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BUSINESS RE-OPENING DURING THE COVID-19 PANDEMIC

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ABSTRACT

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Abstract

The COVID-19 pandemic led to dramatic economic disruptions, including government-imposed restrictions that required millions of American businesses to temporarily close. We present three main facts about business decisions to reopen at the end of the lockdown, using a nation-wide survey of thousands of small businesses. First, the plurality of firms reopened within days of the end of legal restrictions, suggesting that the lockdowns were generally binding for businesses - although a sizable minority delayed their reopening. Second, decisions to delay reopenings were not driven by public health concerns. Instead, businesses in high-proximity sectors planned to reopen more slowly because of expectations of stricter regulation rather than concerns about public health. Third, pessimistic demand projections played the primary role in explaining delays among firms that could legally reopen. Owners expected demand to be one-third lower than before the crisis throughout the pandemic. Using experimentally induced shocks to perceived demand, we find that a 10% decline in expected demand results in a 1.5 percentage point (8%) increase in the likelihood that firms expected to remain closed for at least one month after being legally able to open.

1 Introduction

The COVID-19 pandemic led to economic disruptions that have not been seen since the great depression (Baker et al., 2020; Bartik et al., 2020; Forsythe et al., 2020). Government-imposed restrictions or lockdowns, including regulations on what businesses could operate, forced millions of businesses throughout the United States to temporarily shut down. At the time of the lockdowns, there was some optimism that lifting regulations would result in a speedy recovery. For example, then-President Trump tweeted that if we "reopen our country" then businesses will rapidly come back online because "our people want to return to work." At the same time, important barriers to reopening may have existed even absent restrictions. An important input for understanding the efficacy and need for regulation is understanding how small business owners responded both to pandemic-related risks and to government-imposed operating restrictions.[1]

[1] The pandemic has led to some unusual patterns when compared to typical business cycles. Moscarini and Postel-Vinay (2012) show that small businesses are less sensitive to standard negative aggregate productivity shocks.The pandemic recession appears to be different from business cycle fluctuations they consider. We find small businesses are hurt by demand side factors, including lockdowns, in-person restrictions, and lower demand due to contagion fears.

First, business owners might have concerns about their own health, as reopening may have exposed them or their employees to COVID-19 as the disease spread. Thus a business that could legally reopen may have chosen to delay. Second, the enormous dislocation associated with the pandemic may have created coordination problems up and down the supply chain – making it difficult for businesses to reopen. Third, even before any government policies were imposed, many households began self-isolating to reduce the risk of transmission of COVID (Couture et al., 2020; Glaeser et al., 2020; Gupta et al., 2020; Sears et al., 2020). Thus, businesses faced significant demand reductions that predated the lockdowns. Businesses might have expected that lower demand– even after restrictions were lifted– would provide insufficient margin to cover the fixed and variable costs of even limited operations.

In this paper, we investigate businesses' decisions about reopening. We ask how sensitive were business re-opening decisions to regulatory restrictions versus other factors, such as health concerns, demand expectations and supply chain factors? To answer this question, we use responses from a survey of tens of thousands of small businesses conducted by the small-business network Alignable in early May of 2020. An information provision experiment on customer demand projections embedded in the survey allows us to recover causal estimates of the link between expected demand and intentions to reopen. To understand other factors influencing business operations, we merge the survey-experiment results with O-NET data on workplace conditions, crowd-sourced data on industry attributes, and county level data on COVID prevalence and related covariates.

Our first main finding is that regulations were a binding constraint for firms' operating decisions, suggesting that firms would not have remained shutdown several months into the pandemic without government-imposed orders to do so. The modal owner reported an intention to open immediately after the lifting of legal restrictions on operations. The median firm owner expected to open two weeks after legally being able to open. We corroborate this suggestive evidence on the binding nature of restrictions by studying actual re-opening decisions following the surprise lifting of two state restrictions. Wisconsin and Florida lifted restrictions due to a surprising State Supreme Court order, and an executive order[2], respectively. Through the summer and fall, we conducted follow up surveys to trace whether owners projections about reopening could be corroborated. Our follow up surveys and difference-in-differences analyses show that lifting regulations resulted in owners reopening more quickly compared to comparable firms in other states.

While our results show that regulations and lockdowns do constrain owner behavior, they do not capture the full picture for all owners. Eighteen percent of firms reported intentions to delay reopening at least one month after the end of restrictions on their operations, and this estimate is likely a lower bound. Why do these businesses expect additional delay? Our second main finding is that expectations of prolonged low demand play an important and causal role in explaining re-openings that are delayed beyond the lifting of regulation. Overall, the demand projections were grim. Heading into the summer of 2020, the average firm in our sample expected that demand for

[2]The executive order extended "full phase one" reopening to all counties. This reopening included the statewide reopening of indoor dining, retail, gyms, and libraries and museums at 50% capacity.

their services would be 35.3 percent of pre-crisis levels the following fall.[3] Other factors, such as health concerns and supply chain concerns, play a more minor role in delaying re-opening. For example, only 5% of firms that were not fully open at the time of the survey cited supply concerns as a barrier that would prevent reopening. Furthermore, the interaction between local COVID case loads with measures of physical proximity to coworkers or customers, owner age or share of high-risk older customers do not offer additional explanatory power for the timing of individual business re-openings.

All sectors were hard hit, but the drop in demand was expected to be most severe in three sectors: educational services, food and accommodation and arts, and entertainment and recreation. Demand projections were more optimistic for essential businesses, for businesses with older customers, and for businesses whose service cannot be provided online. We also find a correlation with political preferences: the Republican vote share strongly and positively predicts higher levels of projected future demand.

These demand reductions lead to delayed openings, as firms with higher expected demand in the future are more likely to report opening quickly. To provide a causal interpretation, we use an instrumental variables approach to estimate the link between future demand and the intentions to reopen. We instrument for future demand using a survey experiment that presented aggregated projections about similar businesses' anticipated future demand to a subset of owners. We expected that receiving information on demand from similar businesses would cause owners to update their own beliefs, as observing information about overall demand may be hard to ascertain for individual owners. Optimistic owners receiving the information rationally shift beliefs downward, while pessimistic owners have rosier forecasts after receiving the information treatment. Comparing firms with similar initial beliefs, but with different information treatments, reveals that delayed reopening hinged on customer demand. Over the longer-term, consumer demand is correlated with the firm's reported expected probability of surviving until the end of the year.

Our evidence from early in the pandemic suggests owners were eager to return to work despite salient reports on health risks and an uncertain disease progression. This response to health risks diverged from the behavior of consumers - who remained hesitant to frequent small businesses (Chetty et al., 2020; Glaeser et al., 2020). These divergent responses raise new questions: did small business owners believe they could adapt practices to operate safely? Were they desperate for operating revenue? Did stimulus packages encourage re-opening before owners would have otherwise chosen to open? We shed some light on these questions in this paper. We asked owners whether they would choose to open or close over two weeks if they received a grant. We randomized the size of the grant, and whether or not the grant included a requirement that the business remain closed. When the grant was not conditional on closing, around three-quarters of businesses chose to open regardless of the grant size, even when the grant was close to 0 or as large as $50,000. Hence, we find no evidence that additional funds helped "tide over" businesses,

[3] Unfortunately, we do not have price data, unlike Jaravel and O'connell (2020), so we focus on the share of customers returning relative to before the crisis.

allowing them to cover fixed costs while remaining closed in order to weather the health risks of the pandemic. When the grant was conditional on closing, half of small businesses would remain closed for an additional two weeks in exchange for a modest sum of $2,500, but a quarter of firms would reject $25,000 to reopen immediately. This indicates that for about a quarter of businesses, opening was perceived to be extremely valuable. For the majority of firms, the benefits of reopening for two weeks is limited but of higher value than being closed. These results suggest that stimulus packages with modest incentives to change operating status, such as the Payroll Protection Program's incentives to continue active employment, likely shifted the decisions these firms on the margin.

Firm behavior during the pandemic has received less attention than the consumer response. Thus far, research on the pandemic has documented several features about the consumer response to COVID-19. The response included a rapid and dramatic reduction in mobility, which has now been documented with cellphone data in a large number of papers (Brinkman and Mangum, 2020; Couture et al., 2020; Glaeser et al., 2020). The reduction in mobility also occurred outside the U.S., and it often preceded formal legal rules (Abu-Rayash and Dincer, 2020; Cintia et al., 2020; Huang et al., 2020; Linka et al., 2020; Soucy et al., 2020). These declines in mobility echo centuries of people responding to plagues by either sheltering in place or taking flight. In the 19th century, according to Rosenberg (1987), "the appearance of cholera in even the smallest hamlet was the signal for a general exodus of the inhabitants, who, in their headlong flight, spread the disease throughout the surrounding countryside."

Neither flight nor immobility, however, necessarily implies reductions in business activity or economic dislocation. Samuel Pepys' diary kept during the London plague from the Summer of 1665 may provide the earliest direct discussion of purchasing behavior during a pandemic. Pepys continued to engage in some face-to-face retail buying during the outbreak of bubonic plague, but shunned other forms of commerce. On July 14, 1665, he "bespoke two fine shirts of my pretty seamstress."[4] On September 3, he wondered "what will be the fashion after the plague is done, as to periwigs, for nobody will dare to buy any haiire, for fear of the infection, that is had been cut off of the heads of people dead of the plague."[5]

More recently, many papers have shown pandemic induced declines in foot traffic to stores and expenditures using GPS data and transaction data as in Baker et al. (2020); Chetty et al. (2020); Dunn et al. (2020); Goolsbee and Syverson (2020); Sheridan et al. (2020); Velde (2020). The majority of these papers find a strong relationship between spending and health considerations, while regulations play a more minor role. However, there are exceptions: Coibion et al. (2020) estimate a significant impact of the lockdowns themselves. Alexander and Karger (2020) also document that stay-at-home orders before March 27th had a large impact. In sum, on the demand side (at least in the early days of COVID) the pandemic itself seemed to have an independent impact on mobility and consumer purchasing that is much larger than the impact of regulations. But this analysis has

[4]https://www.pepysdiary.com/diary/1665/07/14/

[5]https://www.pepysdiary.com/diary/1665/09/03/ In the same year, the village of Eyam appears to have caught the disease from wool cloth that was shipped to a local tailor from London.

little to say about the firm side.

In the absence of health concerns, a risk-neutral employer might make a calculation based on the expected profit of opening and the carrying costs of closing temporarily versus shutting down entirely. Conditional on remaining open in some fashion, the firm would also consider the financial returns to mitigating health hazards. These calculations would depend on firm expectations about customer demand, and employee productivity given risks of contagion. However, recent research on "behavioral firms" raises the possibility that owners making decisions may be just as likely as consumers to fear contagion personally, and make decisions with these personal fears in mind (DellaVigna and Gentzkow, 2017).

Empirically, there is little evidence that 18th or 19th century firms paid much attention to the safety of their workers, and illness often spread through the dense confines of the early factories. However, a primary reason why employers may choose to reduce workplace safety risk is that workers will demand higher wages for riskier jobs, and labor was often unpaid or could not move freely under feudalism.[6] The United Kingdom's first significant workplace safety regulation, the "Health and Morals of Apprentices Act," passed in 1802 when Sir Robert Peel, the Act's sponsor, faced repeated outbreaks of "malignant fever" at his own factories. Regulation may have been used to impose costs on competitors, or equalize costs of providing healthy working conditions across firms. By the late 20th century, firms had a stronger incentive to invest in safety even without regulation since workers increasingly demanded higher wages for riskier work (Black and Kniesner, 2003).

What did firms do in response to the Influenza Pandemic of 1918-1919? In some cities, they were forced to comply with local closing regulations, but business closures were well described by *Bradstreet's Journal* as "below anything witnessed for a third of a century," according to Velde (2020). Firms, including coal mines, scaled back production because so many of their employees were sick, but Velde (2020) does not find that firms proactively shut down to reduce the risk of illness to either employees or workers. Moreover, as we discussed above, the shocks to demand were of limited duration.

The literature on the 2020 Pandemic seems to confirm that consumer demand in many industries fell dramatically because of COVID-19, and many firms closed. Yet there is little clarity about whether the firms are shut because of reduced demand or because of other issues, including both suppliers' fears of contracting disease or bankruptcy. Bartik et al. (2020) provided an early survey of small businesses that found that 45 percent of their sample was not in operation around April 1, 2020. Closure rates were much higher for businesses that dealt in face-to-face services, like the arts, than in information services, like finance. Similarly, Fairlie (2020) found that the "number of active business owners in the United States plummeted by 3.3 million or 22% over the crucial 2-month window from February to April 2020."

[6] Fishback and Kantor (2000) examine whether 19th century employers really did have to pay their workers more to put up with less healthy conditions. They find that "child workers received higher hourly earnings in industries associated with more days lost to illness, but adult workers generally did not" suggesting that employers had little incentive to promote safety from illness.

Chetty et al. (2020) also look at business closures, which they measure as a business with zero credit card payments over multiple days, effectively combining temporary and permanent closures. They estimate that business closure regulations explain almost fifteen percent of the variation in business closures over time and space, which is modest but far more than the variation these regulations explain for spending or employment. They do not try to distinguish whether the businesses are shut because of reduced demand or concerns for worker safety. Papanikolaou and Schmidt (2020) look at the default probabilities that are implied by the premium firms must pay in their borrowing. They find both that employment drops more during the pandemic in industries which cannot easily switch to remote work, and that markets expect more defaults in those industries. They interpret this as a labor supply shift due to the pandemic, but it is difficult to differentiate between consumer demand and labor supply using their measure. de Vaan et al. (2020) find that the closing decisions of national brands also influence the closing decisions of community establishments nearest the establishments of the parent brand, suggesting local social learning.

Our paper contributes to this literature by assessing the importance of consumer demand, supply-side factors and the extent to which business owners internalize the risk of contagion when choosing whether to reopen. Weighing these relative factors helps inform policy decisions about whether to regulate businesses and how best to channel resources to them. For example, our results suggest that stimulus packages that boost consumer spending can in turn encourage the re-opening of small businesses. Our results also suggest that the voluntary behavior of small businesses is unlikely to help mitigate health risks in the absence of sweeping regulation. Legal restrictions on business operations were binding and that health concerns generally did not prevent businesses from reopening. Our results also suggest that expectations about depressed consumer demand caused some firms to delay re-opening when it was legal to do so.

2 Data Sources

The small business owner data used in our analysis was collected through surveys conducted by Alignable, Inc. Alignable is the largest network and community of Small Business Owners in North America. We combine the survey data with Alignable's business profiles, O-NET details about physical proximity of working conditions at the industry level, and data on geographic variation of COVID-19 cases obtained from the New York Times. Together, these data help to shed light on the factors driving business decisions about whether to reopen.

In this section, we describe the Alignable survey, its representativeness compared to Census data, and detail the other data sources used in the analysis.

2.1 About Alignable and the Alignable Small Business Survey

The Alignable platform has approximately 5 million registered small businesses across North America. Each week, Alignable distributes a survey link through email to their members. This link allows them to merge the individual responses of participants to data from their user profiles.

Our primary sample comes from one wave of Alignable surveys that focused on business reopening, with the link emailed out to users on May 9, 2020. This survey received 35,069 total responses to at least one question. 27,263 respondents completed all core questions that form the bulk of the analysis. The core questions contained several modules. The first module collected information about the current operational status of the business (fully open, partially open, temporarily closed, permanently closed) and any potential dependencies with other businesses that may affect their decision to fully open or their ability to remain fully open.The second module asked about future expectations about the return of customers to their business. To get an estimate of conditions on the ground, independent of the operational status of the business, owners were asked about the share of customers that would return in the event that they were fully open on a specified date in the future. The future date was randomized over survey respondents, allowing us to trace out owners' expectations about the pandemic over varying horizons. To further separate the evolution of the pandemic from individual circumstances and to trace out dependencies between businesses, an additional question asked about the expected reopening of other businesses. In the third module, respondents were asked about when they expected legal restrictions impacting their business to be lifted, and when they would be most likely to re-open fully if they were not fully open at the time of the survey. A final question asked about the likelihood that the business would be operational come December 2020.[7]

In the middle of the survey, before questions regarding expected demand and expected reopening and survival, a subset of respondents were shown information about how prior survey respondents had projected demand. The message read "based on your profile, location, and concerns, our polls show that similar businesses anticipate [X%] of customers will return by [date]. The variable X was calculated using data from the first 16,038 respondents. One third of the respondents after the first batch received this message."[8] The complete survey tool is available in the Appendix. Table 1 Panel A provides more detail about the data and the measures collected from the main May 9 survey.

We supplement this survey wave with questions from other survey waves. From earlier and later survey waves, we are able to construct a time series of business operational status and demand using responses from 190,600 unique business owners from March to September, 2020. We merge in demographic details about the owner's age and industry collected by Alignable in later surveys. We also include data on industry classification that comes from respondents entering their industry using a JavaScript predictive text entry box. Available options were the text of 4 and 6 digit NAICS industry descriptions. We also use a question, delivered toward the end of May in an external survey conducted by Harvard Business School, to assess how participants would evaluate tradeoffs between cash and health considerations. We presented users with a hypothetical grant, in amounts we randomized between \$2,500 and \$50,000. The grant could be one of two types: either the grant stipulated that the business would have to remain closed for two weeks to receive the

[7] A module tracking responses to CARES Act PPP status came prior to the final question about long-term business operations prospects, causing drop off to 17,098 completed responses for this last question.

[8] One third of respondents saw a different message, but its mapping to a concept like demand is less clear.

grant, or the grant did not have conditions for receipt. We then asked users whether they would remain closed over the next two weeks under their particular hypothetical grant condition.

2.2 Comparison of Survey Responses with US Census Data

One challenge in conducting surveys of businesses is the potential for selection bias. This sample is selected in two ways: (1) they are firms that have chosen to join Alignable, (2) they are Alignable firms that have chosen to take surveys. Bartik et al. (2020) provide a variety of diagnostic checks for a survey of Alignable businesses conducted in late March / early April to assess its representativeness, and shed light on sample selection. The sample provides broad coverage across the United States, across industries, and across business size (within small businesses). Roughly speaking, the sample matches Census data reasonably well along the dimensions of industry and geography, but the sample skews toward smaller businesses relative to the full set of US small businesses. A cross-validation against a phone survey suggests that these surveys provide reasonable estimates of business closure, though the random phone survey suggested the survey might over represent closed businesses.[9] This is consistent with expectations of Alignable executives, who believe that owners of permanently closed businesses will be less likely to respond to surveys.

Validation exercises of the May 9 survey wave reach similar conclusions to those in Bartik et al. (2020), indicating that the survey has nearly representative coverage by firm size and geography (see Appendix Figure A1). Appendix Figure A2 displays how closures co-vary with the local COVID caseload and unemployment rate.

2.3 Other Data Sources

Table 1 Panel B provides details about outside data sources that we merged with the Alignable data. We supplement the survey data with detailed characteristics about the industries of businesses at the 4-digit NAICS level. We determine the extent that each industry is able to serve online customers, and the likely age distribution of those customers, by posting a description of each industry on Amazon's Mechanical Turk, and asking a series of questions related to the nature of the industry and its customers. The first question asked is, "how easy or common would it be for this business to provide services or goods online?" The second question is, "how likely is it for customers of this business to fall in each age bracket (listed below)?" We offer answers that correspond with 0-10 percent, 10-25 percent, 25-75 percent and greater than 75 percent. Five unique individual Mechanical Turk responses were collected for each industry code and description. We average responses from these individuals at the industry level. The table presents the raw responses, while later analysis uses Z-Scores for these variables to ease interpretation.

