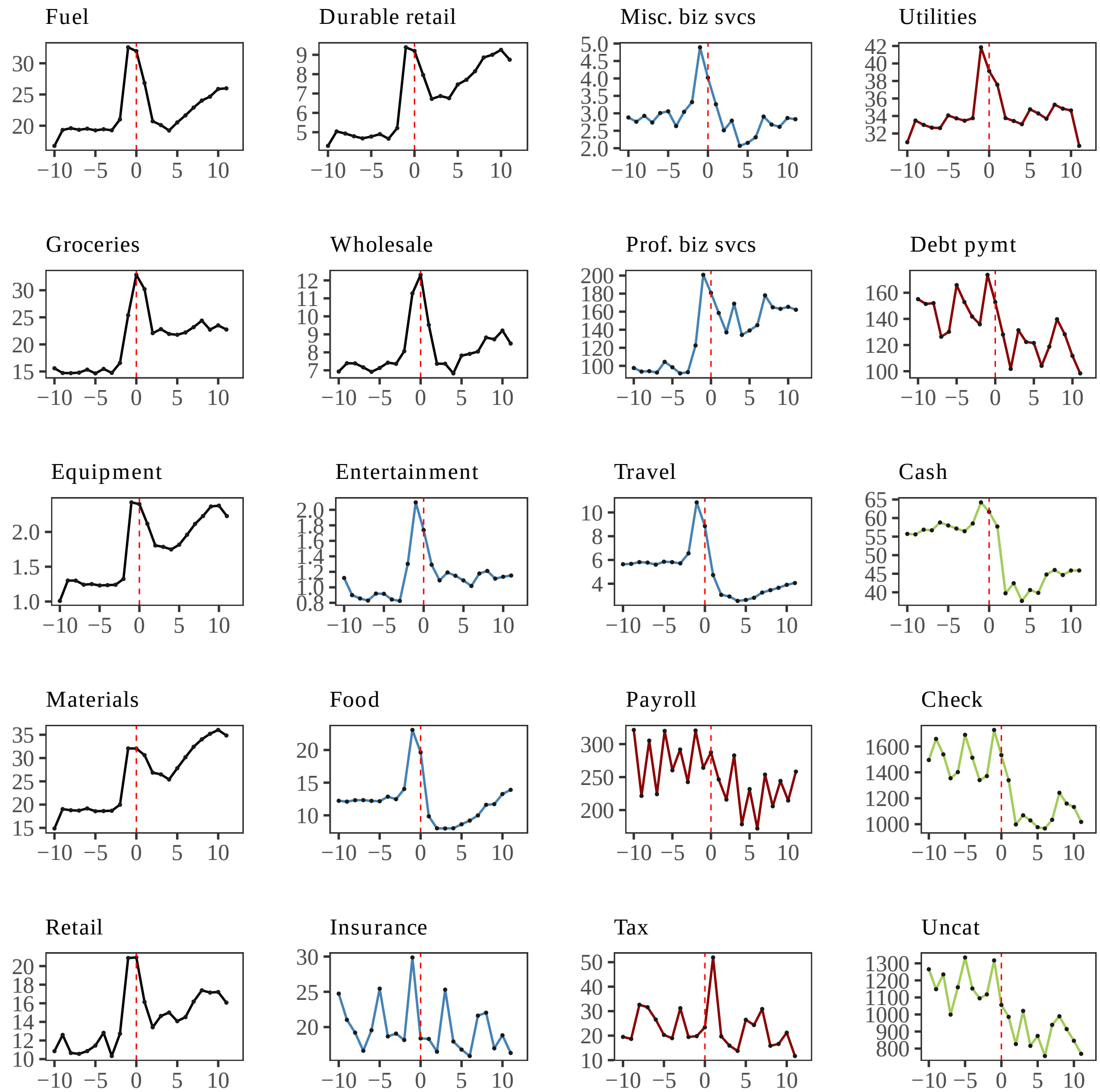


Figure 6: Average household expenses in 2020 across spending categories

Notes: This figure plots detailed categories of average weekly dollar levels of business owner's household expenses in 2020. See section 1.2 for details on household expense categorization. "Goods" expenses are plotted in black. "Services" are plotted in blue. "Other major expenses" are plotted in red. Uncategorizable cash, check, or wire transfer expenses are plotted in green. Dotted vertical lines denote the week of national emergency, which was declared the week starting March 9th, 2020.

