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# The impact of <br> Covid-19 on US firms 

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#### Abstract

We use survey data on an opt-in panel of around 2,500 US small businesses to assess the impact of COVID19. We find a significant negative sales impact that peaked in Quarter 2 of 2020, with an average loss of $29 \%$ in sales. The large negative impact masks significant heterogeneity, with over $40 \%$ of firms reporting zero or a positive impact, while almost a quarter report losses of more than $50 \%$. These impacts also appear to be persistent, with firms reporting the largest sales drops in mid-2020 still forecasting large sales losses a year later in mid-2021. In terms of business types, we find that the smallest offline firms experienced sales drops of over $40 \%$ compared to less than $10 \%$ for the largest online firms. Finally, in terms of owners, we find female and black owners reported significantly larger drops in sales. Owners with a humanities degree also experienced far larger losses, while those with a STEM degree saw the least impact.


Key words: Covid-19, US firms, offline firms, online firms

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## 1. Introduction

COVID-19 early impacts on businesses across the U.S. were record breaking in their swiftness. Many businesses closed in response to state government mandates, while others closed on their own accord, and many of those that remained open have had to substantially alter their operations (Balla-Elliott et al. 2020). While most states have since removed their initial mandates and businesses have begun to recover, there remain large questions about what the recovery will look like going forward. Using an innovative panel survey of business founders, we show that the brunt of the economic impact was not evenly felt by businesses in the economy, and that the recovery will likely further reveal these inequalities rather than dissipate them.

The panel survey, known as The Study of Internet Entrepreneurship, is an ongoing, opt-in quarterly survey of businesses that began in early 2019 with a focus on business forecasts (Bloom, Fletcher, Yeh 2020). The survey is innovative in soliciting information from firms on the past, present and future impacts of COVID, with a reward for accuracy based on alignment with transactions data. Using this framework, we were well positioned to survey firms throughout the onset of pandemic and elicit their estimates of impacts and forecasts for the future impacts of COVID-19.

We use the survey to first confirm that many businesses experienced a large and negative shortrun impact of the pandemic, a result corroborated by other firm surveys as well (e.g., Fairlie 2020, Bartik et al. 2020). Our results most notably show that firms on average saw their sales drop 29\% over quarters 2 and 3 of 2020. Other papers have shown similar negative short-run impacts on numerous other measures including employment (Barrero et al. 2020a), business closures (Gourinchas et al. 2020), and business activity (Fairlie 2020).

We further highlight that these impacts have been incredibly varied by business, and these differences are likely to persist well into 2021. While almost $25 \%$ of firms lost more than half their sales at the peak of the impact, over $40 \%$ of firms report either no impact or a positive impact. Continuing into 2021 firms whose sales benefitted expect to maintain their bump in sales almost entirely, while firms who lost sales will only have a partial recovery by quarter 2 of 2021, a year after the peak of the impact. These two very different experiences mimic the similar split recession and recovery found by Chetty et al. (2020) and Cajner et al. (2020) in the labor market.

Some of these differences can be explained by firm characteristics. We find that offline firms are much more negatively impacted than online firms as the online economy has been largely able to escape the worst of the pandemic. Large employers have likewise fared much better than small employers and non-employers. In particular, small offline firms are significantly worse off than their larger online counterparts: non-employer firms who receive less than $50 \%$ of their revenue online lost over $45 \%$ of their sales while $20+$ employee firms with at least $50 \%$ of their revenue online lost only $10 \%$. This highlights the great inequality of the economic impact of COVID-19.

Last of all, these impacts were not equally shared across demographics. Women-owned businesses fared significantly worse. Black-owned businesses likewise were more negatively impacted. These results echo the earlier findings of Fairlie (2020), Alekseev et al. (2020), and (Bloom, Fletcher, and Yeh 2020), and broader findings of the particularly damaging impact of the COVID-19 pandemic on women (e.g., Alon et al. 2020). Controlling for business characteristics explains most of the difference between men and women, although it does not appear to explain the difference between White-owned and Black-owned businesses.

This links to a rapidly growing literature showing the damaging impact of COVID on firms (e.g. Bartik et al. 2020a, Gourinchas et al. 2020, Papaniklaou and Schmidt 2020, and Buffington et al. 2020), labor markets (e.g. Chetty et al. 2020, Kahn et al. 2020, Cajner et al. 2020 and Barrero et al. 2020b), and its particularly damaging impact on women and lower educated groups (e.g. Adams-Prassl et al. 2020, Alon et al. 2020, Hupkau and Petronglo 2020, Mongey et al. 2020 and Sevilla and Smith 2020). Our survey is distinct in eliciting detailed current and future survey data on the impact of COVID-19, and obtaining high survey and item response rates by paying firms for survey participation and accuracy.