[9] As a test of selection into taking surveys, Bartik et al. (2020) reports the results of randomly calling 400 business owners using the contact information collected by Alignable at registration. The current status of these 400 business owners, open or closed, matches the ratio of open versus closed in a prior survey wave. This suggests that the survey responses are unlikely to understate the degree of businesses being permanently closed, at least conditional on having registered with Alignable.

We collect information at the occupational level about the proximity of employees with each other and with customers the O-NET proximity variable "To what extent does this job require the worker to perform job tasks in close physical proximity to other people?" The underlying encoding of the proximity measure ranges from "I don't work near other people (beyond 100 ft)" as the lowest category to "Very close (near touching)" as the highest category. We follow Mongey and Weinberg (2020) by merging the O-NET version 24 proximity variable to the Occupational Employment Statistics (OES) data collected by the BLS. The OES data provides a mapping between occupation codes and NAICS industries. We take the employment weighted average of proximity by 4 digit NAICS code.[10] Data about coronavirus cases at the county level were collected by The New York Times. While coverage is extensive, some counties were grouped together.[11]

Subsequent surveys help with validation exercises and confirm these early responses. Alignable asked about operations status at a monthly frequency at starting at the end of July. We utilize the July, August, and September waves of these surveys to validate our early responses. These surveys asked respondents about the share of customers returning in the previous month, as well as the current operating status of their business. Using a unique account ID, we are able to match respondents in our main survey wave in May to the later surveys. While these surveys are designed as repeated cross-sections, not as panels, in practice we observe more than 3,000 of the initial respondents in at least one of the subsequent surveys.

3 Analytical Framework

To fix ideas about the drivers of re-opening, we consider the following simplified framework. A business owner's decision to open is a function $g(.)$ of consumer demand c_t, supplier availability s_t, owner or employee health concerns h_t, and government regulations θ_t. A government lifts mandatory business closures for firms when COVID prevalence, x_t, is below a threshold. The thresholds may depend on how operations contribute to contagion. For simplicity we consider two types of business, high and low proximity, associated with two different regulatory thresholds, $\tau^{\text{high proximity}}$ and $\tau^{\text{low proximity}}$ respectively. Let θ_t be an indicator for whether the business remains below the threshold and hence, is allowed to be open. Let y_t be an indicator for whether a business is actually open.

Each of c_t; s_t; h_t; and θ_t is a function of COVID prevalence, x_t, and other factors outside the model. Our model predicts that certain characteristics of the business and owner will exacerbate the re-opening response to local COVID prevalence. For example, if health concerns drive re-opening decisions, we predict that personal characteristics of the owner and business, namely owner age, customer age and the proximity of employees interacted with local COVID prevalence

[10]Examples of high proximity industries are retail establishments, personal care (i.e. barber & beauty shops), and restaurants. In contrast, low proximity industries are insurance agents, legal services, designers/architects, and credit intermediaries.

[11]For example, a single value for New York City is reported, comprising New York, Kings, Queens, Bronx and Richmond Counties. The data are available at https://github.com/nytimes/covid-19-data

will be highly correlated with re-opening decisions. If customer demand channels are pivotal for the reopening decision, the model predicts that the risk characteristics of customers, namely age and in-person contact, will interact with local case prevalence to predict re-opening. If supplier availability or downstream businesses clients enter the reopening calculus, the case prevalence local to those businesses will interact with the proximity conditions in those businesses, or essential business status, to predict the reopening decision of the businesses we study.

Hence, we write expected demand for direct-to-consumer (B2C) firms as a function of the interaction of local case loads with customer age, and the demand for business-to-business (B2B) firms as a function of the status of downstream businesses which may in turn depend on COVID case loads and regulations in their local environment, $c(x_t, \{\text{customer risk factors}\})$ or $c(\bar{Y}_t(\bar{X}_t, \bar{\text{T}}_t^{\text{proximity}}))$, where $\bar{Y}_t$ and $\bar{X}_t$ and $\bar{\text{T}}_t^{\text{proximity}}$ refer to the open-status of downstream businesses and their local health and regulatory conditions respectively. The decision function is then

$$y_{\text{type},t}^{\text{proximity}} = g(c_{\text{type}}(.)_t; s(x_t); h(x_t); \theta(x_t; \tau^{\text{proximity}})) \tag{1}$$

Where *type* indicates whether the firm is direct-to-consumer or business-to-business, and $c_{\text{type}}(.)$ is the corresponding consumer demand function for B2C firms, $c(x_t, \{\text{customer risk factors}\})$ or B2B firms, $c(\bar{Y}_t(\bar{X}_t, \bar{\text{T}}_t^{\text{proximity}}))$. To gather evidence about the importance of the health channel x_t in determining the choice to reopen, we make use of our theoretical prediction that the relevance of the local COVID case load increases with the health risk factors of the owner and employees. In other words, if the owner's direct health concerns drive the re-opening decision, then the likelihood of reopening should be falling in the age of the owner, and falling faster with high levels of local exposure to the coronavirus. If the owner is concerned about the health of customers or liability for their health, then the likelihood of reopening should be falling with the share of customers that are in the high risk demographic groups, and falling faster when local exposure to the coronavirus is high. We estimate the equation

$$\begin{aligned} Y_i = &\beta_1(\text{Owner-Age} \times \text{COVID case load}) + \\ &\beta_2(\text{Share Older Customers} \times \text{COVID case load}) + \gamma X_i + \epsilon_i \end{aligned} \tag{2}$$

We estimate this linear function using ordinary least squares regressions. We then check the sensitivity to using OLS on censored outcomes.[12] We proxy for COVID-19 prevalence in the outside population with COVID-19 cases per capita in the county in which the business is located. We jointly address exposure to co-workers and customers by using a measure of workers' physical proximity to others, based on O-NET data. For most firms in our sample, the owner's age is

[12] For open firms, the time to reopening is censored from below at zero. For the closed firms, the time to reopening is censored above because the latest date for reopening they could report was September or later. To address censoring, Appendix Table A4 presents results using a Tobit regression. The results are similar in sign, but the Tobit coefficients when including all businesses are often larger in magnitude.

available in Alignable's administrative data. Customer age is measured through the MTurk survey instrument detailed in Section 2.

To test if firms fail to reopen because of problems further back in their supply chain, we directly ask whether respondents anticipate supply problems or problems with downstream businesses and whether those problems will delay their reopening.

To test the causal role of government regulation on reopening decisions, we are able to use sharp changes in the regulatory environment that occurred in mid-May between two survey rounds to identify how businesses changed their behavior and beliefs when restrictions were suddenly lifted. In Wisconsin, a State Supreme Court decision suddenly lifted restrictions on May 14 [13]. In Florida, an executive order issued by Governor DeSantis on May 14 (effective May 18) accelerated and standardized reopening statewide. We use a difference-in-difference model to compare the changes between survey rounds (running from May 9 to May 13 and then from May 14 through June 1) in Florida and Wisconsin to the changes in the other states.[14]

We estimate the following equation, where Y_i is the re-opening decision of business owner i, or the projected demand of business owner i.

$$Y_i = \delta\left(\text{Reopened State}_i \times \text{Post}\right) + \beta_1 \text{Post} + \beta_2 \text{Reopened State}_i + \gamma X_i + \epsilon_i \tag{3}$$

Post is an indicator equal to one for responses after the shocks to regulations. Reopened State$_i$ is an indicator equal to one for responses in states that experience the surprise reopening.[15] X_i contains separate vectors of fixed effects for states and 4 digit NAICS industries, and ϵ_i captures shocks outside the model that we assume are orthogonal to the surprise re-opening. Our coefficient of interest is δ, which identifies the effect of the surprise regulatory changes on outcomes.

To further help us identify the importance of the demand channel, we isolate factors that shift perceptions of future customer demand and yet are orthogonal to COVID prevalence. For example perceptions of future demand can be influenced by the projections of similar business owners (de Vaan et al., 2020), a dimension we vary experimentally. The survey asked all survey respondents that were not permanently closed at the time of the survey to report their expectations regarding future demand. After collecting several thousand responses, we were able to calculate the average expected demand in each region for various types of businesses.[16]

We then randomly assigned the remaining respondents to control and treatment arms. In

[13] The decision was announced late in the evening of May 13.

[14] While the later survey remained open until the following survey was distributed, over 95% of responses were collected by May 18.

[15] We will estimate three versions of this model: in the first, Wisconsin and Florida are both treated. In the second and third versions, we consider Wisconsin only and Florida only, respectively. In the specification looking only at the effect in Wisconsin, respondents from Florida are omitted from the regression (and vice versa) to avoid biasing the estimates.

[16] We created groups of business by pooling together respondents of the same business type (serving business customers or consumers), who gave similar answers to our survey questions about downstream and upstream business dependencies, in the same region of the U.S., and who were asked about the same date in the future.

the treatment arm, the survey revealed predicted changes in demand by similar respondents.[17] Respondents were then asked about their own beliefs about demand and finally about their predicted behavior around re-opening. Respondents in the control group were asked for the demand projections without being shown any information. For individuals whose initial beliefs were below those of similar businesses in the industry/region conditioning set, the revelation pushes beliefs upward. For those with more pessimistic beliefs, the revelation pushes beliefs downward. Overall, beliefs for treated firms should be less diffuse after treatment. As a result, we use the gap between the aggregated information displayed and the initial beliefs as our instrument.

We can express the process by which the information treatment changes demand projections with a Bayesian learning model. In a simple framework, the mean of the posterior belief is a weighted average between the signal and the mean of the prior belief:

$$D_i^{post} = \alpha \cdot D_i^{signal} + (1-\alpha) \cdot D_i^{prior}$$

where the parameter α is the learning rate. The parameter α ranges from 0 (respondents completely ignore the signal) to 1 (respondents fully update their beliefs to exactly match the signal), and depends on the relative precision between the prior belief and the signal (Hoff, 2009).[18]

We can rearrange this identity and write the change in the means of the demand belief distributions as a linear function of the difference between the signal and the mean of the prior.

$$D_i^{post} - D_i^{prior} = \alpha \cdot \left(D_i^{signal} - D_i^{prior} \right) \tag{4}$$

Initial beliefs are elicited through a related set of questions at the beginning of the survey before the information is shared. Because these earlier questions allow us to infer demand expectations (but do not ask about them directly), we combine the questions that precede the information treatment in a linear model, estimated with ordinary least squares, to predict beliefs for the exact question about return customers. The prediction model is estimated only using an early batch of respondents that did not receive any information and who are excluded from the remaining analysis.

Using 16,038 early respondents who were not shown the information treatment, we estimate the model

$$\hat{D}_{i_{training}}^{prior} = \hat{\boldsymbol{\beta}} X_{i_{training}} + \epsilon \tag{5}$$

[17] The precise wording of the message was: "Based on your profile, location, and concerns, our polls show that similar businesses anticipate [X]% of customers will return by [date]." Date in this case is the same date used for subsequent questions about expected demand. These estimates are derived from a subset of the earliest responses to the survey. We used these early responses to estimate these demand signals that were then randomly shown to an experimental subset of the main body of survey respondents.

[18] This form of updating characterises a Bayesian model in which both the prior and posterior distributions are normal with known variance. In our setting with an unknown variance and a variable (demand) that is bounded at zero, an exponential likelihood model is more appropriate. In order to build intuition, we interpret the first-stage coefficients in the simplified normal-normal setting; interpretation of the parameter α becomes more complicated if beliefs are not normally distributed (e.g. follow an exponential distribution).

We use this $\hat{\boldsymbol{\beta}}$ to estimate the implied prior beliefs $\hat{D}_i^{prior} = \hat{\boldsymbol{\beta}} X_i$ using the full matrix X for the experimental sample. This yields a sample analog $\hat{D}_i^{prior}$ of the prior belief distribution in equation 4.

This prediction, and the Bayesian learning model, combine to provide the first stage of this instrumental variables model. Since we experimentally provide the information treatment to only some of the sample, we can write the first stage of the instrumental variables specification as

$$D_i^{post} - \hat{D}_i^{prior} = \gamma T_i \left(D_i^{signal} - \hat{D}_i^{prior} \right) + \lambda \left(D_i^{signal} - \hat{D}_i^{prior} \right) + \beta X_i + \epsilon_i \tag{6}$$

Where T_i is an indicator that evaluates to one if the respondent received the information treatment and X_i is a vector of controls. In this model, γ captures the Bayesian learning parameter, after λ nets out spurious updating (i.e. mean reversion) among respondents who never receive a signal. In the second stage, we can use the exogenous component of the shift in the posterior belief distribution to identify the causal effect of changes in demand projections on reopening plans. This second stage equation is then

$$Y_i = \eta \left(D_i^{post} - \hat{D}_i^{prior} \right) + \beta X_i + \xi_i \tag{7}$$

Where Y_i is our outcome of interest, (i.e. months until reopening, an indicator for a lag of at least one month between expected reopening, and the expected lifting of restrictions and finally the probability that the business would still be open in December 2020) and X_i is the vector of control variables. In the baseline specification, X_i contains controls for the share of similar businesses that are open, current operating status, an indicator for whether or not the business is essential, and the future date to which the demand projections correspond. Additionally, we non-parametrically adjust for time trends in the composition of respondents within the survey by including controls for the time of the response. In an alternative specification, we add industry level controls for physical proximity, ease of doing business online, and the share of customers over 65, as well as county level controls for COVID cases per capita, population density, Republican vote share in the 2016 election, and the age of the owner. We cluster standard errors at the industry level.

4 Results

At the time of the survey (May 9th, 2020), 32% of surveyed small businesses were fully open (offering the same products and services as before the pandemic), 34% were partially open (offering more limited products and services than before the pandemic), 32% had closed temporarily (offering no products and services for a temporary period), and the remaining 2% had closed permanently with no plan to reopen.[19] In Figure 1, we show how the operational status of businesses at the

[19] In the survey received by business owners, the question asking about business status specified that fully open and partially open are respectively defined as ”offering the same” and ”offering more limited” products or services than before COVID. We point out that an alternative definition of partially open could have been premised on employment, however Kurmann et al. (2020) show that businesses very quickly regained employment after re-opening. In our sample, fully open businesses were at 101% of their pre-pandemic employment and partially open businesses were at 93%.

time of the survey vary with respect to industry characteristics, location characteristics, and owner characteristics that are each intended to capture contagion risk experienced by the employees, customers and owner.[20] Most of these contagion-related characteristics are uncorrelated with operating status, including the share of sales that can be carried out online, and share of elderly customers at high risk of serious illness. While measurement error could mask a correlation, the modest relationship between business operating status and health factors is replicated across a number of alternative proxies, with two exceptions: the first being proximity status at the industry level, known to be highly correlated with regulation. High-proximity industries account for a full two-thirds of temporarily closed businesses, but only 37% of fully open businesses. In Panel A of Appendix Figure A4, we show that this gap persists through later survey rounds in the summer and early fall. We also see a correlation with the age of the owner and permanent closures. Closed businesses are more than 25% more likely to have an owner over 65, potentially a category of owners who were considering retirement when the pandemic began.

4.1 Are Regulations Binding?

To distinguish between the effects of restrictions *per se* and the effects of the underlying factors that drive both restrictions and the reopening decisions, we focus on the roughly 66% of businesses that are temporarily closed or partially open. We elicit beliefs regarding their reopening timeline, future regulations (and their expiration), and future demand.

Figure 2 shows the joint distribution of firm expectations about when all lockdown regulations will end (x-axis) and when they expect to fully reopen their businesses (y-axis). The share of firms along the diagonal gives us the share of firms that say that they will reopen fully at the moment that they are legally allowed to do so. The entries above the diagonal represent those firms that expect to take longer to reopen. [21] The plurality expect to reopen as soon as they are able to do so. However, there is also a large minority of owners that anticipate a gap between the expected end of the lockdowns and the expected time of reopening. [22]

Respondents in high and low proximity industries believed they would face different regulatory hurdles. Panel A of Figure 3 shows the cumulative share of firms in a given industry that expect to open fully on or before a given date. About sixty percent of firms in low proximity industries say that they were legally allowed to open at the start of May. Approximately forty-five percent of high

Even if we exclude the top 1% of firms, then fully open businesses were at 97% of their pre-pandemic employment and partially open businesses were at 92%.

[20] Please refer to Section 2 for detailed definitions of each data source represented in this graph.

[21] Somewhat surprisingly, there are also firms that expect to be fully open before the restrictions on fully opening end. We believe that this reflects the gray area around the words "restrictions" and "fully." For example, a state order that mandated social distancing in retail establishments can be interpreted as a limitation on the ability to fully open. Yet the same firm that expected that limitation to persist through July might choose to think of itself as being fully open at the time of the survey or at some other point before July.

[22] For all survey respondents that listed August as their expected date of deregulation, at least 23 percent expected to take some time before reopening. Fifteen percent of firms that expected the restrictions to end by early June also expected to remain at least partially closed until July. Thirty-one percent of firms that expect lockdowns to end in late June expected that they would remain closed until July.

proximity firms say that they will legally be able to open in early May. By mid-June three quarters of the high proximity firms say that they can be fully open, as the series begin to converge.

For the purpose of our empirical analysis, we underscore that the regulations are correlated with but not perfectly determined by local COVID conditions. In our framework, different regions choose different thresholds, τ_t, for the imposition of restrictions. Among other explanatory variables, local politics (proxied by share of Republican votes in the 2016 presidential election) explains substantial variation in threshold choices, holding fixed local pandemic conditions. In Figure A3 we explore heterogeneity across states in the expected length of the lockdowns, and show that despite large differences, the average gap between reopening and the end of lockdown is between one and two weeks.

Focusing on the surprising changes in regulations in Florida and Wisconsin, the timing of which is arguably orthogonal to local conditions, we corroborate our other findings about regulation's impact on the timing of business re-openings. In Table 2, we present evidence that the abrupt lifting of restrictions increased the share of open businesses in these states by an additional 5.5 percentage points (15%). We also see a statistically significant, but economically small, increase in customer demand conditional on reopening by 0.4 percentage points (<1%) relative to the national trend. In this way, we see that that the surprise regulatory reopening caused a meaningful subset of firms in the affected states to reopen, but without a corresponding increase in demand projections. This suggests that the regulations bind per se, not that business owners think that regulations directly reduced demand or communicated information about the safety of patronizing these businesses to consumers. [23]

To explore the trade-offs of re-opening versus remaining closed for an additional two weeks, we asked owners what they would choose to do under hypothetical scenarios. Owners were either asked about a scenario where they received an unconditional cash grant, or they received a scenario where the cash grant was conditional on remaining closed for two weeks. In both scenarios we randomized the size of the grant. We show the results graphically in Figure 5. Around three-quarters of businesses chose to open with any sized grant when there was no condition to accepting the grant. When the grant was conditional on closing, half of small businesses would remain closed for an additional two weeks in exchange for a modest sum of $2,500, but a quarter of firms would reject $25,000 to reopen immediately. This indicates that for about a quarter of businesses, opening as soon as possible was of extreme value. For the majority of firms, the benefits of reopening for two weeks was limited but of higher value than being closed. Finally, we found no evidence that additional funds helped "tide over" businesses, allowing them to cover fixed costs while closed in order to weather the health risks of the pandemic. Small businesses were no more likely to remain closed when offered unconditional grants of any size: that is, the gradient of reopening with respect to the size of the grant offered is flat.