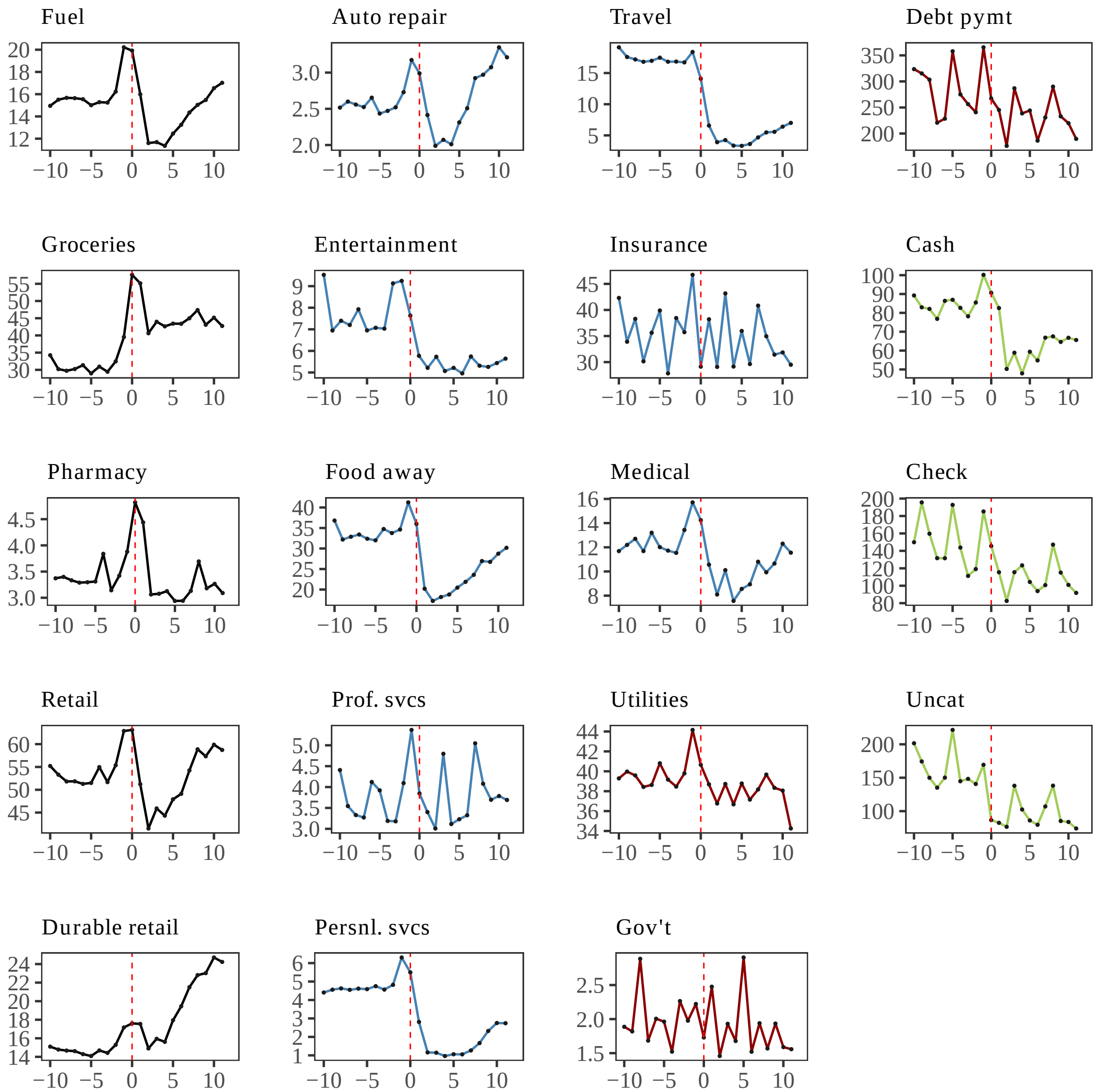


Figure 7: Share of states with NPI policies in effect

Notes: This figure shows the share of states that have respective NPIs enacted over time. Dotted vertical lines denote the week of national emergency, which was declared the week starting March 9th, 2020. For example, panel A shows that more than 80% of the states in our sample imposed shelter in place restrictions 5 weeks into the national emergency. ”Nonessential”, ”Public venue”, ”Religious gathering”, and ”School” refer to closures or restrictions on the said activities. The numbers in parenthesis for ”Gathering limit” restrictions refer to gathering limits (e.g., limit of 10 people). Source: State-level NPI data are obtained from Keystone Strategy.

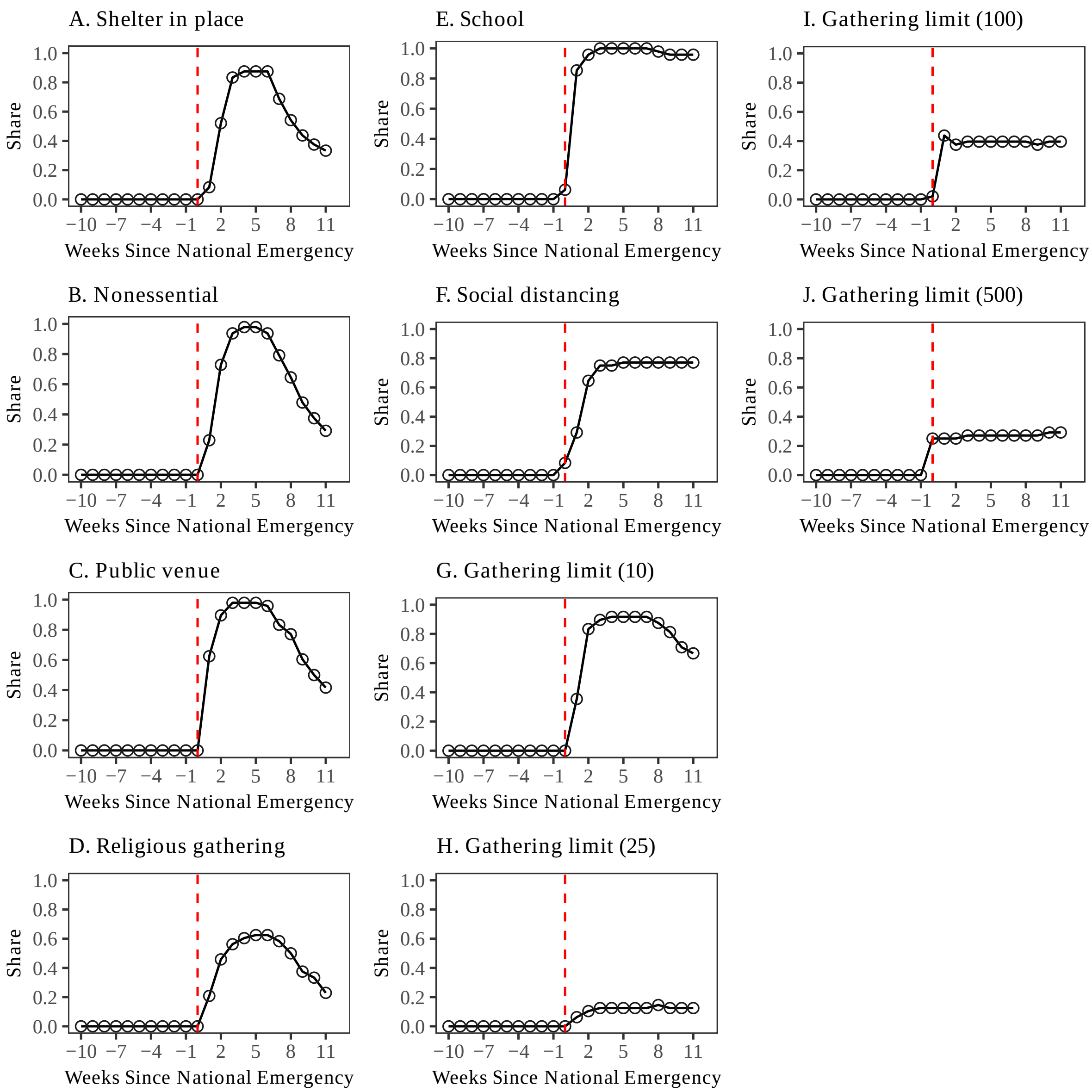


Figure 8: County-level infections per capita

Notes: This figure shows county-level infections per 1,000 residents for three counties that illustrate areas with low, medium, and high-risk for disease growth. Disease growth is determined using terciles of cumulative infection rates per 1,000 in the county. Counties with lower than the first tercile of cumulative infection rates (1.01) are classified as ”low-risk” counties; counties with infection rates above the first but below the third tercile (2.94) are ”medium-risk”; and those with above the third tercile are ”high-risk” areas. The counties illustrated in this figure have the highest cumulative infections per 1,000 residents within each risk bin. Panel A plots the number of new cases and panel B plots the cumulative number of cases per 1,000 residents. For panel A, the example counties with low (Colorado, TX) and medium (Dakota, MN) caseloads use the left axis. The example county with high (New York, NY) use the right axis. County-level population corresponds to total population estimate as of July 1, 2019. Dotted vertical lines denote the week of national emergency, which was declared the week starting March 9th, 2020. Source: Population data from the U.S. Census Bureau and Coronavirus data from New York Times, based on reports from state and local health agencies.