[23]This is consistent with the literature on consumer behavior that finds a strong relationship between spending and health considerations, while regulations play a more minor role (Chetty et al., 2020; Dunn et al., 2020; Goolsbee and Syverson, 2020; Velde, 2020). As mentioned in Section 1, it is now well documented that the fall in mobility and consumer activity precedes formal restrictions (Abu-Rayash and Dincer, 2020; Huang et al., 2020; Soucy et al., 2020).

4.2 Will Health Fears Deter Reopening?

We now look at the correlation between reopening speed and health related variables, including the level of COVID-19 cases, employee proximity and owner and customer age. Table 4 provides our core results. We estimate equation 2, looking at firm expectations about reopening, future restrictions and reopening conditional upon restrictions being lifted.

In regressions (1) and (4), we look at the expected time, in months, to fully reopen. Regressions (2) and (5) focus on expectations about how many months it will take for restrictions on fully reopening to be lifted. Regressions (3) and (6) estimate the impact of health-related variables on reopening, controlling for the expected number of months until the full lifting of restrictions.

Regressions (1)-(3) include our entire sample of firms. Regressions (4)-(6) include only those firms that are not currently open. Both samples have benefits and disadvantages. Using the entire sample for a table that is focused on barriers to reopening includes many zeros, as those firms have already either reopened or never been closed. But using the closed subsample is also problematic, because the sample of firms that are closed looks quite different in low and high COVID counties.

In the first column of Table 4, we look at the overall correlates of time to reopening. The specification includes firms that are already open and does not control for expectations about the lifting of current restrictions. The first row shows that businesses expect to be closed longer in counties where the number of COVID cases is higher. Using population-weighted statistics, the difference between the 90th and 10th percentile of log deaths per capita is 2.85, implying an opening delay of about 7 days between hard-hit and less affected counties.

The next two rows show the impact of worker proximity alone and then the interaction between worker proximity and COVID-19 prevalence in the county. Employee proximity is a significant predictor of delayed reopening. A one standard deviation increase in this variable is associated with a 0.26 month, or 8 day, delay in reopening. Perhaps more surprisingly, there is no interaction between COVID-19 prevalence and employee proximity. We hypothesized that employee proximity would be more problematic in high COVID environments, but there is little evidence that this interaction enters into firms' expectations about reopening. Panel B of Figure 3 presents the cumulative distributions of total time to reopening by industry. Patterns look very similar to the patterns regarding time to restrictions being lifted in Panel A, with low proximity industries opening sooner.

The fourth and fifth rows look at owner age and the interaction with COVID prevalence. We expected that reopening would be less attractive to older owners who face greater mortality risk from COVID and that this effect would be larger in high COVID environments. But older owners do not seem to expect to delay reopening and there is no significant interaction between age and the prevalence of the pandemic.

The sixth and seventh rows look at customer age and interactions with COVID prevalence. We expected to find that firms with older customers would be more likely to delay their opening, either because of reduced demand from skittish customers or out of concern for customers or legal liability. The coefficient goes in the opposite direction, where firms that serve older customers expect that they are more likely to open sooner. One possible explanation for this fact is that firms who serve older customers specialize in products, including health services, that are more likely to face robust demand. We also do not find a positive interaction between customer age and the COVID rate in the county.

The eighth row shows that essential businesses expect that they will open 0.3 months (or nine days) sooner than non-essential businesses. The ninth row shows the ease of operating online. This variable does predict an earlier reopening, but the effect is relatively small.

The last two rows show the impact of our two other county level variables: density and the Republican vote share in 2016. Density is negatively associated with time to reopening, either because of health-related concerns or because of regulation. Republican vote share is even more strongly negatively related to time to reopening.

The second column attempts to separate expectations about regulation alone from other firm beliefs about their own decisions. The outcome variable in this column is the number of months until all restrictions on business for this firm are lifted. Somewhat remarkably, almost all of the coefficients are quite close to the coefficients estimated in the first column. For example, a 100 percent increase in the number of COVID cases per capita is associated with a .08 month increase in the amount of time until all restrictions are lifted. The similarity of slopes with respect to health concerns and other factors suggests that a constant offset between lifting restrictions and reopening fits the data quite well. For example, a one standard deviation increase in physical proximity is associated with a one-third month increase in the expected time until restrictions are lifted. The coefficient is slightly larger but similar to Column 1.

One modest difference between the two columns is that owner age is negatively associated with the expected time until restrictions are lifted. That effect withstands county fixed effects, which is shown in Appendix Table A5, so it does not reflect any spatial correlation between owner age and local regulatory regimes. Older owners may be in industries that are less subject to local regulation, or they may just be more optimistic. Overall, the second regression shows that our proxies for health concerns, when they matter for delays at all, seem to matter just as much for prognostications about the end of regulation. Consequently, health fears may play little direct role in deterring firms' reopening patterns. To test this hypothesis, the third column looks at expectations about reopening, controlling for the expected time until restrictions are expected to be lifted. The coefficients in this column can be interpreted as telling us whether particular variables predict delays after reopening becomes legally feasible.

If firms intended to delay reopening because of health fears for either their workers or customers, then we would expect many of these coefficients to be significant both statistically and in magnitude. Yet we find that almost none of them are sizable. Both the COVID case and physical proximity coefficients retain statistical significance, but they are much smaller in size. The COVID cases coefficient drops by about 75 percent between regressions (1) and (3). The coefficient on employee proximity drops by over 80 percent.

Figure 4 shows the gap in post-lockdown reopening between high and low proximity industries.

There is no visible difference in time to reopening after lockdowns end. As we have already seen, this fact does not imply that there is no delay after the restrictions end. There is a delay, but the average delay seems to be essentially independent of the duration of the restrictions and is only loosely related with the health-related factors that we have explored. Instead, regulations appear to explain most of the variation in reopening times.

Policymakers and public health officials should take note of a key distinction between the role of regulations in binding consumer and business behavior. The difference between the reopening plans of high and low proximity businesses was driven by differences in the expected duration of restrictions. The reopening plans of high and low proximity businesses are essentially identical once we adjust for these differences in when owners expected to be able to reopen. This contrasts with how consumers responded; travel, for example, fell before restrictions were put into place. Further, local case prevalence can explain travel reductions, even after controlling for regulations (Brinkman and Mangum, 2020).

In this way, individual contagion concerns complimented government restrictions to limit travel to locations with the highest caseload. We don't find evidence of this same kind of complimentary among business owners. That is, owners of high-proximity businesses did not analogously plan to delay reopening beyond the legal requirements. Policymakers should note that this suggests legal restrictions were the mechanism by which business owners expected health concerns to affect their reopening plans.

Regression (4) of Table 4 considers an indicator for a reopening time greater than 1 month from the lifting of restrictions. At the mean, 17.7% of the sample reports their planned date of fully reopening will occur more than 4 weeks after the date they believe restrictions will end. This estimate is likely a lower bound because we cannot calculate this lag for firms that believe restrictions will end after August. Over 80 percent of firms anticipate reopening within a month of being able to do so, but a significant share anticipate drawn out delays before fully reopening. There are only two significant variables, essential business and Republican vote share, suggesting that much of the variation in long delays is unrelated to health concerns.

Regression (5)-(8) repeat these regressions looking only at those firms that were currently closed or partially open at the time of the survey. These firms are a selected sample, and the selection depends on COVID cases at the county level. A larger share of businesses were not fully open in counties with high levels of COVID. Panel A of Appendix Figure A2 shows the relationship between the share of businesses that were open and the level of COVID at the county level across counties with more than 110 businesses in our sample. Over forty percent of firms were fully open in the counties with low COVID rates. Less than twenty percent of firms were open in the counties near New York City that had the highest COVID rates. This selection may explain why the level of COVID cases does not predict time to reopening in the fourth regression among firms that were then closed. In the high COVID counties, most firms were closed and many of these closed firms had attributes that would make it easy for them to reopen. In the low COVID counties, the firms that were well suited for being open were already open and consequently only the most vulnerable firms are closed. This selection problem makes it difficult to interpret all of the county level variables in this later sample.

Only a few variables are significant in regression (5). Firms with older customers expect that they will open sooner. Firms in essential industries expect that they will open sooner. Firms in counties with a higher Republican vote share also expected to open sooner.

The sixth regression again looks at beliefs about when regulations will end. Those same coefficients again predict expectations about deregulation. Essential businesses expect regulations to end more quickly. Firms in more Republican counties expect that regulations will end sooner. Firms with older customers also expect that their regulations will end more quickly.

In the seventh regression, we look at the correlates of post-regulatory delay among the sample of firms that were closed. The patterns in this regression are broadly similar to those before, except physical proximity and the measure of local pandemic severity become insignificant for explaining the lag among these businesses. These patterns continue to hold in column 8, where 28% of the businesses that were not fully open anticipated having delays in reopening greater than 1 month. The primary difference between this and other columns is that the sign on COVID cases becomes negative, underscoring that the set of businesses in this regression are selected based on differences in county characteristics.

This table and the related figures tell a clear story that health concerns matter greatly for regulation, but much less so for firms' behavior post-regulation. Firms with older customers expected to reopen sooner rather than later. Greater COVID-19 prevalence predicts expected regulatory delay, but does not predict economically significant differences in firm choices absent regulation. We interpret this as suggesting that firms opening behavior might suggest there are health concerns, but digging deeper suggests these patterns arise because of regulations.

Another piece of evidence that supports this view is shown in Figure 5. We gave respondents a hypothetical question about whether they would be willing to remain closed if they received either an unconditional grant or a grant that is conditional upon remaining closed. We randomly varied the size of the hypothetical grant. If owners wanted to remain at home because of health fears, then we would expect the unconditional grant to have a large impact that increases with the size of the grant, as larger grants would allow owners to consume or pay their bills without the need to access cash flows generated from the business. Reopening decisions were invariant to the size of the cash grant, which we interpret to suggest that owners minimally traded off liquidity concerns with worries about well-being.[24]

This suggests there is substantial residual variation in reopening times that is not captured by average health risk, conditions on the ground (cases, density), industry characteristics (proximity, essential), or attitudes (GOP vote share). While regulation explains a substantial portion of the

[24]These findings contrast with other work that shows commuting often slowed dramatically before lockdown regulations were put into place, suggesting that some firms stopped in-person work before they were forced to do so. On the reopening question, our analysis would point to more firms reopening quickly, but it is possible that our analysis is putting more weight on small firms that had lower capacity for telecommuting or were less exposed to potential health-related lawsuits.

reopening variability, much remains. We explore two additional hypotheses in the next section: coordination with other businesses in the ecosystem and reductions in (or uncertainty about) demand.

4.3 Reopening and Coordination between Customers and Suppliers

Figure 6 illustrates the complementary nature of businesses throughout the U.S. The top panel asks those businesses that are currently open "Although you are currently open, if these other businesses closed, would it affect your ability to remain open? (Select the category that matters most.)" Thirty-six percent of open businesses said their ability to remain open would be impacted if their business customers closed. A business' survival is naturally contingent on the presence of demand for its services or products. Suppliers mattered less than customers among this group, but both were important. A smaller share also cited the importance of businesses that refer them customers. If we add together the businesses that refer and the business customers, we find that almost fifty percent of firms emphasized downstream linkages. That share is almost double the 25 percent of firms that highlighted upstream linkages.

This difference between upstream and downstream connections is also shown in the bottom panel of Figure 6. This panel shows the responses to a question that was asked only of firms that were temporarily closed or partially open: "are you waiting on other businesses to open before fully opening yourself?" Somewhat surprisingly, more than one-half of our small businesses said no. A majority of currently closed businesses do not require any coordination with other businesses. Sixty-five percent of respondents to this question are in consumer-facing businesses, helping to explain these results. For the business-to-business respondents presented with this question, it is likely that their business customers were already open at the time of the survey.

Nonetheless, almost one-half of businesses did note that they were waiting on other businesses. The largest category in this group was firms waiting on business customers. Together, more than 20 percent of respondents said that they were waiting for either customers and businesses that refer customers to them. This represents more than 40 percent of the dependency in this sample.

Another 20 percent said that they were waiting on businesses that were similar to themselves to open. While we might usually think that the reopening of other competing businesses would depress demand for a particular enterprise, the respondents seemed to take the opening of their competitors as a signal that demand has returned. There may also be some advantage to waiting and learning from the reopening experience of similar firms (de Vaan et al., 2020).

Only five percent of respondents cited the need to wait until suppliers reopen. This share does not mean that suppliers are unimportant. The top panel confirmed that if supply relationships end, then this can shut down a business. Instead, this means that currently closed firms were not worried as much about supply, presumably because upstream firms were more likely to be open, or because global supply chains allow them to source inputs from somewhere else. If upstream suppliers produce goods in lower density factories, then it was likely easier for them to remain operational than downstream businesses.

These results confirm the importance of linkages for reopening, but also suggest that slightly more than one-half of closed firms in May 2020 could reopen without any other firm reopening as well. The results suggest that downstream linkages seem likely to be most important. For that reason, we now turn to the firm's forecasts about future demand and the impact of future demand on projected reopening behavior.

4.4 Forecasting Post-Crisis Demand

We start with the firms' forecasts about future demand. The survey asked owners to predict what share of their pre-COVID demand would return in the future. The future date was one of six randomized dates ranging from early May to September 2020. The exact wording was: "If you are fully open in [date], what share of your customers do you expect at that time, compared to before the crisis? Please provide your best guess." Response options were top-coded at "greater than 90 percent." [25]

On average, across all industries, demand was expected to return to 65% of its pre-COVID level by September. Table A3 reports both the share of firms that expected their demand to fully return (90 percent or more of their pre-crisis levels) and also reports the mean level of demand predicted, again relative to pre-crisis levels.[26]

The first row shows that only seven percent of respondents in "arts, entertainment and recreation" expected demand to exceed ninety percent of pre-crisis levels in May. That share only rises to 11 percent in September. Consequently, ninety percent of these firms expected to experience a decline in demand of ten percent or more through the fall. The mean level of projected demand in this industry begins at 37 percent of pre-crisis levels and reaches 55 percent of pre-crisis levels by September.

Whereas the arts appear to be the more vulnerable sector, finance and insurance appears to be the sector with the smallest reductions in demand. Even in May, the financial firms believed that they will have two-thirds of their pre-crisis demand. That forecast rises to seventy percent by September. Still only twenty-seven percent of all financial services firms project that their demand would be ninety percent of pre-crisis demand or more by September.

The other face-to-face sectors, including educational services, retail trade and restaurants and accommodation, all expected large decreases in demand through September. Accommodation and food service providers expected their demand to be 58 percent of its pre-crisis level in September. Eighty-seven percent of firms in educational services expected a ten percent or greater drop in demand in September.

Industries that deliver information-intensive products were the most optimistic about future demand. Professional and technical service providers predicted that their demand will return to

[25] It is possible that our estimates miss some reallocation of demand because of top-coding of survey responses (Barrero et al., 2020). Table A3 allows an assessment by examining the share of responses indicating demand would exceed 90% of its pre-pandemic level.

[26] Appendix Table A6 shows a more granular industry breakdown.

two-thirds of pre-crisis levels by September. Information service providers predicted that their demand will be at 65 percent of pre-crisis levels by the same date.

These businesses expected a quite significant reduction in demand, and there is considerable heterogeneity across industries in the expected drop in demand. Before we examine whether these drops in demand can explain slow rates of re-opening, we turn to a more systematic exploration of the correlates of predicted drops in demand.

Table 5 shows predictors of demand for all businesses (column 1) and businesses that were not fully open (column 2). The regressions pool results for projected demand across future months, and include a control for the reference month that was contained in the survey question. To separate the impact of regulations from other factors, we control for the months until reopening restrictions are lifted. In both columns, the length of delay until the lifting of restrictions is associated with lower levels of demand. One more month of restrictions is associated with 17.4 percent lower demand in the entire sample and a 13 percent reduction in demand in the sample that is currently not fully open.

One interpretation of the correlation between the expected length of restrictions and the reduction in demand could be that firms anticipate that consumers will switch to alternative suppliers and alternative products if the delay lasts longer. In this case, the lost demand might be recouped across different sectors of the economy, even though this specific firm has lost customers. An alternative interpretation is that restrictions are correlated with reduced demand because both reflect omitted factors, such as aspects of the health crisis that are not captured by our COVID case measure.

With the exception of employee proximity, most of our health related variables are not correlated with projected demand. The level of COVID cases itself is unrelated to the expected drop in demand. Owner age is uncorrelated with projected future demand, while customer age is positively correlated. Presumably, this reflects the tendency of older customers to have more stable consumption patterns and to purchase services, like health care, that they are still likely to need going forward.

A notable exception is businesses where employee proximity is higher. A standard deviation increase in proximity reduces demand forecasts by between 7 to 9 percent across specifications. There is also a negative interaction effect with COVID cases, and magnitudes are larger for businesses that were not fully open. Comparing these magnitudes for demand reductions in high proximity businesses to these businesses' reopening plans suggests that despite the potential for demand to decline, owners intended to reopen high proximity businesses to serve a smaller customer base. These workplaces appear able to operate at a smaller scale than their pre-pandemic levels, possibly because the opportunity cost of operating (a service provider's outside option) deteriorated.

Two other industry-specific variables also predict demand. Projected demand is about 11 percent higher, in almost all specifications, for essential businesses than for non-essential businesses. If demand were not top-coded at "greater than 90 percent" we might have detected an even larger boost in demand for essential businesses.

There is also a greater drop in demand for businesses than can be performed online. One interpretation for this fact is that the businesses in our sample expect that they will lose their customers to online competitors. An alternative view is that ease of online delivery captures relatively non-essential services.

Two place-based variables predict expected future demand. Future demand is generally higher in more dense areas, possibly because these larger markets will make it easier for the businesses to find a new set of customers. Future demand is strongly related to the share of Republican voters in 2016.

4.5 The Impact of Demand on Re-opening

We now turn to the impact that projected demand has on future reopening intentions. To identify the causal effect of demand projections on reopening plans (generally, and conditional on restrictions lifting) and long term business viability, we use experimental variation in information provision about future demand.

We turn to the estimation of equations 6 and 7, our IV approach, using experimental variation in information provision about future demand. Panel B of Table 7 displays the first stage regression. The instrument, which is the interaction between receiving information in the survey and the difference in the logarithm of the signal and the constructed prior belief, has a strong positive impact on predicted demand. A 10 percent larger gap between the signal and prior, or a 0.1 log point increase, leads to a roughly 2 percent increase in the owner's projected demand. This shows the posterior beliefs move in the direction of the signal. Note that throughout this table, we present results with a standard set of controls germane to the instrumental variable specification in particular. We also add columns with an additional set of controls from the more expansive OLS specification in Table 4. Results are stable across these two alternative specifications.