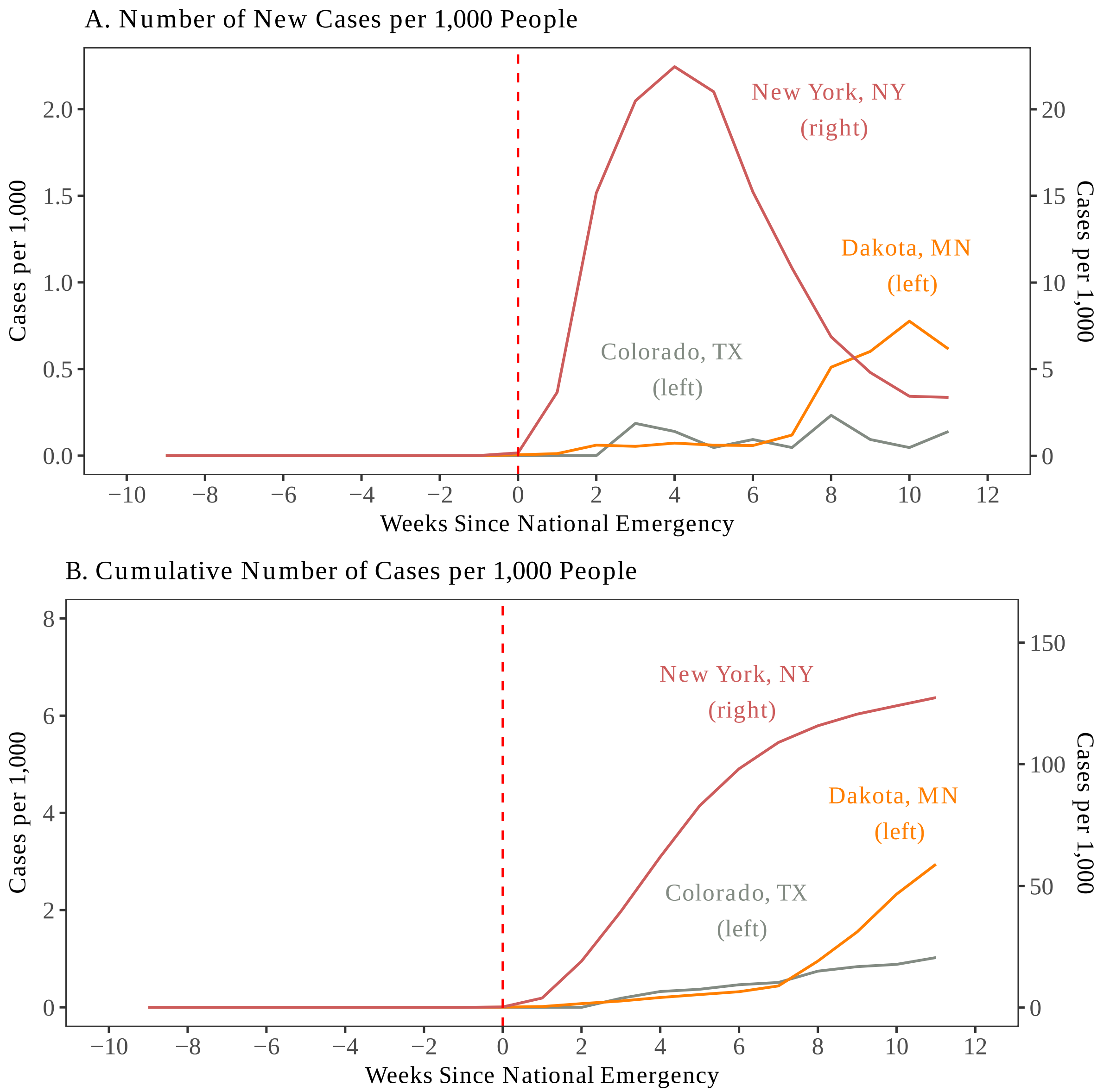


Figure 9: Average county-level infection rates per thousand and shelter in place by week

Notes: This figure shows the average county-level infection rates per 1,000 residents (red) and the share of states that enacted shelter in place order (black). The red line shows that the average county-level infection rates at the peak corresponds to 0.48 cases per thousand residents. The black line shows that at most 