Columns 3- 10 show reduced form estimates, where the various outcomes (lags to reopening, lags to reopening with restriction date fixed effects, indicators for long lags, and indicators for long-run prospects) are regressed directly upon the instrument. These results are again stable across specifications. The reduced form coefficients show the importance of the instrument, presumably through the demand channel, on these outcomes.

Panel A presents the two-stage least squares estimates of the causal effect of changes in projected demand. In column 1, we estimate that a 10 percent increase in projected demand decreases the time to reopen by 0.088 months or roughly 2.7 days. This point estimate is stable when we include additional controls for a range of industry (proximity, ease of conducting business online, etc) and geography (COVID cases, population density, GOP vote share, etc). However, when we include fixed effects for the projected date that restrictions will be lifted, the coefficient falls to 0.53, meaning that a 10 percent demand increase will reduce time to open by about 1.6 days.

The estimates in columns 1-4 reflect changes in the average time to reopen caused by shifts in demand projections. However, these means necessarily obscure differences across various margins. Columns 5-6 look at long-lags of greater than 1 month. Here a 10 percent increase in demand reduces the probability of a long delay in reopening by about 1.6 percentage points, or an 8 percent reduction relative to the mean. This highlights the long-tail of reopening times, and suggests that pessimistic owners are influenced by changes in their demand projections.

In column (7), we look at the probability of being operational by the end of 2020 as our dependent variable. A 0.1 log point increase in the gap between the signal and the prior increases the expected probability of survival by 3.1 percentage points. In other words, a twenty percent increase in demand is predicted to increase the survival probability by six percentage points. Given that the mean failure rate is twenty percent, a drop from twenty to fourteen percent is economically highly significant.

4.6 The Impact of Demand and Other Variables on Survival

One of the most important questions about the COVID related lockdown is whether a temporary period of firm closure will lead to permanent elimination of thousands or millions of American businesses. Consequently, we now look at whether any of our variables predict survival until December of 2020. We have already estimated the impact of demand on survival in the last two columns of Table 7, but we have not linked this survival rate with any of our other variables. In both exercises, demand is positively related with long-run survival rates, often substantially so. Although we note that tracing out actual survival ex-post is notoriously difficult, these projected survival rates have been shown to correlate with follow-up phone audits done by Bartik et al. (2020).

In Table 6, we build in the correlation between our core set of additional variables and the probability of survival until December. The first two rows look at the impact of projected demand and months until the end of restrictions. Projected demand positively predicts survival, but the estimated coefficient is smaller than in all of the two stage least squares estimations.

The most striking and important fact is that the length of expected restrictions is strongly negatively associated with the probability of survival. As the expected restriction duration increases by 1 month, the probability of survival drops by 2.6 percentage points. This fact does not mean that restrictions are wrong, but it does suggest that the economic cost of longer lockdowns, especially as experienced by small entrepreneurs, is likely to be large.[27]

Three other variables are significant in every specification. Essential businesses were between 1.2 and 2.1 percentage points more likely to survive. This gap could reflect the advantage of being able to continue in business throughout the crisis, or it could reflect more stable demand for essential businesses. Firms with higher worker proximity were less likely to report optimism about survival. A one standard deviation increase in worker proximity is associated with more than a 1.5 percentage point decrease in the probability of survival. This may reflect the expected difficulty of operating in a high contact work environment. Finally, businesses with older customers are more

[27] Past work, since at least Hamilton (2000), suggests that many small businesses are likely to be fragile even in good times. Related work studies how business owners respond to shocks over their careers (Catherine, 2018; Dillon and Stanton, 2017; Hincapié, 2020)

likely to survive, possibly because this customer base is more stable. None of the other variables have reliable correlations with the probability of survival.

4.7 Reliability of Demand and Reopening Projections

Subsequent surveys help with validation exercises and confirm these early responses. In the subsequent Alignable series, cross-sections of small business owners were surveyed at the end of July, August, and September. These surveys asked respondents about the share of customers returning in the previous month, as well as the current operating status of their business. Using a unique account ID, we are able to match respondents in our main survey wave in May to the later surveys. While these surveys are designed as repeated cross-sections, not as panels, in practice we observe more than 3,000 of the initial respondents in these later surveys.

In Panel A of Table A7, we compare demand projections to the retrospective realized demand when resurveyed. Respondents with the most optimistic demand projections – those projecting more than 90% of their pre-COVID customers returning by the date in question – report relative demand of 93% in July, 87% in August, and 89% in September. In these waves, roughly 85% to 90% of these respondents report being fully open.

In contrast, respondents with the lowest demand projections – those anticipating less than 10% of their pre-COVID demand – report 44%, 50%, and 37% of their customers returning in July, August, and September, respectively. While these figures are significantly higher than ten percent, we note that only roughly 30%-40% of these businesses were open when resurveyed. Since we only observe retrospective demand for businesses that were open in the preceding month, we don't see the counterfactual demand level for the majority of these businesses that are still closed later in the summer. In this way, these demand estimates come from the best performing third of these businesses. Even conditional on being open when surveyed, demand in this group is roughly half of the realized demand for respondents projecting over 90% of their customers returning.

In Panel B, we can compare the projected reopening date to the share of businesses that are open in each successive survey round. At each survey round throughout the summer, respondents who project reopening by early May are two to three times as likely to be open than their counterparts who project remaining closed through September or later. While there is a strong gradient, small business owners do appear to be optimistic in their reopening estimates. When we resurveyed respondents in July, 80% of respondents who project reopening in early May were open, but only 25% of those who project reopening in September were open. However, this means that even in the most optimistic group, 20% of businesses who project being open in May remain closed in July; by September, as case loads began to rise, 28% of respondents who projected reopening in early May were closed. By September, only 35% of businesses who projected reopening in August were open.

The reopening projections have strong explanatory power; the reopening regressions displayed in Panel B are linear probability models that regress an indicator for being open on a vector of indicators that correspond to each possible reopening date; the R^2 statistics range from 0.71 to 0.73. While these projections correlate well with realized reopening behavior, the projections appear to systematically underestimate delays in reopening.

In Appendix Table A8, we show that differential attrition as a function of the variables of interest is minimal. The industry distribution is broadly similar in the baseline and re-sampled wave. There is a statistically significant but economically small shift away from finance & insurance and professional services (two percentage points in each category) and towards retail (+ 2pp) and other services (+ 1.5pp). The geographic mix remains broadly stable.

We do see a slight shift in the composition of the small business owners with respect to the business status in May when we compare the subset who reply to the later survey to the full survey, but these shifts are modest. The share of businesses that are fully open in May is roughly three percentage points higher in the subset that can be matched to a later round. However, these changes are qualitatively small: businesses fully open in May are 31.6% of the baseline sample and 34.8% of the validation sample; partially open businesses shift in the opposite direction from 34% of the main sample to 32% of the validation sample.

The composition with respect to the share of customers has similarly small shifts. Perhaps counter intuitively, businesses projecting fewer than 10% of their customers returning make up a slightly larger share of the validation sample than the full sample (13.7% relative to 10% in the baseline), and there is a similar shift in the opposite direction for businesses projecting 50%-75% relative demand (22.3% relative to 25.1% in the baseline). These differences in weights are too modest to threaten the qualitative results of this exercise.

Additionally, we validate that the Alignable measures on business operations are correlated with administrative data on labor market performance. Panel B of Appendix Figure A2 plots the share of business that were currently open against the county level unemployment rate, indicating that the impact is not being felt equally nationwide. The striking correlations suggest the Alignable measures are accurately picking up economic activity at a granular level. Of course, as mentioned above, part of the county differences are driven by differences in regulations.

A final important driver of behavior and expectations is the partisan environment. People living in strongly Democratic or strongly Republican areas of the country made decisions based on different information about the underlying health risks posed by the virus (Bursztyn et al., 2020). We find that county-level Republican vote share in the 2016 election is very strongly correlated with all of the outcomes of interest. In Figure 7, we show that Republican vote share is associated with expectations of earlier reopening, removal of restrictions, and shorter gaps between reopening and when it is legal to do so. It is striking that this result is robust to controls for population, population density, COVID prevalence, state and granular industry (NAICS 4 digit). By considering the time to reopen conditional on it being legal to do so, the estimates of the delay in Panel C even adjust for differences in the regulatory environment. This raises important questions that are beyond the scope of this paper. How much this effect reflects attitudinal differences of business owners in these counties? How much is driven by differences in customer demand caused by different attitudes among local consumers? And how much is driven by misinformation about health risks, rather than different levels of risk tolerance. Understanding how partisan and ideological commitments interact with public health interventions is of vital importance for policy makers.

5 Conclusion

The Alignable Survey of Small Business Owners provides a snapshot of small business behavior and expectations during the unprecedented COVID-19 crisis. Firms gradually reopened, but some places reopened faster than others.

Although restrictions were an important determinant of the reopening decision, many businesses expected to delay reopening when the restrictions lift. The average business in our sample expected to be closed two weeks longer than the restrictions lasted, although some businesses expected to be closed for months after they are legally allowed to reopen. When considering future regulations, policy makers will likely seek to understand both average behavior and sources of heterogeneity. Were owners responding to health concerns for themselves, changes in demand, or other factors? Which of these arise due to regulations themselves, and which of these would remain in the absence of restrictions on behavior?

The delay in reopening did not appear to be related to health concerns, at least for the small businesses in the survey. The lag between the predicted end of restrictions on operations and the predicted time for reopening is not correlated with any of our measures of health risk. Neither older customers nor an older owner predicted a longer delay after the end of restrictions. And while COVID case prevalence predicted the presence of restrictions on operations into the future, COVID cases per capita did not predict delays in opening after restrictions on operations were lifted. These facts suggest that small firms' reopenings are driven more by their economic needs to survive than by their worries about public health.

Several other findings underscore the importance of demand projections and interdependencies among businesses for owners' reopening decisions. We use an information provision experiment to show that the reopening decision depends on expectations about future demand. If downstream businesses don't open, then this will reverberate up through the network of firms.[28] Adding to the headwinds businesses face, this crisis is both a health crisis and an economic crisis. Businesses expected that the level of demand for their services would be greatly depressed for many months, likely justifying some of the government aid to businesses that would allow them to weather lower projected demand while health risks to consumers linger.

[28] See Akbarpour et al. (2020) for a discussion of other aspects of networks related to reopening policy.

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Tables and Figures

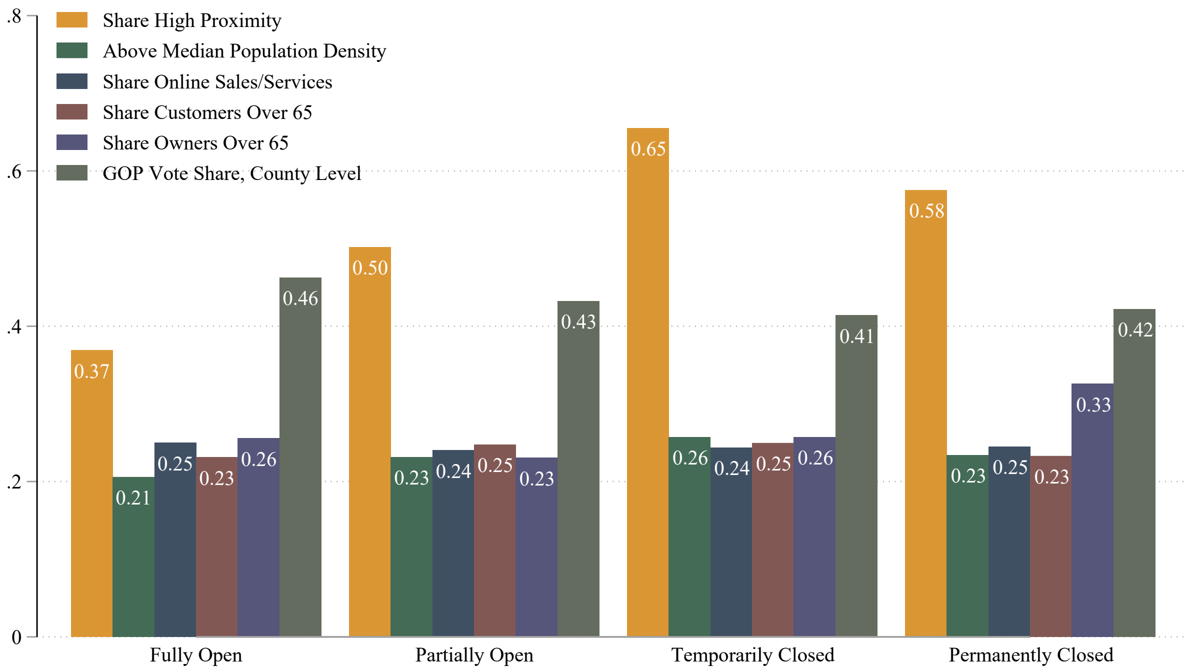
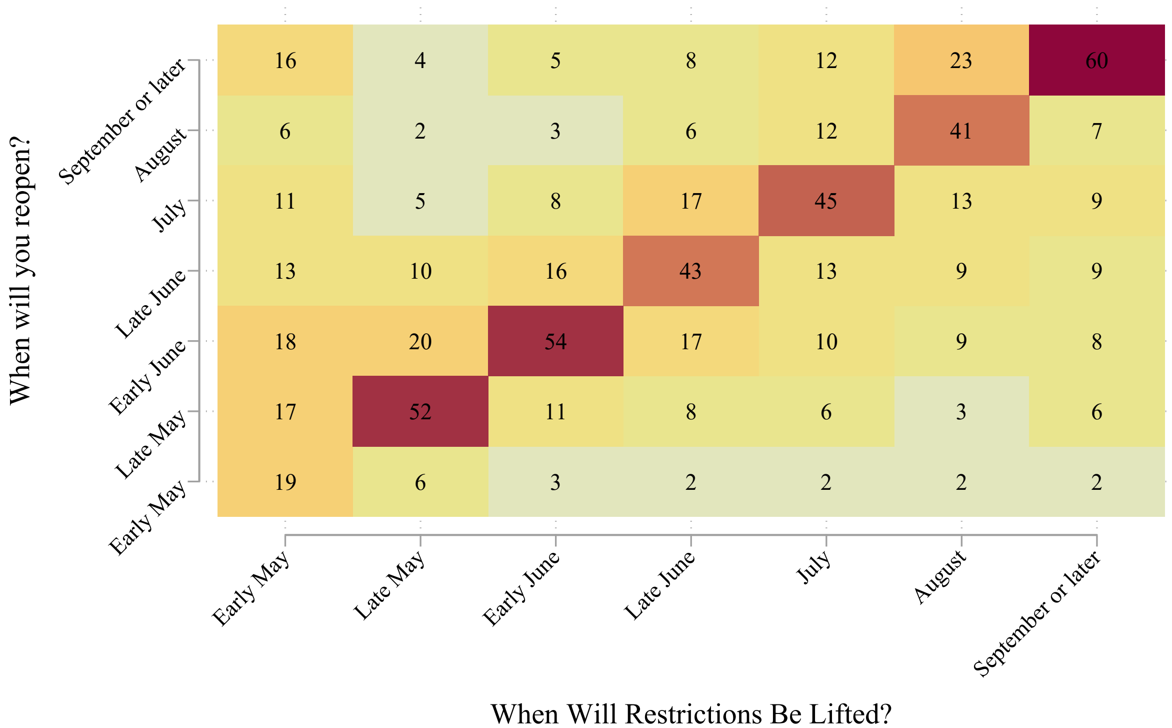


Figure 1: CHARACTERISTICS OF BUSINESSES BY OPERATIONAL STATUS AS OF MAY 9, 2020

This figure plots characteristics of different businesses based on their industry characteristics, location characteristics, or owner characteristics. Bars represent means and data are grouped by the operational status of the business as reported in the May 9, 2020 survey. Please refer to Section 2 of the corresponding paper for detailed definitions of each data source represented in this graph.



The percent of respondents in each cell is displayed, normalized within columns. Due to rounding, columns may not sum to 100.

Figure 2: PATTERNS IN REGULATION AND REOPENING AT THE INDIVIDUAL BUSINESS LEVEL

This figure displays when each business owner expects easing of legal restrictions around "fully reopening" (x-axis) and the expected date when they will "fully reopen" (y-axis). The x-axis is derived from the question "If there are legal restrictions on fully reopening your business, when do you expect them to be lifted?". Response possibilities ranged from "There are no legal restrictions." to "September or later". The y-axis is derived from the question "When will your business be fully open? Please provide your best guess." Responses possibilities ranged from "Early May" to "September or later". Businesses that were fully open were not asked the question and are coded as 0. Numbers in each cell are percent of responses within column.

PANEL A: Share of Businesses Expecting to be Legally Able to Reopen

PANEL B: Share of Businesses Expecting to be Fully Open

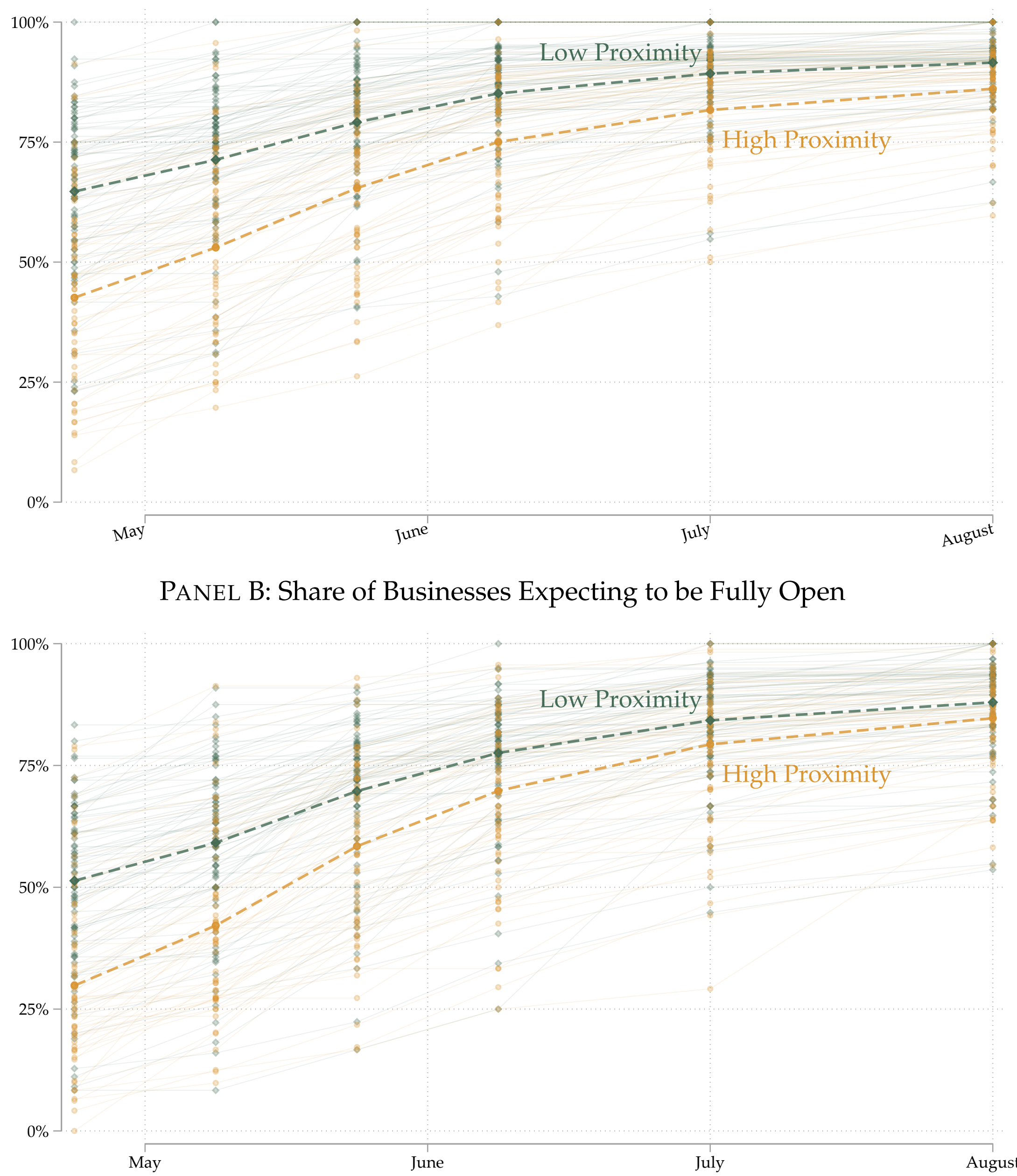


Figure 3: AVERAGE SHARE OF BUSINESSES PROJECTED TO BE FULLY OPEN IN EACH INDUSTRY BY DATE

Panel A plots the average share of businesses fully open or projected to be fully open at future dates. Each line represents a 4-digit NAICS code and is constructed using the cumulative distribution of individual responses to the question "When will your business be fully open? Please provide your best guess." Panel B plots the average share of businesses legally able or expected to be legally able to reopen open at future dates. Fully open businesses are included in both panels and are coded as open and legally able to open in the first period. High proximity businesses, in yellow, are those above the median according to the proximity score. Green indicates low proximity businesses.

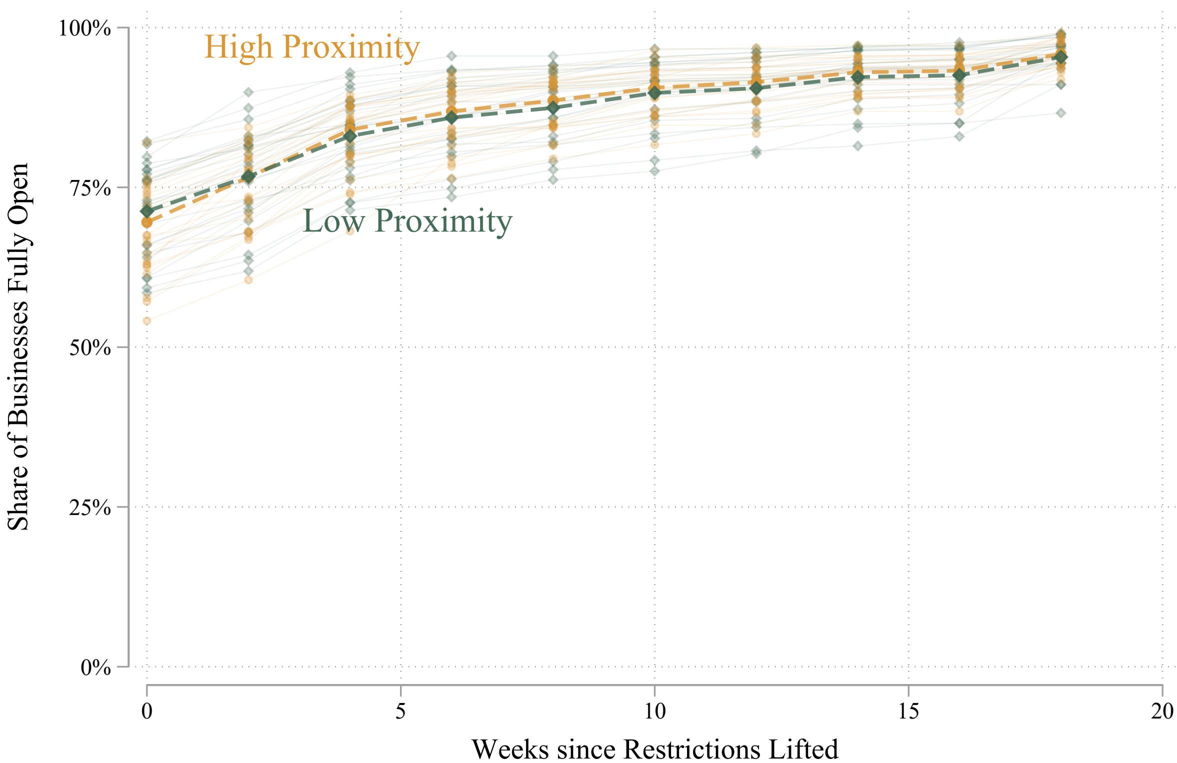


Figure 4: Average Share of Businesses Reopening in Each Industry, Represented as Elapsed Weeks after Restrictions are Lifted

This figure plots the lag time in reopening between when respondents plan to reopen and when they are legally allowed to do so. This is calculated as the difference between respondents' projected reopening date and their perceived date by which legal restrictions on operations will be lifted. Businesses that are fully open are included at 0.

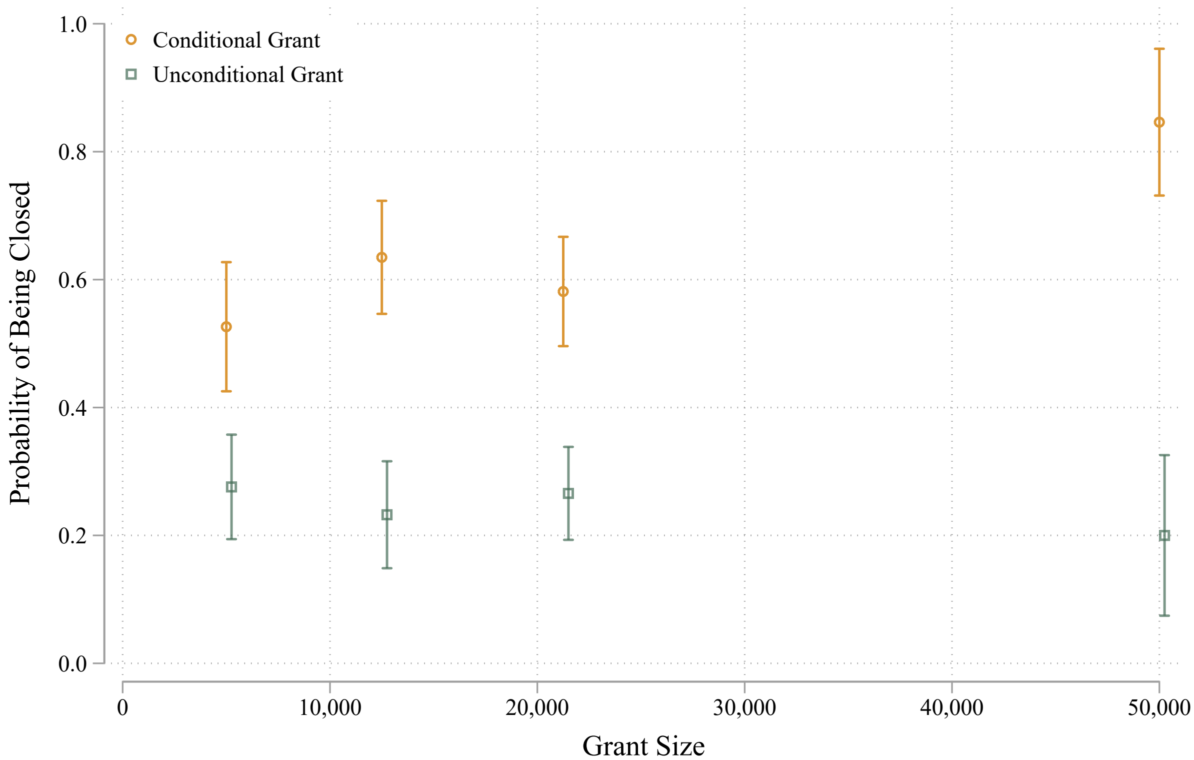


Figure 5: ESTIMATES OF HOW CASH ON HAND AND CONDITIONAL CASH ON HAND CHANGE THE DECISION TO REMAIN CLOSED

This figure plots how answers to a question about willingness to stay closed over the next 2 weeks changes as a function of different hypothetical amounts of cash on hand. This is captured by "grant size" on the x-axis, which comes from two parallel questions. Half of respondents (Unconditional Grant) were asked "Suppose we could extend you a cash grant of [Grant Size]. Would you choose to open over the next two weeks?" The other half of respondents (Conditional Grant) were asked "Suppose we could extend you a cash grant of [Grant Size] but only on the condition that you remained closed for the next two weeks. Would you choose to open over the next two weeks instead of taking the cash grant?" The sample for this figure comes from the first wave of a panel survey of Alignable users conducted through Harvard Business School between May 20, 2020 and May 28, 2020 (N=780).

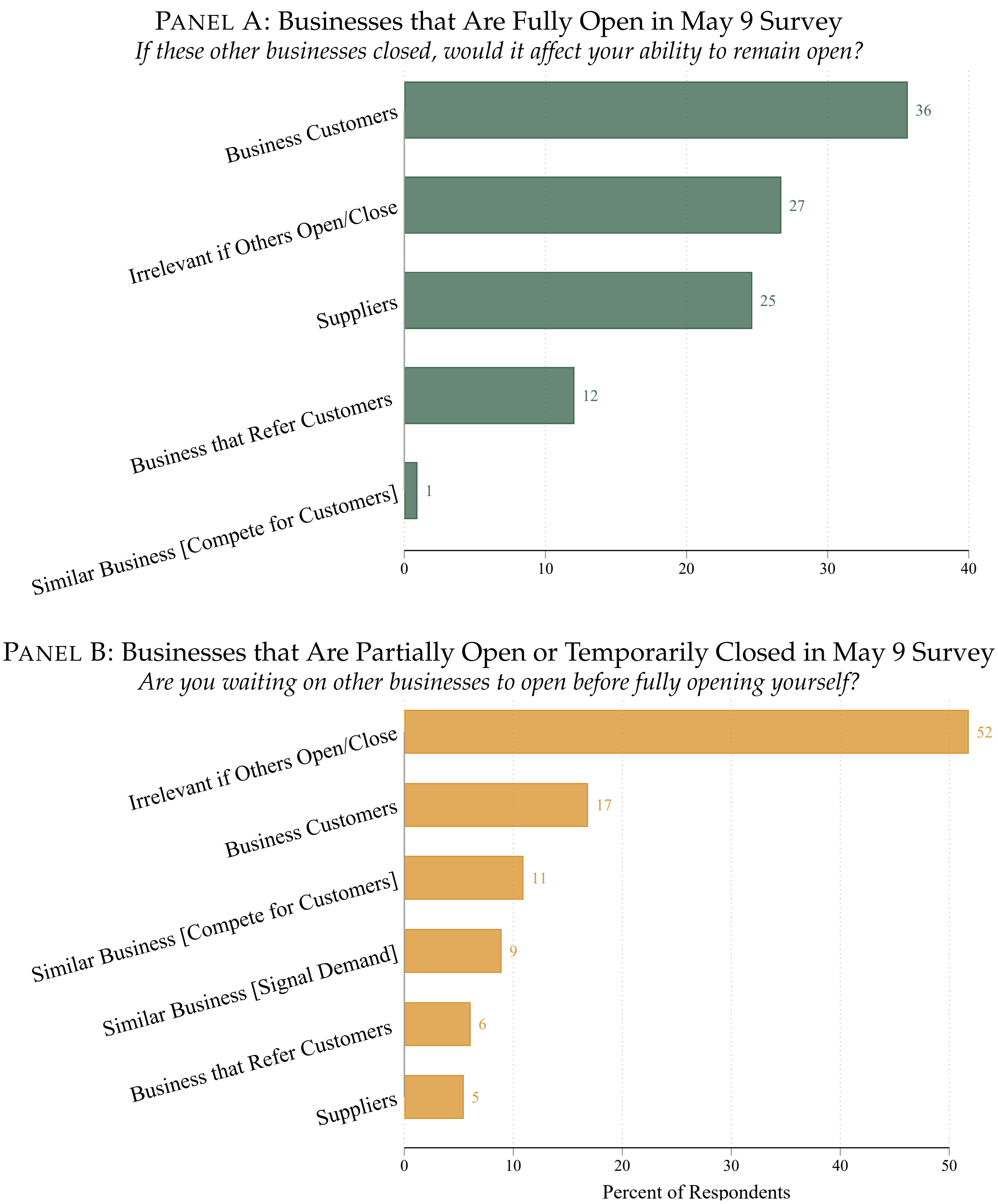


Figure 6: REOPENING DECISIONS AS A FUNCTION OF OTHER BUSINESSES' ACTIONS

This figure displays patterns of business dependency. Partially open or temporarily closed were asked "Are you waiting on other businesses to open before fully opening yourself? (Select the category that matters most.)." Fully open businesses were asked "Although you are currently open, if these other businesses closed, would it affect your ability to remain open? (Select the category that matters most.)".

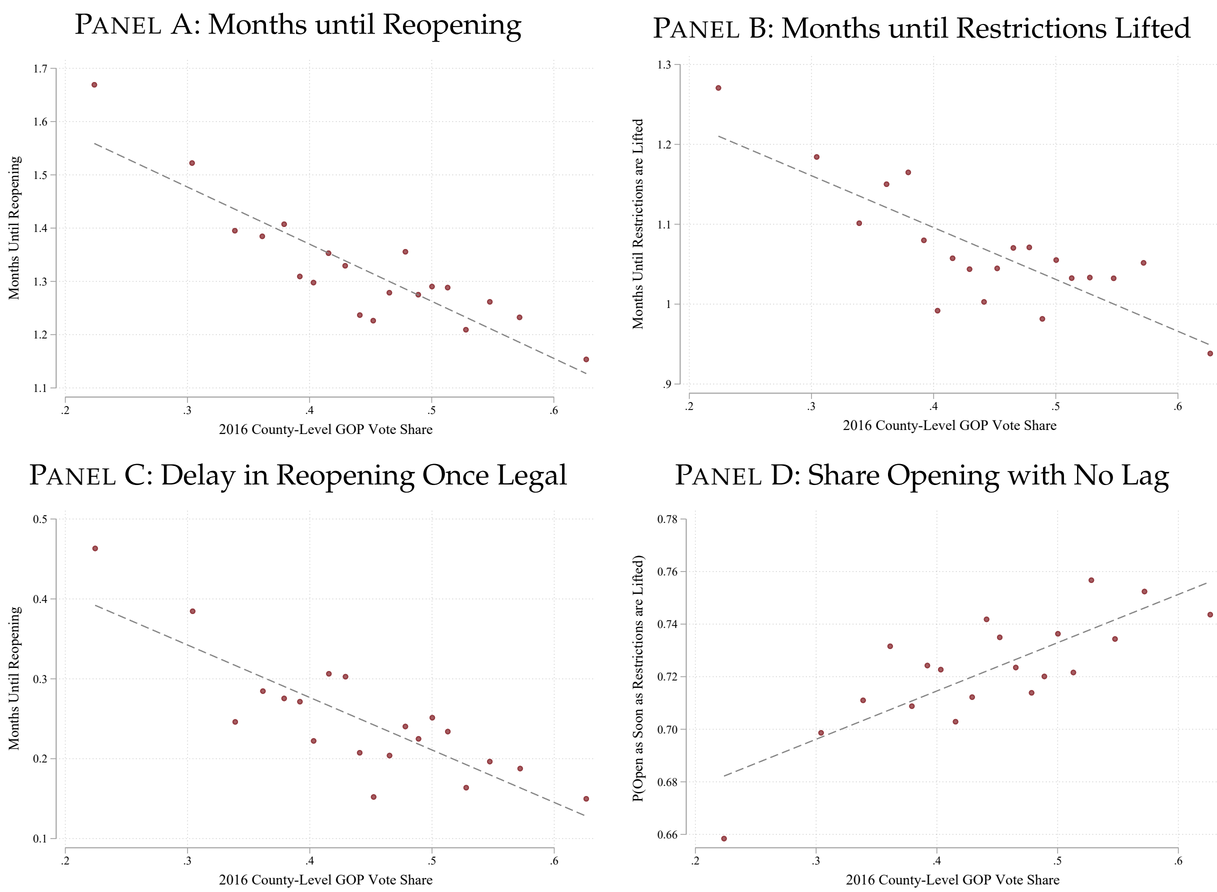


Figure 7: EFFECT OF 2016 GOP VOTE SHARE ON PROJECTED TIME TO REOPEN AND TIME UNTIL RESTRICTIONS LIFTED

The x-axis in every panel is the county-level GOP vote share in the 2016 Presidential election. Panel A plots the projected months until the business reopens. Panel B plots the projected months until restrictions are lifted. Panel C replicates Panel A, but nets out fixed effects for projected months until restrictions are lifted. Panel D plots the share of respondents who selected the same period for projected reopening date and the projected date by which restrictions will be lifted. All plots contain state and 4-digit NAICS fixed effects, and control for population, population density and COVID cases (all control variables have been transformed by the natural logarithm).