87% of states in the sample have enacted shelter in place. County-level population corresponds to total population estimate as of July 1, 2019. Source: Population data from U.S. Census and Coronavirus data from the New York Times, based on reports from state and local health agencies. NPI data from Keystone Strategy.

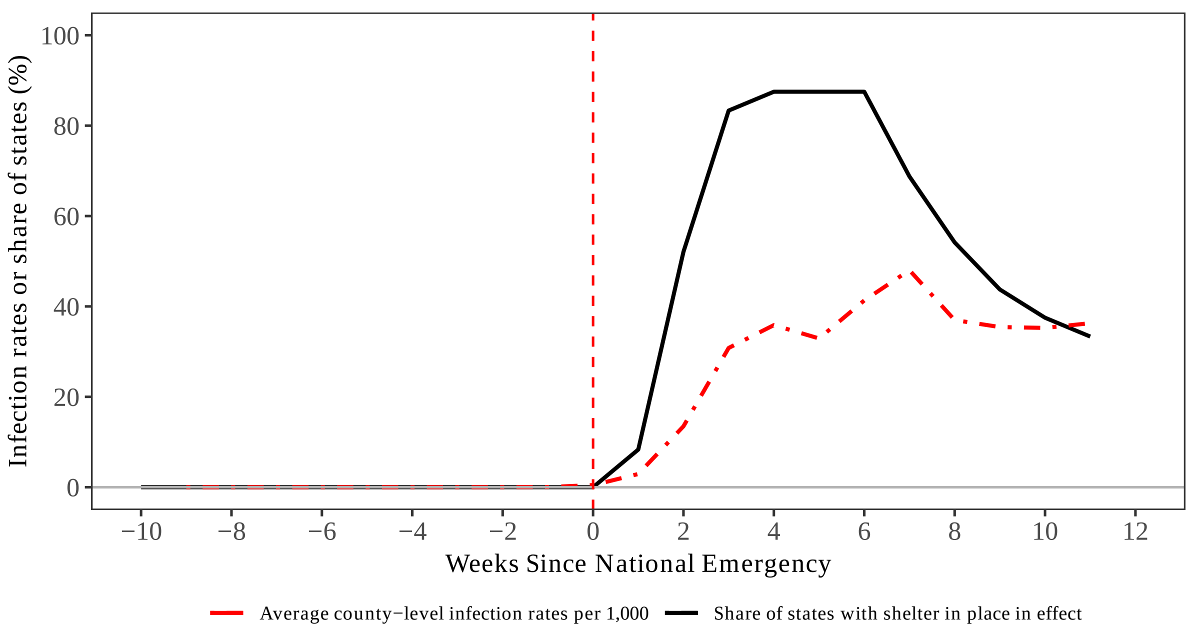


Figure 10: Decomposition of average changes in business outcomes and household consumption