Table 1: Summary Statistics on Data from Survey and Additional Sources

Panel A: Data from Alignable Survey

	Mean	Std. Dev.	25th P'tile	75th P'tile	min/max	Obs.
Mo. until Reopen	1.33	1.49	0.00	1.75	0.00–4.50	29,305
Mo. until No Restrictions	1.06	1.42	0.00	1.75	0.00–4.50	28,763
Lag $\geq$ 4wks	0.18	0.38	0.00	0.00	0.00–1.00	28,538
Share Returning Customers	54.01	29.42	37.50	82.50	5.00–95.00	27,571
N. Employees (Jan, 2020	10.63	32.77	1.00	7.00	0.00–500.00	20,505
Fully Open in May 9 Survey	0.32	0.46	0.00	1.00	0.00–1.00	33,356
Partially Open in May 9 Survey	0.34	0.47	0.00	1.00	0.00–1.00	33,356
Temporarily Closed in May 9 Survey	0.32	0.47	0.00	1.00	0.00–1.00	33,356
Permanently Closed in May 9 Survey	0.02	0.15	0.00	0.00	0.00–1.00	33,356
P(Open in December)	0.78	0.20	0.61	0.94	0.13–0.94	17,105

Panel B: Data from Additional Sources

	Mean	Std. Dev.	25th P'tile	75th P'tile	min/max	Obs.
COVID Cases per 1k	4.45	5.83	1.12	5.33	0.00–71.52	32,426
Emp. Physical Proximity	3.48	0.44	3.08	3.83	2.16–4.42	19,162
Likelihood Customers Over 65	24.26	13.91	12.50	30.50	5.00–87.50	22,856
Ease Operating Online	24.48	14.99	10.00	37.00	5.00–65.00	22,856
Essential Business (DE & MN)	0.53	0.50	0.00	1.00	0.00–1.00	22,883
GOP Vote Share (County)	0.44	0.16	0.33	0.55	0.04–0.90	33,117
Share Output $\rightarrow$ Intermed. Input	0.53	0.35	0.15	0.91	0.00–1.00	18,213
Share Business Buyers in Essential Ind.	0.55	0.30	0.33	0.73	0.00–1.00	20,995

Note: Panel A presents summary statistics for survey responses. "Mo. until Reopen" and "Mo. until No Restrictions" are the perceived months until the business will be fully open, and the perceived months until it is legal to fully open, respectively. These figures are relative to the survey date of May 9. Responses were topcoded at "September or Later", which we top code at 4.5 months from early May. "N. Employees (Jan, 2020)" is the self reported number of employees, including the respondent, in January 2020. The four indicator variables regarding current status as of the May 9 survey correspond to the four options of the first question asked to respondents. For this reason, these variables have the most observations. "P(Open in December)" is the numeric probability that a businesses remains open in December, 2020. We code these probabilities from a multiple choice question shown to respondents. This is the last question in the survey, which accounts for the fact that this variable has the fewest responses. The text provides more detail about survey completion rates. par Panel B presents summary statistics for data taken from outside sources. "COVID Cases per cap." is the county-level number of COVID cases per capita. "Emp. Physical Proximity" is the the weighted average of a 5 point occupational proximity scale over the industry-level (4-digit NAICS) distribution of occupations. "Likelihood Customers Over 65" and "Ease Operating Online" are derived from MTurk answers at the 4-digit NAICS level. (See appendix for the MTurk data collection tool.) "Essential Business (DE & MN)" is an indicator variable that indicates if a businesses was considered essential in the guidelines made available in Deleware and Minnesota. "GOP Vote Share (County)" is the share of votes for the Republican Presidential candidate in 2016. "Share Output $\rightarrow$ Intermed. Input" is derived from the BEA 2012 Use table and is the share of total 3-digit industry output that used as intermediate inputs. "Share Business Buyers in Essential Ind." is derived from the same BEA series, as well as the "Essential Business (DE & MN)" measure. This is the share of output that is used as an input by industries we identify as essential divided by the total output that is used as intermediate inputs.

Table 2: DIFFERENCE-IN-DIFFERENCE: REOPENING AND PROJECTED CUSTOMERS RETURNING

Percentage:	Business Fully Open			Customers Returning		
After May 14	14.79***	14.83***	14.80***	6.756***	6.513***	6.768***
	(0.814)	(0.821)	(0.808)	(1.019)	(1.038)	(1.030)
× Pooled WI & FL	5.552***			0.482**		
	(0.441)			(0.235)		
× Just WI		3.114**			0.104	
		(1.138)			(0.204)	
× Just FL			6.092***			0.557**
			(0.137)			(0.240)
R^2	0.11	0.11	0.11	0.17	0.17	0.17
N	24,248	22,209	23,842	24,248	22,209	23,842

Note: In this table, we present difference in difference estimates of the effect of unexpected changes in the regulatory environment on the share of businesses that are currently open and on demand projections in the future. In column 1, we present difference in difference results with Wisconsin and Florida pooled together to form the treatment group. In columns 2 and 3 we estimate the results separately for Wisconsin and Florida, respectively. To avoid biasing these DiD estimates towards zero, Florida is excluded from the regression in 2 and Wisconsin is excluded from column 3 to avoid contaminating the control group. We present analogous estimates of the effect of the regulatory change on demand projections in columns 4 to 6.

We supplement the main survey data (collected from May 9 to May 13) with data from a later survey (collected from May 14 to June 1); since the policy changes were announced on May 13 (WI) and 14 (FL), the main survey is the pre-period, and the follow-up survey is the post-period. We reweight the post-period to match the pre-period at the 4-digit NAICS by county level, cells that do not include at least one observation in both surveys are dropped. Note that while the second survey remained open until the following survey was distributed, over 95% of responses were collected by May 18. Since the first survey was distributed starting on May 9th, the majority of responses are collected over a nine day period in early May. See equation 3 and the discussion for more information.

Table 3: FACTORS CONTRIBUTING TO DIFFERENCES IN OPERATIONAL STATUS

	(1) Fully Open	(2) Partially Open	(3) Temp. Closed	(4) Perm. Closed
Emp. Physical Proximity	-0.1047***	-0.0159***	0.1170***	0.0036***
	(0.0039)	(0.0043)	(0.0041)	(0.0013)
Owner Age	0.0011*	-0.0010*	-0.0006	0.0004**
	(0.0006)	(0.0006)	(0.0006)	(0.0002)
Customers Over 65	-0.0085***	0.0132***	-0.0028	-0.0019*
	(0.0033)	(0.0035)	(0.0033)	(0.0010)
Essential Business	0.1193***	0.0434***	-0.1587***	-0.0040*
	(0.0063)	(0.0068)	(0.0070)	(0.0023)
Ease Operating Online	-0.0157***	-0.0085**	0.0235***	0.0007
	(0.0039)	(0.0039)	(0.0040)	(0.0010)
ln(COVID cases per cap.)	-0.0317***	0.0059**	0.0260***	-0.0002
	(0.0044)	(0.0028)	(0.0047)	(0.0008)
ln(Pop. Density)	0.0147***	-0.0042	-0.0103***	-0.0002
	(0.0039)	(0.0026)	(0.0038)	(0.0007)
GOP Vote Share (County)	0.3222***	-0.0822***	-0.2303***	-0.0097
	(0.0287)	(0.0247)	(0.0337)	(0.0066)
DV Mean	0.317	0.340	0.321	0.022
DV SD	0.465	0.474	0.467	0.147
Residual SD	0.451	0.472	0.450	0.147
R^2	0.0596	0.0059	0.0708	0.0024
N	32,763	32,763	32,763	32,763

Note: These columns correspond to answers to the question "Are you currently open?". These options are collectively exhaustive and mutually exclusive. *Employee Physical Proximity*, *Customers Over 65*, and *Ease Operating Online* are converted to z-scores. Standard errors are clustered at the county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: OLS: Contribution of Various Factors to the Small Business Reopen Decision

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Reopen	Restrictions	Lag	Lag $\geq$ 4wk	Reopen	Restrictions	Lag	Lag $\geq$ 4wk
	All Businesses				*Excluding Fully Open Businesses*			
ln(COVID cases per cap.)	0.0813***	0.0812***	0.0219***	0.0055*	0.0211*	0.0444***	0.0101	-0.0003
	(0.0125)	(0.0127)	(0.0077)	(0.0030)	(0.0111)	(0.0128)	(0.0098)	(0.0037)
Emp. Physical Proximity	0.2556***	0.3068***	0.0457*	0.0128	0.0195	0.1177*	-0.0189	-0.0060
	(0.0542)	(0.0654)	(0.0273)	(0.0109)	(0.0486)	(0.0621)	(0.0353)	(0.0106)
$\times$ ln(COVID cases p.c.)	0.0034	0.0015	0.0037	0.0006	0.0072	-0.0049	0.0066	0.0023
	(0.0089)	(0.0106)	(0.0047)	(0.0018)	(0.0082)	(0.0103)	(0.0061)	(0.0018)
Owner Age	-0.0014	-0.0063***	0.0031	0.0007	0.0009	-0.0068**	0.0028	0.0004
	(0.0026)	(0.0024)	(0.0022)	(0.0007)	(0.0028)	(0.0030)	(0.0025)	(0.0008)
$\times$ ln(COVID cases p.c.)	0.0002	-0.0002	0.0003	0.0001	0.0002	-0.0003	0.0002	0.0000
	(0.0002)	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0003)	(0.0002)	(0.0001)
Customers Over 65	-0.1135***	-0.0908	-0.0498	-0.0073	-0.0709*	-0.0462	-0.0722**	-0.0139
	(0.0377)	(0.0566)	(0.0316)	(0.0100)	(0.0405)	(0.0678)	(0.0313)	(0.0124)
$\times$ ln(COVID cases p.c.)	-0.0124**	-0.0068	-0.0075	-0.0021	-0.0012	0.0063	-0.0068	-0.0021
	(0.0063)	(0.0091)	(0.0051)	(0.0016)	(0.0070)	(0.0111)	(0.0053)	(0.0022)
Essential Business	-0.3010***	-0.3267***	-0.0720***	-0.0265***	-0.1222***	-0.2291***	-0.0488**	-0.0186***
	(0.0226)	(0.0232)	(0.0170)	(0.0056)	(0.0277)	(0.0304)	(0.0216)	(0.0067)
Ease Operating Online	0.0451***	0.0275**	0.0252**	0.0048	0.0226	0.0068	0.0256*	0.0031
	(0.0128)	(0.0119)	(0.0107)	(0.0034)	(0.0151)	(0.0158)	(0.0132)	(0.0042)
ln(Pop. Density)	-0.0430***	-0.0471***	-0.0100	-0.0024	-0.0180*	-0.0358***	-0.0071	-0.0006
	(0.0106)	(0.0113)	(0.0062)	(0.0021)	(0.0102)	(0.0118)	(0.0088)	(0.0029)
GOP Vote Share (County)	-1.3072***	-1.0771***	-0.5805***	-0.1707***	-0.9999***	-0.8412***	-0.6130***	-0.1573***
	(0.0847)	(0.0940)	(0.0600)	(0.0211)	(0.0893)	(0.1063)	(0.0791)	(0.0264)
Restriction FE	No	No	Yes	Yes	No	No	Yes	Yes
DV Mean	1.306	1.051	1.306	0.177	2.073	1.669	2.073	0.280
DV SD	1.487	1.408	1.487	0.381	1.386	1.455	1.386	0.449
Residual SD	1.451	1.368	1.116	0.375	1.372	1.439	1.160	0.379
R^2	0.0484	0.0567	0.4366	0.0329	0.0194	0.0227	0.2993	0.2884
N	28,034	28,034	28,034	28,034	17,659	17,659	17,659	17,659

Note: *Reopen* is the expected months to reopen. *Restriction* is the estimated months until restrictions are lifted. *Lag* takes the same outcome as Reopen, but adds a fixed effect for *Restriction*. *Lag* $\geq$ *4wk* is a indicator variable that evaluates to 1 if the firm's estimated reopening date is at least one month/four weeks after the estimated date restrictions are lifted. Businesses that were permanently closed at the time of the survey are excluded from these regressions; businesses that were fully open at the time of the survey are excluded from columns $5-8$. *Employee Physical Proximity*, *Customers Over 65*, and *Ease Operating Online* are converted to z-scores. Standard errors in parentheses, clustered at county level. Note that the survey questions in which reopening and restriction beliefs are elicited is mid-way through the survey, thus in some columns we are able to have more observations than we have complete survey responses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: CONTRIBUTION OF VARIOUS FACTORS TO PROJECTED LN(SHARE RETURNING CUSTOMERS)

	(1) *All Businesses*	(2) *Excluding Fully Open Businesses*
Mo. until No Restrictions	-0.1739***	-0.1296***
	(0.0044)	(0.0051)
ln(COVID cases per cap.)	-0.0063	-0.0016
	(0.0065)	(0.0080)
Emp. Physical Proximity	-0.0785***	-0.0840***
	(0.0238)	(0.0233)
$\times$ ln(COVID cases p.c.)	-0.0114***	-0.0175***
	(0.0039)	(0.0040)
Owner Age	0.0001	-0.0007
	(0.0014)	(0.0018)
$\times$ ln(COVID cases p.c.)	-0.0001	-0.0001
	(0.0001)	(0.0002)
Customers Over 65	0.0628**	0.0530*
	(0.0270)	(0.0281)
$\times$ ln(COVID cases p.c.)	0.0069	0.0033
	(0.0044)	(0.0048)
Essential Business	0.1217***	0.1110***
	(0.0118)	(0.0150)
ln(Pop. Density)	0.0150**	0.0178**
	(0.0059)	(0.0076)
Ease Operating Online	-0.0382***	-0.0409***
	(0.0069)	(0.0089)
GOP Vote Share (County)	0.4473***	0.4952***
	(0.0482)	(0.0608)
DV Mean	3.727	3.557
DV SD	0.876	0.921
Residual SD	0.798	0.844
R^2	0.1694	0.1608
N	26,784	17,880

Note: The outcome in all columns is the logarithm of projected demand, measured as the answer to the question "If you are fully open by *randomized date*, what share of your customers do you expect at that time, compared to before the crisis? Please provide your best guess". *Employee Physical Proximity*, *Customers Over 65*, and *Ease Operating Online* are converted to z-scores. Standard errors in parentheses, clustered at county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: FACTORS CONTRIBUTING TO THE PROBABILITY OF BEING OPEN IN DECEMBER, 2020

	(1)	(2)	(3)
Mo. until No Restrictions	-0.0256***		-0.0164***
	(0.0011)		(0.0011)
ln(Share Returning Customers)		0.0637***	0.0567***
		(0.0018)	(0.0019)
ln(COVID cases per cap.)	0.0014	-0.0001	0.0011
	(0.0015)	(0.0015)	(0.0015)
Emp. Physical Proximity	-0.0213***	-0.0213***	-0.0168***
	(0.0050)	(0.0058)	(0.0052)
× ln(COVID cases p.c.)	-0.0017*	-0.0009	-0.0010
	(0.0009)	(0.0010)	(0.0009)
Owner Age	0.0000	0.0001	0.0000
	(0.0004)	(0.0004)	(0.0004)
× ln(COVID cases p.c.)	-0.0001*	-0.0001	-0.0001*
	(0.0000)	(0.0000)	(0.0000)
Customers Over 65	0.0154***	0.0116**	0.0110**
	(0.0055)	(0.0049)	(0.0046)
× ln(COVID cases p.c.)	0.0009	0.0004	0.0004
	(0.0009)	(0.0008)	(0.0008)
Essential Business	0.0212***	0.0172***	0.0128***
	(0.0031)	(0.0030)	(0.0030)
ln(Pop. Density)	-0.0002	-0.0000	-0.0006
	(0.0014)	(0.0013)	(0.0013)
Ease Operating Online	-0.0012	0.0007	0.0009
	(0.0017)	(0.0016)	(0.0016)
GOP Vote Share (County)	0.0165	0.0042	-0.0077
	(0.0123)	(0.0114)	(0.0114)
DV Mean	0.792	0.792	0.792
DV SD	0.185	0.185	0.185
Residual SD	0.180	0.175	0.174
R^2	0.0594	0.1087	0.1225
N	16,677	16,677	16,677

Note: The outcome in all columns is the answer to the question "What is the likelihood of your business remaining operational by Dec. 31, 2020? Please provide your best guess.". Businesses that were permanently closed at the time of the survey are excluded from these regressions. *Employee Physical Proximity*, *Customers Over 65*, and *Ease Operating Online* are converted to z-scores. Standard errors in parentheses, clustered at county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Instrumenting Expected Customer Demand: Information Treatment

Panel A: 2SLS

	(1) Reopen	(2) Reopen†	(3) Lag	(4) Lag†	(5) Lag $\geq$ 4wk	(6) Lag $\geq$ 4wk†	(7) Open Dec.	(8) Open Dec.†
ln(Share Customers Returning)	-0.881***	-0.860***	-0.531**	-0.533**	-0.168**	-0.155*	0.318***	0.333***
	(0.187)	(0.194)	(0.217)	(0.211)	(0.084)	(0.083)	(0.043)	(0.044)
Restriction FE	No	No	Yes	Yes	Yes	Yes	No	No
Additional Controls	No	Yes	No	Yes	No	Yes	No	Yes
Kleibergen-Paap F stat	8.3	9.4	8.3	9.3	8.3	9.3	9.0	10.2
Mean Dep. Var.	1.38	1.38	0.19	1.37	0.19	0.19	0.79	0.79
Std. Dev. Dep. Var.	1.49	1.49	0.39	1.49	0.39	0.39	0.18	0.18
R^2	0.70	0.70	0.79	0.79	0.46	0.47	0.90	0.90
Observations	16,275	16,275	16,183	16,183	16,183	16,183	13,391	13,391

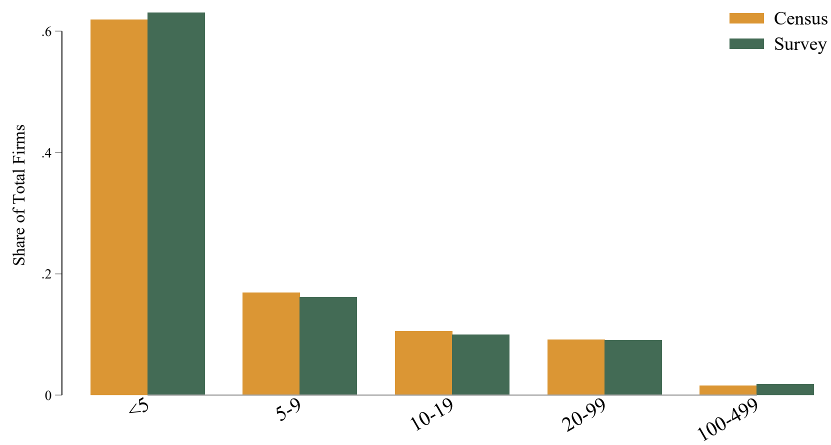
Panel B: First-Stage and Reduced Form

	First Stage		Reduced Form							
	(1) Demand	(2) Demand†	(3) Reopen	(4) Reopen†	(5) Lag	(6) Lag†	(7) Lag $\geq$ 4wk	(8) Lag $\geq$ 4wk†	(9) Open Dec.	(10) Open Dec.†
ln(Signal/Prior) $\times$ Shown Info	0.190***	0.188***	-0.237***	-0.234***	-0.144**	-0.145***	-0.042*	-0.039*	0.083***	0.085***
	(0.045)	(0.042)	(0.049)	(0.045)	(0.055)	(0.050)	(0.023)	(0.021)	(0.006)	(0.005)
Restriction FE	No	No	No	No	Yes	Yes	Yes	Yes	No	No
Additional Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean Dep. Var.	3.72	3.72	1.38	1.38	1.37	1.37	0.19	0.19	0.79	0.79
Std. Dev. Dep. Var.	0.87	0.87	1.49	1.49	1.49	1.49	0.39	0.39	0.18	0.18
R^2	0.34	0.34	0.52	0.52	0.63	0.63	0.39	0.39	0.10	0.10
Observations	16,275	16,275	16,275	16,275	16,183	16,183	16,183	16,183	13,391	13,391

Note: In Panel A, the dependent variable in Col. (1,2) *Reopen* is the expected months to reopen. The dependent variable in Col. (3,4) *Lag* is the same outcome (that is, months until reopening), but includes a fixed effect for the date restrictions are lifted. In Col. (5,6) *Lag* $\geq$ *4wk* is a indicator variable that evaluates to 1 if the firm's estimated reopening date is at least one month/four weeks after the estimated date restrictions are lifted. In Col. (7,8) the dependent variable *Open Dec.* is the self-reported probability of being operational by December 31st, 2020. Controls across all regressions include the prior and the gap between the signal and the prior (log units), date fixed effects, the current status of business, the essential classification. In Panel B, the dependent variable in Col. (1) is the log expected demand, the response to the question "If you are fully open by *randomized date*, what share of your customers do you expect at that time, compared to before the crisis? Please provide your best guess." The instrument for expected demand is an information instrument is shown to a random subset of participants before we elicit demand expectations. The message received is "Before continuing, we want to share some interesting information. Based on your profile, location, and concerns, our polls show that similar businesses anticipate [rolling mean] % of customers will return by [future date]." †: Columns with additional controls contain the additional controls from the main OLS specification in Table 5, namely the natural logarithm of (1+COVID cases per capita), physical proximity, owner age, likelihood of having customers over 65, ease of conducting business online, the natural logarithm of population density, and the county-level share of the vote that went to the Republican candidate in the 2016 presidential election. Standard errors are clustered at the region $\times$ business type level, which is the level at which the information treatment is assigned. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A Appendix: Additional Figures and Tables

PANEL A. Firm Size in the Survey and Census



PANEL B. Firm Locations in the Census and Survey

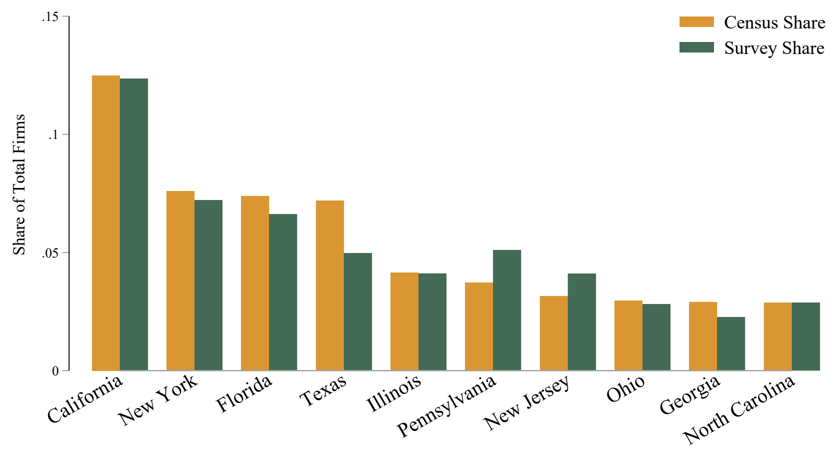
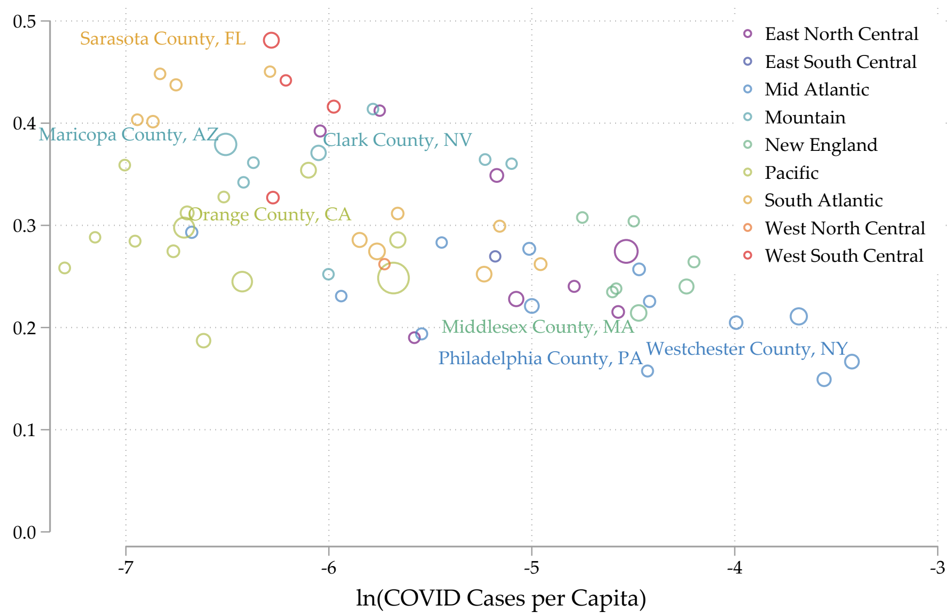


Figure A1: FIRM SIZE AND LOCATION IN THE SURVEY AND CENSUS

This figure plots the share of firms in each employment category and state for the 2017 Census of US Businesses and the survey respondents for May 9, 2020. The sample size is 22,492 responses from May 9th survey wave with non-missing employment data and 34,941 responses with non-missing state data.

Panel A: Local COVID Prevalence



Panel B: Local Unemployment

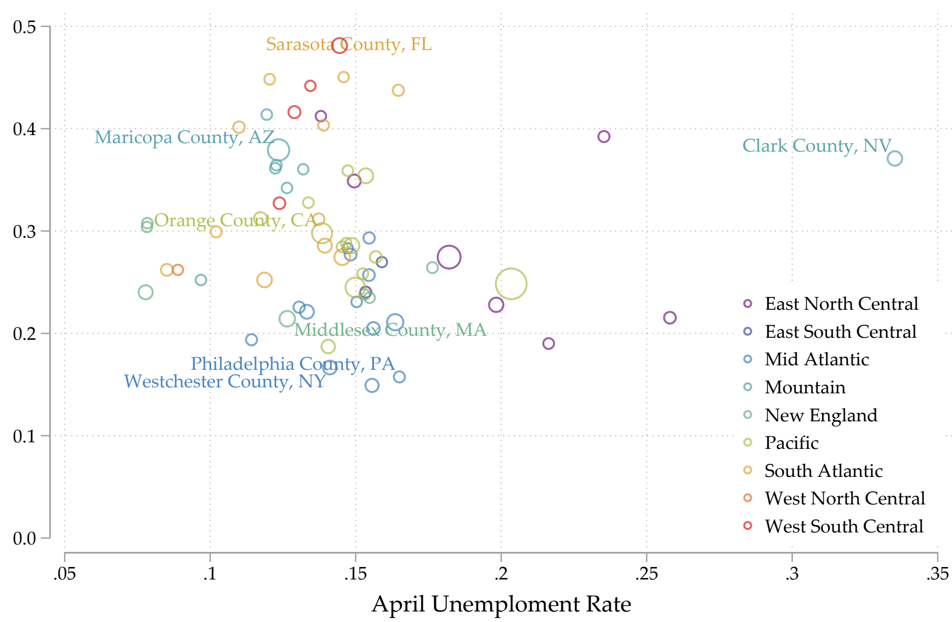


Figure A2: Share of Small Businesses Open by COVID Cases and Unemployment

This figure plots the share of firms that are fully open as of the May 9th survey wave against COVID cases per capita, and the unemployment rate, at the county level. Counties with fewer than 100 observations not plotted; rings representing counties with more responses are drawn larger than those representing counties with few responses.

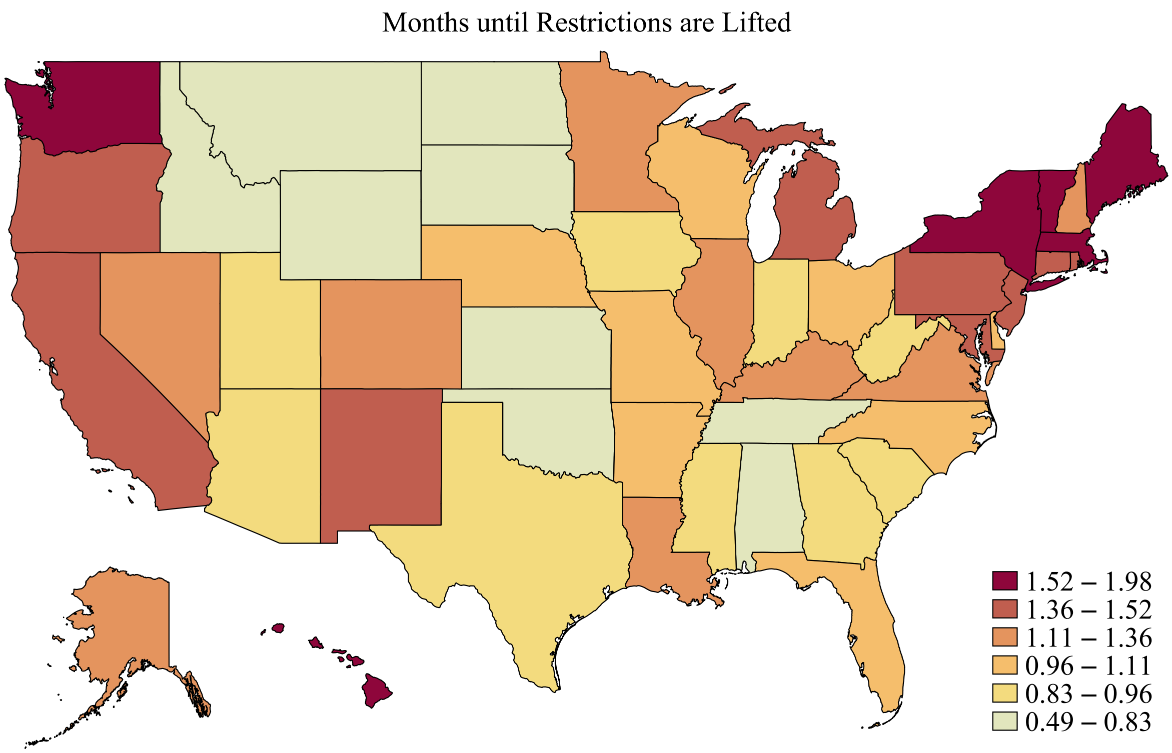
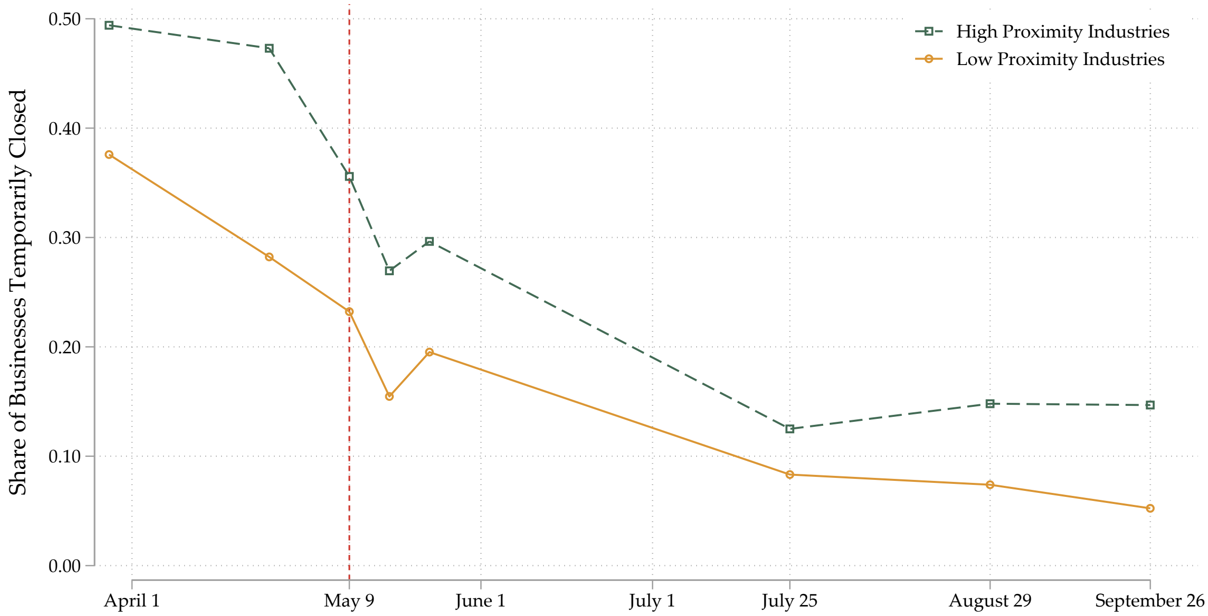


Figure A3: PERCEIVED MONTHS UNTIL RESTRICTIONS LIFTED, BY STATE

PANEL A: Shares of Businesses that are Temporarily Closed by Above and Below Median Proximity



PANEL B: Shares of Businesses by Essential and Non-Essential Industry Classifications

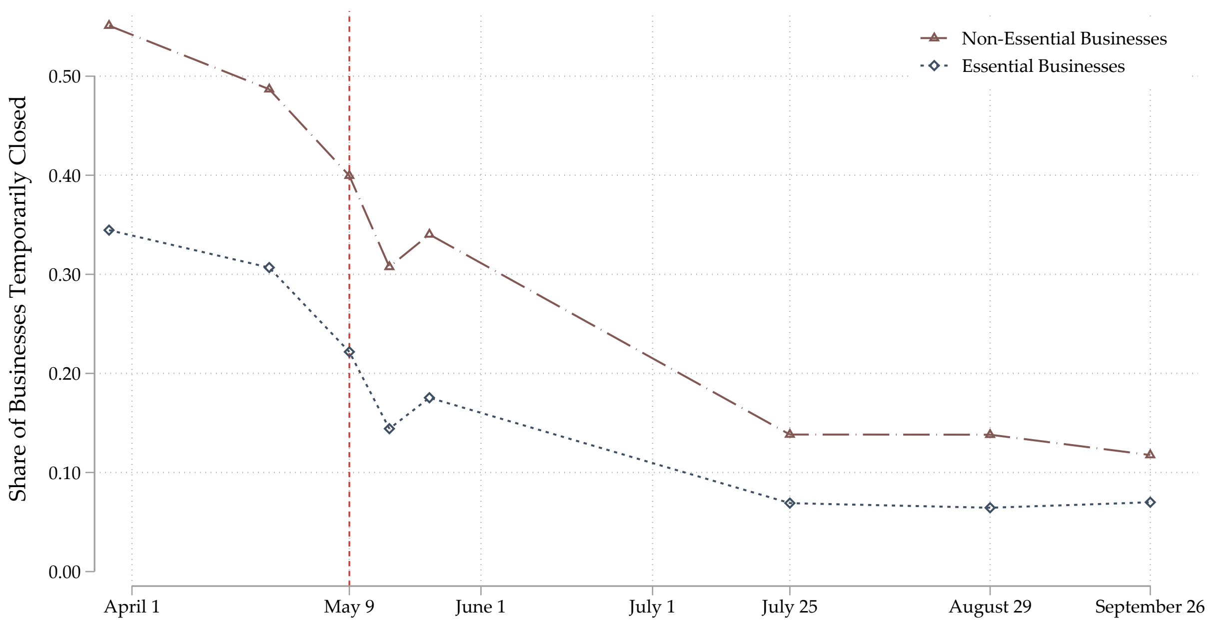


Figure A4: SHARES OF BUSINESSES THAT ARE TEMPORARILY CLOSED

This figure plots the share of firms that are temporarily closed across waves of Alignable's data collection, split by whether the business is in an above or below median proximity industry. Proximity is defined by the O-NET Physical Proximity measure "To what extent does this job require the worker to perform job tasks in close physical proximity to other people?" We merge the proximity measure to the OES data based on occupation and then take an employment-weighted average by industry. We thank Simon Mongey and Alex Weinberg for publicly sharing this measure. Industries are classified as essential if they are on the list of essential NAICS codes in both Delaware and Minnesota, two states that have done this classification based on NAICS industries.

Table A1: CENSUS INDUSTRY VERSUS SURVEY INDUSTRY BREAKDOWN

Industry	Census Percentage	Survey Percentage
Agriculture, Forestry, Fishing and Hunting	0.4	1.1
Mining, Quarrying, and Oil and Gas Extraction	0.3	0.3
Utilities	0.1	0.3
Construction	11.7	7.6
Manufacturing	4.1	6.0
Wholesale and Retail Trade	15.7	13.1
Transportation and Warehousing	3.1	1.2
Information	1.3	2.1
Finance and Insurance	4.0	6.8
Real Estate and Rental and Leasing	5.2	8.8
Professional, Scientific, and Technical Services	13.5	14.6
Management of Companies and Enterprises	0.3	0.0
Administrative and Support and Waste Remediation Svcs	5.8	3.8
Educational Services	1.5	3.3
Health Care and Social Assistance	10.9	8.8
Arts, Entertainment, and Recreation	2.2	6.9
Accommodation and Food Services	9.0	5.2
Other Services (except Public Administration)	11.6	9.2

Notes. This table reports results of Census and Survey shares by industry for firms with fewer than 500 employees. Survey response shares are conditional on being able to classify industries, with unavailable or "Other" industry classifications omitted from the denominator. We combine wholesale and retail trade.

Table A2: TIME TO REOPEN BY INDUSTRY (2-DIGIT NAICS) FOR FIRMS THAT ARE NOT FULLY OPEN

	Reopen	Lag	Lag $\geq$ 4 weeks
Accommodation and Food Services	2.241	0.461	0.204
Other Services, Except Public Administration	1.828	0.496	0.217
Management of Companies and Enterprises	0.750	0.500	0.000
Retail Trade	1.755	0.534	0.228
Arts, Entertainment, and Recreation	2.647	0.585	0.241
Finance and Insurance	1.783	0.589	0.277
Real Estate and Rental and Leasing	1.928	0.611	0.275
Construction	1.747	0.625	0.278
Educational Services	2.482	0.706	0.271
Agriculture, Forestry, Fishing and Hunting	2.034	0.711	0.311
Manufacturing	2.008	0.740	0.305
Health Care and Social Assistance	1.986	0.762	0.317
Public Administration	2.519	0.776	0.333
Utilities	1.938	0.793	0.348
Administrative and Waste Services	2.388	0.835	0.337
Wholesale Trade	1.870	0.845	0.331
Professional and Technical Services	2.154	0.872	0.356
Information	2.698	0.954	0.381
Mining, Quarrying, and Oil and Gas Extraction	1.884	1.019	0.308
Transportation and Warehousing	2.376	1.027	0.416

Table A3: EXPECTED DEMAND BY INDUSTRY (NAICS 2-DIGIT)

Industry	May		June		July		September		N
Share Expecting	>90%	Mean	>90%	Mean	>90%	Mean	>90%	Mean	
Arts, Entertainment, & Recreation	0.07	0.37	0.07	0.43	0.07	0.44	0.11	0.55	1851
Educational Services	0.08	0.47	0.07	0.47	0.11	0.53	0.13	0.60	832
Accommodation & Food Services	0.02	0.42	0.05	0.48	0.06	0.50	0.14	0.58	1452
Retail Trade	0.10	0.51	0.13	0.55	0.15	0.57	0.17	0.64	3057
Admin. and Waste Services	0.14	0.47	0.13	0.48	0.18	0.51	0.18	0.60	1085
Real Estate & Leasing	0.14	0.54	0.16	0.57	0.20	0.60	0.20	0.61	2162
Information	0.15	0.53	0.19	0.57	0.22	0.59	0.20	0.65	586
Manufacturing	0.12	0.56	0.14	0.60	0.13	0.59	0.21	0.67	1744
Health Care & Social Assistance	0.07	0.55	0.13	0.58	0.15	0.61	0.22	0.70	2331
Professional & Technical Services	0.18	0.54	0.18	0.58	0.19	0.62	0.24	0.67	3985
Other Services, Except Public Admin.	0.12	0.54	0.15	0.58	0.16	0.60	0.24	0.68	2322
Construction	0.17	0.59	0.18	0.60	0.19	0.63	0.25	0.69	1998
Finance and Insurance	0.19	0.66	0.28	0.66	0.26	0.65	0.27	0.70	1629

Note: This table reports answers to a question about the expected share of customers returning by a certain randomly chosen date in the future. Each cell reports a share of customers relative to pre-COVID customers conditional on being able to classify industries. Columns are the share of respondents who report having greater than 90% of pre-COVID customers (the highest category) and then mean share of pre-COVID customers using the mid-point of categorical answers.