Notes: This figure shows a decomposition of the observed decline in business outcomes and owner's consumption. Outcomes are normalized by the centered 9-week average from a year ago, and the change is defined as a percent change from its own average between January 13, 2020 and February 9, 2020 (i.e., two months before the week of national emergency). Black lines plot average weekly changes in respective outcomes. Red and blue lines plot average changes net of changes predicted by the effects of local infections and SIP on these outcomes. Specifically, we subtract predicted changes in outcomes using the estimated effects of local infections and SIP reported in columns 5 and 6 of Table 3 that include time effects (blue) and do not include time effects (red): $Y_{i,t} - \hat{\beta}_1 D_{c(i),t} - \hat{\beta}_2 1[\text{SIP}_{s(i),t}] - \mathbb{X}_{i,t}$. Since the combined effects of local infections and SIP on revenues, for example, are negative, the red line in panel A can be interpreted as average changes in revenues that would have prevailed in the absence of changes in infections, SIP, or other factors that correlate with infections and SIP. The gap between the black and red lines capture the effect of revenue changes explained by infections and SIP. Since the blue lines are constructed using estimates including time-effects, the gap between the blue and black lines capture the effect of local infections and SIP that is solely driven by cross-sectional differences. Dotted vertical lines denote the week of national emergency, which was declared the week starting March 9th, 2020.

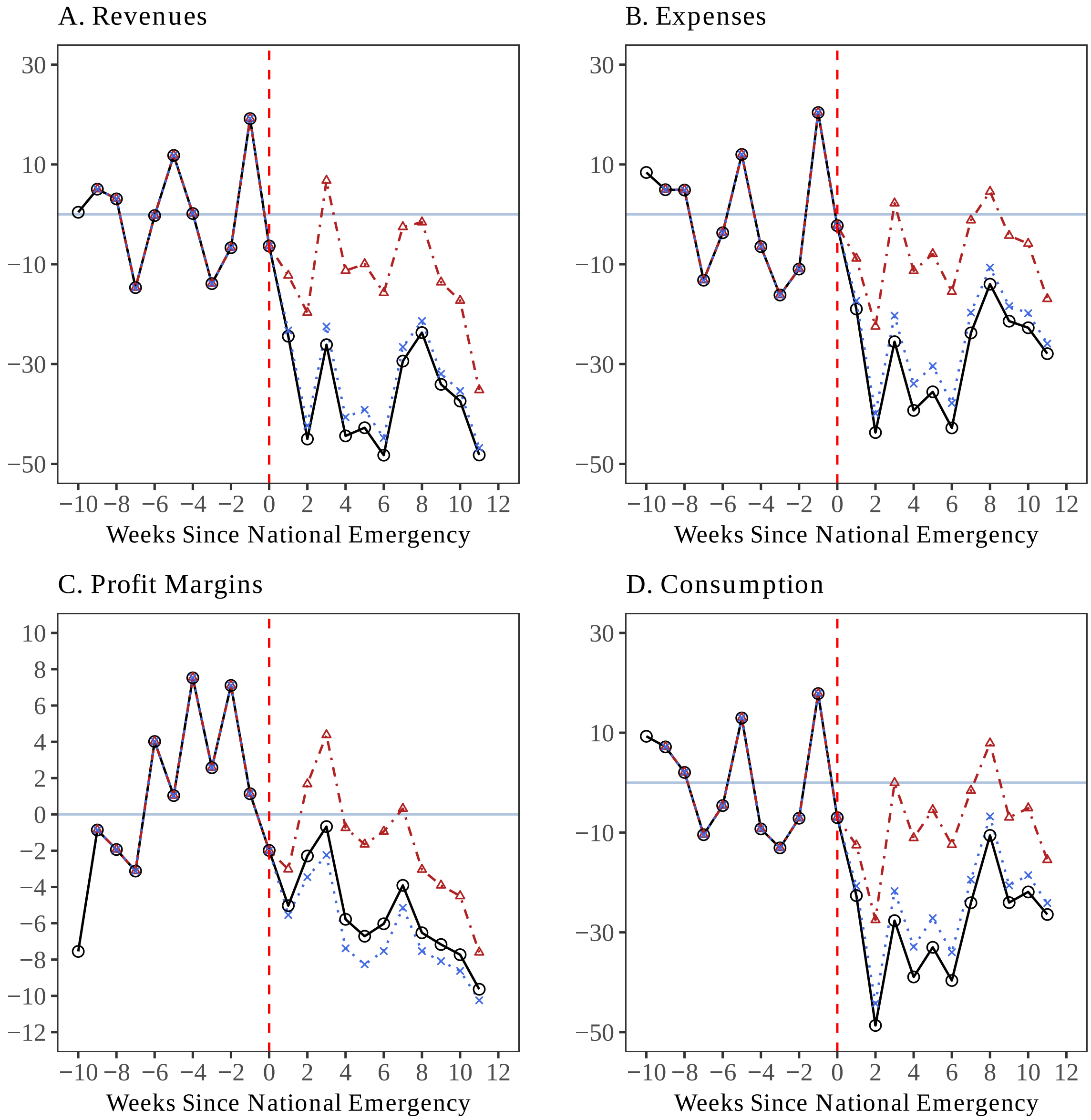


Figure 11: Average changes in business revenues and owners' consumption by industry performance