Table A4: TOBIT: CONTRIBUTION OF VARIOUS FACTORS TO THE SMALL BUSINESS REOPEN DECISION

	(1) Reopen	(2) Restrictions	(3) Lag	(4) Lag $\geq$ 4wk	(5) Reopen	(6) Restrictions	(7) Lag	(8) Lag $\geq$ 4wk
	All Businesses				*Excluding Fully Open Businesses*			
ln(COVID cases per cap.)	0.1764***	0.1679***	0.0506***	0.0055*	0.0239*	0.0468***	0.0133	-0.0003
	(0.0250)	(0.0239)	(0.0143)	(0.0030)	(0.0134)	(0.0146)	(0.0117)	(0.0037)
Emp. Physical Proximity	0.4474***	0.5168***	0.0603	0.0128	0.0136	0.1480**	-0.0398	-0.0060
	(0.0879)	(0.0930)	(0.0469)	(0.0109)	(0.0612)	(0.0734)	(0.0444)	(0.0106)
$\times$ ln(COVID cases p.c.)	-0.0135	-0.0132	-0.0039	0.0006	0.0074	-0.0025	0.0053	0.0023
	(0.0146)	(0.0154)	(0.0081)	(0.0018)	(0.0102)	(0.0121)	(0.0076)	(0.0018)
Owner Age	-0.0033	-0.0098**	0.0056	0.0007	0.0013	-0.0077**	0.0035	0.0004
	(0.0046)	(0.0040)	(0.0039)	(0.0007)	(0.0035)	(0.0036)	(0.0030)	(0.0008)
$\times$ ln(COVID cases p.c.)	0.0002	-0.0002	0.0005	0.0001	0.0002	-0.0003	0.0002	0.0000
	(0.0004)	(0.0004)	(0.0004)	(0.0001)	(0.0003)	(0.0004)	(0.0003)	(0.0001)
Customers Over 65	-0.2057***	-0.1552*	-0.0701	-0.0073	-0.0983**	-0.0622	-0.0940**	-0.0139
	(0.0652)	(0.0812)	(0.0617)	(0.0100)	(0.0474)	(0.0750)	(0.0380)	(0.0124)
$\times$ ln(COVID cases p.c.)	-0.0252**	-0.0151	-0.0133	-0.0021	-0.0032	0.0058	-0.0092	-0.0021
	(0.0110)	(0.0132)	(0.0100)	(0.0016)	(0.0082)	(0.0123)	(0.0064)	(0.0022)
Essential Business	-0.6093***	-0.6167***	-0.1445***	-0.0265***	-0.1499***	-0.2614***	-0.0627**	-0.0186***
	(0.0404)	(0.0385)	(0.0308)	(0.0056)	(0.0336)	(0.0358)	(0.0262)	(0.0067)
Ease Operating Online	0.0962***	0.0660***	0.0502**	0.0048	0.0287	0.0069	0.0334**	0.0031
	(0.0242)	(0.0210)	(0.0200)	(0.0034)	(0.0183)	(0.0183)	(0.0159)	(0.0042)
ln(Pop. Density)	-0.0881***	-0.0919***	-0.0204*	-0.0024	-0.0203*	-0.0411***	-0.0077	-0.0006
	(0.0217)	(0.0216)	(0.0115)	(0.0021)	(0.0122)	(0.0135)	(0.0105)	(0.0029)
GOP Vote Share (County)	-2.4602***	-2.0610***	-1.0669***	-0.1707***	-1.1861***	-0.9779***	-0.7219***	-0.1573***
	(0.1699)	(0.1717)	(0.1115)	(0.0211)	(0.1080)	(0.1218)	(0.0944)	(0.0264)
Restriction FE	No	No	Yes	Yes	No	No	Yes	Yes
DV Mean	1.306	1.051	1.306	0.177	2.073	1.669	2.073	0.280
DV SD	1.487	1.408	1.487	0.381	1.386	1.455	1.386	0.449
Psuedo R^2	0.0249	0.0288	0.1800	0.0458	0.0130	0.0135	0.1066	0.2813
N	28,034	28,034	28,034	28,034	17,659	17,659	17,659	17,659

Note: *Reopen* is the expected months to reopen. *Restriction* is the estimated months until restrictions are lifted. *Lag* takes the same outcome as Reopen, but adds a fixed effect for *Restriction*. *Lag* $\geq$ *4wk* is a indicator variable that evaluates to 1 if the firm's estimated reopening date is at least one month/four weeks after the estimated date restrictions are lifted. Businesses that were permanently closed at the time of the survey are excluded from these regressions; businesses that were fully open at the time of the survey are excluded from columns $5-8$. *Employee Physical Proximity*, *Customers Over 65*, and *Ease Operating Online* are converted to z-scores. Standard errors in parentheses, clustered at county level. Note that the survey questions in which reopening and restriction beliefs are elicited is mid-way through the survey, thus in some columns we are able to have more observations than we have complete survey responses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table A5: CONTRIBUTION OF VARIOUS FACTORS TO THE SMALL BUSINESS REOPEN DECISION, COUNTY FIXED EFFECTS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Reopen	Restrictions	Lag	Lag $\geq$ 4wk	Reopen	Restrictions	Lag	Lag $\geq$ 4wk
	All Businesses				*Excluding Fully Open Businesses*			
Emp. Physical Proximity	0.333***	0.412***	0.0487	0.000176	0.0632	0.215***	-0.00528	-0.0228
	(0.0629)	(0.0681)	(0.0494)	(0.0164)	(0.0709)	(0.0818)	(0.0638)	(0.0192)
× ln(COVID cases p.c.)	0.0160	0.0186*	0.00458	-0.00126	0.0135	0.0111	0.00813	-0.000494
	(0.0103)	(0.0111)	(0.00822)	(0.00272)	(0.0118)	(0.0136)	(0.0108)	(0.00328)
Owner Age	-0.000917	-0.00779***	0.00460*	0.00107	0.00169	-0.00868**	0.00422	0.000744
	(0.00321)	(0.00277)	(0.00264)	(0.000809)	(0.00360)	(0.00353)	(0.00308)	(0.000949)
× ln(COVID cases p.c.)	0.000229	-0.000286	0.000454	0.000122	0.000322	-0.000314	0.000378	0.0000788
	(0.000339)	(0.000350)	(0.000307)	(0.0000939)	(0.000394)	(0.000470)	(0.000362)	(0.000119)
Customers Over 65	-0.163***	-0.164**	-0.0427	-0.00834	-0.110	-0.115	-0.0964	-0.0304
	(0.0602)	(0.0680)	(0.0465)	(0.0171)	(0.0710)	(0.0864)	(0.0603)	(0.0201)
× ln(COVID cases p.c.)	-0.0201**	-0.0181*	-0.00646	-0.00220	-0.00745	-0.00472	-0.0111	-0.00496
	(0.00983)	(0.0107)	(0.00753)	(0.00278)	(0.0119)	(0.0139)	(0.00996)	(0.00343)
Essential Business	-0.303***	-0.333***	-0.0683***	-0.0254***	-0.121***	-0.240***	-0.0452*	-0.0172**
	(0.0241)	(0.0245)	(0.0180)	(0.00587)	(0.0307)	(0.0329)	(0.0235)	(0.00707)
Ease Operating Online	0.0514***	0.0366***	0.0242**	0.00432	0.0295*	0.0187	0.0280*	0.00208
	(0.0136)	(0.0125)	(0.0115)	(0.00368)	(0.0165)	(0.0171)	(0.0146)	(0.00451)
Restriction FE	No	No	Yes	Yes	No	No	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DV Mean	1.300	1.045	1.300	0.177	2.073	1.668	2.073	0.282
DV SD	1.485	1.404	1.485	0.382	1.385	1.453	1.385	0.450
Residual SD	1.412	1.320	1.090	0.366	1.330	1.385	1.125	0.366
R^2	.0957	.116	.461	.0808	.0782	.0919	.34	.337
N	26,957	26,957	26,957	26,957	16,695	16,695	16,695	16,695

Note: *Reopen* is the expected months to reopen. *Restriction* is the estimated months until restrictions are lifted. *Lag* takes the same outcome as Reopen, but adds a fixed effect for *Restriction*. *Lag* $\geq$ *4wk* is a indicator variable that evaluates to 1 if the firm's estimated reopening date is at least one month/four weeks after the estimated date restrictions are lifted. Businesses that were permanently closed at the time of the survey are excluded from these regressions; businesses that were fully open at the time of the survey are excluded from columns $5-8$. *Employee Physical Proximity*, *Customers Over 65*, and *Ease Operating Online* are converted to z-scores. Standard errors in parentheses, clustered at county level. Note that the survey questions in which reopening and restriction beliefs are elicited is mid-way through the survey, thus in some columns we are able to have more observations than we have complete survey responses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Time to Reopen by Industry (3-digit NAICS), excluding Fully Open in May 9 Survey

2-Digit NAICS Industry	3-Digit NAICS Industry	Reopen	Lag	Lag $\geq$ 4wk
Accommodation and Food Services	Accommodation	2.135	0.662	0.302
Accommodation and Food Services	Food Services and Drinking Places	2.276	0.393	0.171
Administrative and Waste Services	Administrative and Support Services	2.400	0.836	0.339
Agriculture, Forestry, Fishing and Hunting	Animal Production and Aquaculture	2.154	0.711	0.314
Arts, Entertainment, and Recreation	Amusement, Gambling, and Recreation Industries	2.020	0.409	0.171
Arts, Entertainment, and Recreation	Museums, Historical Sites, and Similar Institutions	2.161	0.491	0.222
Arts, Entertainment, and Recreation	Performing Arts, Spectator Sports, and Related Industries	3.180	0.737	0.299
Construction	Construction of Buildings	1.779	0.614	0.266
Construction	Specialty Trade Contractors	1.705	0.628	0.297
Educational Services	Educational Services	2.486	0.696	0.271
Finance and Insurance	Credit Intermediation and Related Activities	1.766	0.500	0.243
Finance and Insurance	Insurance Carriers and Related Activities	1.810	0.696	0.331
Finance and Insurance	Securities, Commodity Contracts, etc.	1.610	0.693	0.310
Health Care and Social Assistance	Ambulatory Health Care Services	1.922	0.782	0.326
Health Care and Social Assistance	Social Assistance	2.246	0.605	0.245
Information	Motion Picture and Sound Recording Industries	3.068	0.784	0.324
Information	Publishing Industries (except Internet)	2.477	1.330	0.509
Manufacturing	Beverage and Tobacco Product Manufacturing	2.075	0.401	0.163
Manufacturing	Food Manufacturing	2.330	1.006	0.337
Manufacturing	Machinery Manufacturing	1.823	0.746	0.328
Manufacturing	Miscellaneous Manufacturing	2.051	0.633	0.265
Manufacturing	Printing and Related Support Activities	1.833	0.654	0.330
Other Services, Except Public Administration	Personal and Laundry Services	1.695	0.383	0.170
Other Services, Except Public Administration	Religious, Grantmaking, Civic, Professional, etc.	2.336	0.782	0.338
Other Services, Except Public Administration	Repair and Maintenance	1.523	0.560	0.246
Professional and Technical Services	Professional, Scientific, and Technical Services	2.156	0.874	0.356
Public Administration	Administration of Human Resource Programs	2.882	0.717	0.309
Real Estate and Rental and Leasing	Real Estate	1.916	0.615	0.278
Real Estate and Rental and Leasing	Rental and Leasing Services	2.041	0.571	0.250
Retail Trade	Clothing and Clothing Accessories Stores	1.592	0.308	0.138
Retail Trade	Food and Beverage Stores	1.906	0.654	0.275
Retail Trade	Furniture and Home Furnishings Stores	1.478	0.477	0.227
Retail Trade	Health and Personal Care Stores	1.776	0.526	0.242
Retail Trade	Miscellaneous Store Retailers	1.781	0.535	0.224
Retail Trade	Motor Vehicle and Parts Dealers	1.378	0.363	0.120
Retail Trade	Sporting Goods, Hobby, Musical Instrument, and Book Stores	2.014	0.681	0.269
Transportation and Warehousing	Transit and Ground Passenger Transportation	2.647	1.016	0.381
Wholesale Trade	Merchant Wholesalers, Durable Goods	1.772	0.731	0.278

Notes. Means are only displayed for 3-digit industries with at least 50 observations. For this reason, these estimates within in a 2-digit industry need not average to the 2-digit industry mean presented in Table 4.

Table A7: CUSTOMERS RETURNING AND BUSINESS REOPENING: PROJECTED VS REALIZED

Panel A: Customers Returning	Real Time: Customer Demand Report, Percent of Pre-Crisis Level					
	July		August		September	
	Demand	Open	Demand	Open	Demand	Open
Projected Customers Returning if Fully-Open						
$< 10\%$	43.75	31.13	50.17	37.82	37.14	35.00
	(3.326)	(2.356)	(5.033)	(4.159)	(6.225)	(5.026)
$10\% - 25\%$	50.21	40.89	53.65	46.02	59.95	56.47
	(2.798)	(2.341)	(4.682)	(4.268)	(4.754)	(4.876)
$25\% - 50\%$	54.83	53.46	54.33	55.75	47.34	54.79
	(1.998)	(1.933)	(3.428)	(3.439)	(3.683)	(3.720)
$50\% - 75\%$	66.91	67.02	67.17	67.58	62.52	74.31
	(1.639)	(1.792)	(3.044)	(3.363)	(3.184)	(3.746)
$75\% - 90\%$	78.96	75.00	73.71	78.87	67.03	84.27
	(1.824)	(2.130)	(3.190)	(3.807)	(3.803)	(4.765)
$> 90\%$	93.37	84.69	87.14	90.35	89.25	83.91
	(1.867)	(2.279)	(3.327)	(4.249)	(3.855)	(4.819)
R^2	0.83	0.65	0.81	0.68	0.80	0.69
N	1,454	2,850	532	844	411	631

Panel B: Business Reopening	Real Time: Percent Fully and Partially Open in the Last Month					
	July		August		September	
	Fully	Partially	Full.	Part.	Full.	Part.
Projected Reopening Date						
NA: Open at Time of Survey	90.78	98.05	92.38	98.68	89.18	96.10
	(1.338)	(0.964)	(2.372)	(1.733)	(2.761)	(1.904)
Early May	79.59	97.96	69.23	80.77	72	88
	(4.223)	(3.041)	(8.085)	(5.906)	(8.391)	(5.787)
Late May	64.83	94.07	66.67	97.10	75	96.88
	(2.721)	(1.960)	(4.963)	(3.625)	(5.245)	(3.617)
Early June	53.74	91.44	62.93	89.66	60.47	90.70
	(2.162)	(1.557)	(3.828)	(2.796)	(4.524)	(3.120)
Late June	42.86	86.07	49.37	82.28	55.56	93.65
	(2.498)	(1.799)	(4.638)	(3.388)	(5.286)	(3.645)
July	38.73	83.10	34.52	83.33	42.31	80.77
	(2.481)	(1.786)	(4.498)	(3.286)	(5.818)	(4.012)
August	29.56	76.73	23.81	71.43	35.48	77.42
	(3.315)	(2.387)	(6.361)	(4.647)	(7.536)	(5.197)
September or Later	25.06	70.20	30.16	75.40	24.05	75.95
	(1.986)	(1.430)	(3.673)	(2.683)	(4.720)	(3.255)
R^2	0.71	0.90	0.73	0.90	0.73	0.91
N	2,850	2,850	844	844	631	631

Notes: In this table, we use subsequent Alignable surveys sent out at the end of July, August, and September to validate demand expectations (Panel A) and reopening plans (Panel B). In Panel A, we plot the mean share of customers returning relative to the pre-crisis level (Demand) and the share of businesses that are fully open (Open). We estimate these means conditional on the respondent's projected share of customers returning by a given date in the initial May survey. The realized demand is only available for firms that report being fully open at the time of the later survey; therefore for each survey round we have more observations for the business status (Open) than for the realized demand measure (Demand). Finally, in pair of columns, we restrict to the set of respondents that appear in both the initial May survey, and the subsequent survey. In Panel B, we report the share of businesses that are open at the time of the subsequent survey. We show both the share that are fully open (Fully) and the share that are either fully open or partially open (Partially). Each row reports these means conditional on the respondent's projected reopening date at the time of the initial survey.

Table A8: ATTRITION ANALYSIS

	Full Survey Sample	Re-Surveyed					
	(May, 2020)	July		August		September	
Number of Respondents	27,340	2,893		859		641	
	Share of Respondents	Share	p-value	Share	p-value	Share	p-value
Five Largest Industries							
Professional and Technical Services	0.160	0.167	0.305	0.127	0.024	0.137	0.178
Retail Trade	0.129	0.128	0.874	0.155	0.060	0.152	0.141
Finance and Insurance	0.084	0.054	< 0.001	0.066	0.094	0.071	0.287
Health Care and Social Assistance	0.081	0.083	0.818	0.056	0.020	0.071	0.402
Real Estate and Rental and Leasing	0.074	0.053	< 0.001	0.049	0.018	0.044	0.014
Five Largest States							
California	0.122	0.129	0.248	0.116	0.583	0.139	0.168
New York	0.071	0.077	0.190	0.078	0.429	0.067	0.684
Florida	0.066	0.072	0.202	0.070	0.614	0.072	0.527
Pennsylvania	0.050	0.042	0.031	0.041	0.217	0.038	0.147
Texas	0.050	0.051	0.807	0.047	0.683	0.041	0.289
Business Status							
Fully Open	0.322	0.337	0.062	0.352	0.060	0.360	0.036
Partially Open	0.332	0.299	< 0.001	0.313	0.222	0.324	0.665
Temporarily Closed	0.319	0.348	< 0.001	0.318	0.939	0.300	0.285
Permanently Closed	0.026	0.015	< 0.001	0.017	0.094	0.016	0.082
(Predicted) Share of Customers Returning							
$< 10\%$	0.099	0.133	< 0.001	0.141	< 0.001	0.127	0.018
$10\% - 25\%$	0.122	0.135	0.027	0.134	0.279	0.135	0.319
$25\% - 50\%$	0.211	0.198	0.060	0.206	0.718	0.231	0.208
$50\% - 75\%$	0.252	0.230	0.005	0.216	0.014	0.228	0.170
$75\% - 90\%$	0.168	0.163	0.431	0.168	0.987	0.141	0.067
$> 90\%$	0.148	0.142	0.330	0.135	0.274	0.138	0.458

Notes: In this table, we test for differential attrition across the subsequent survey waves. In the first column, we present the share of respondents with a given attribute (industry, state) or response (business status, predicted share of customers returning) in the initial May survey. We report the share of businesses with each attribute or response in the subsample of the original survey that can be matched to the later survey round. We also report the p-value of the difference between the share of respondents in the subsequent round and in the initial May round. The last two sections, business status and share of customers returning, are collectively exhaustive, though may not sum to one due to rounding.