Notes: This figure shows average weekly changes in business revenues (blue) and owners' consumption (red) for businesses in the most and the least affected industries. Outcomes are normalized by the centered 9-week average from a year ago, and the change is defined as a percent change from its own average between January 13, 2020 and February 9, 2020 (i.e., two months before the week of national emergency). Dotted vertical lines denote the week of national emergency, which was declared the week starting March 9th, 2020. Solid lines show the average change in outcomes for the five least affected (i.e., best performing) NAICS 4-digit industries in terms of their average drop in revenues since the onset of the national emergency, and dashed lines show the average change in outcomes for the least affected (i.e., worst performing) industries. For this analysis, we restrict the sample to industries with at least 100 businesses. The least and the most affected industries are reported in Appendix Figure A.10.

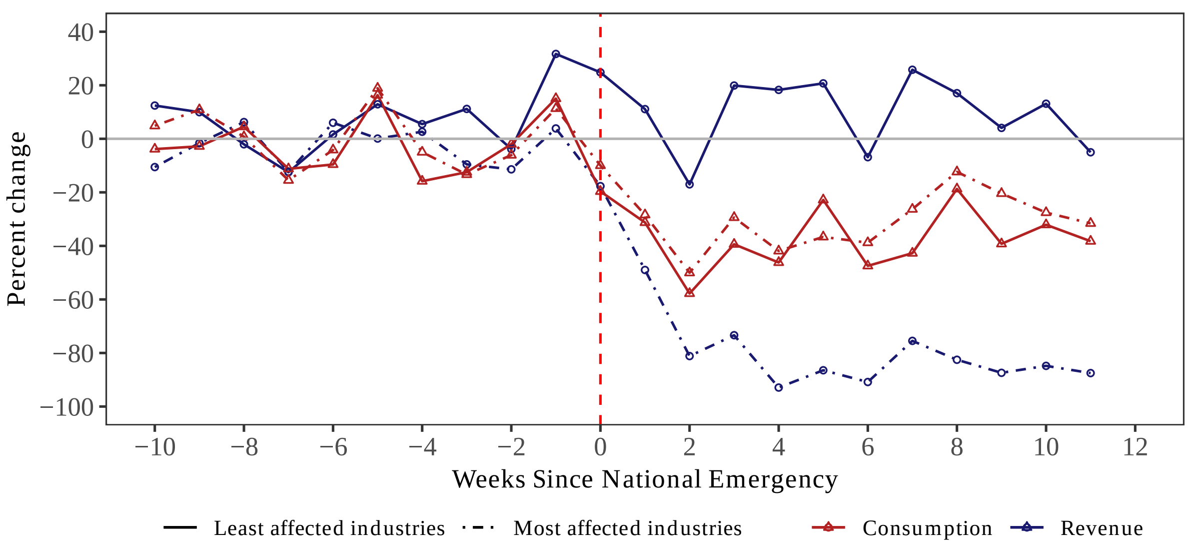


Figure 12: Median business and owner's checking account balances from January

Notes: This figure shows median end of month business (blue) and owner's personal (red) checking account balances. Panel A shows median dollar levels of account balances and Panel B shows median percent change in account balances since January, 2020. For panel A, owner's personal checking account balances use the left axis and business checking account balances use the right axis.

Figure 13: Median changes in checking account balance by industry performance

Notes: This figure shows median changes in end of month business (blue) and owner's personal (red) checking account balances from January, 2020 by industry performance. Solid lines show the for the five least affected (i.e., best performing) NAICS 4-digit industries in terms of their average drop in revenues since the onset of the national emergency, and dashed lines show the average change in outcomes for the least affected (i.e., worst performing) industries. For this analysis, we restrict the sample to industries with at least 100 businesses. The least and the most affected industries are reported in Appendix Figure A.10.