Section 2 gives an overview of the survey and related data used in the analysis. Section 3 presents the results of our analyses on the impact of COVID-19. Section 4 concludes.

## 2. Data

### 2.1. Survey Design and Details

The Study of Internet Entrepreneurship survey is an opt-in panel survey of business founders in partnership with a large payments technology company in the United States, henceforth referred to as TechCo for convenience. ${ }^{1}$ All user data from the survey and in this research was obtained with user permission via written informed consent. The sample was constructed from the universe of businesses using TechCo's online payment services. To be eligible for the survey, businesses had to have had at least ten transactions on TechCo. To limit the inclusion of businesses that had already closed, they also had to have had a transaction in the 90 days prior to when they were sampled. Businesses had to be for-profits, and the emails that TechCo had listed for them had to be non-generic (i.e., they could not consist of phrases such as info@, admin@, or contact@).

Our surveys were targeted at business founders. If the founder was not available or was no longer affiliated with the business, then we accepted the responses of someone who was intimately familiar with the financials of the company and the TechCo account itself. In $92 \%$ of responses, we were able to get a response from the founder themselves.

The eligible firms were divided into three strata: funded, small non-funded and large non-funded. Funded firms were those known to have venture capital backing. Non-funded firms were then split into small and large based on the amount of revenue they had on TechCo in the prior year. Firms with below $\$ 10,000$ in revenue the previous year were labeled small and firms above $\$ 10,000$ were labeled large. Our sample is made up of $1 / 3$ funded, $1 / 3$ small, and $1 / 3$ large.

We sampled a total of 26,400 firms. Firms were contacted with an invitation e-mail and three follow-ups spaced approximately a week apart. Firms were given $\$ 50$ to respond to the first wave of the survey and then $\$ 25$ for each subsequent wave. In addition (as discussed below) they were also given a $\$ 25$ per survey wave accuracy bonus for their TechCo revenues forecasts for the next quarter if they came within $10 \%$ of their realized TechCo revenue.

[^0]Firms who did not respond were then contacted again in the following round of the panel and reinvited to participate with an invitation and two reminder emails. A total of 5,299 firms responded, for a response rate of $23.7 \% .^{2}$ We did not find any significant difference across firms in their response rates beyond size, with smaller firms slightly more likely to respond (see Appendix Table A1).

We contacted 18,000 businesses throughout the spring of 2019. Firms were then re-contacted in the summer of 2019. Those who had not completed the first round were re-invited to take the baseline survey, while those who had already completed the baseline survey were given the second-round survey. The third round of the survey took place at the end of 2019. Firms who had only completed the baseline survey were invited to complete the third round with the other firms, thus skipping the second round. We also refreshed our sample with an additional 4,400 businesses at this point, giving us a total sample of 22,400 firm.

A fourth round was then sent out during April and May 2020. This round coincided with the onset of the COVID-19 pandemic, and so included the questions on the impact of the crisis which form the basis of our COVID-19 analysis. A fifth round was then sent out during September through November 2020. This round followed the peak of the COVID-19 economic impact and so allows us to analyze retrospective data, as well as compare forecasted and actual impacts. As in previous rounds, we added an additional refresh sample of 4,000 firms for a full sample of 26,400 firms.

### 2.2. Founder and Business Characteristics

From the baseline survey, we collected a number of characteristics on the founder and their business. Table 1 and Figure A1 provide some basic demographics on our survey and compare them to businesses from the Annual Survey of Entrepreneurs, which is a nationally representative survey of all (rather than TechCo) small businesses. We see the average entrepreneur in our survey is 39 years old, below the 42 years of age of the average US entrepreneur (from the Annual Survey of Entrepreneurs), with $95 \%$ of TechCo business leaders more than 25 years old. We also see that

[^1]$72 \%$ of firms are run by college graduates, reflecting the increasing importance of education for entrepreneurship in the new-economy. Finally, most of these firms are young, with $65 \%$ of them having been founded within the last 5 years, in contrast to all US firms which have an average age of 17 years.

The firms span the entire United States with coverage across almost all states (as shown in Appendix Figure A2), noting that some smaller states have small samples of less than 10 firms. These firms also have a broad industry mix (Appendix Figure A3), with a skew towards industries like travel and clothing that have a higher online representation.

### 2.3. Payment Data

Through TechCo data we are able to track the aggregate revenue, total transactions and average transaction value for each firm directly. This is valuable in allowing us to assess survey data against businesses actual revenue data - comparing founder expectations against actuals, as well as identifying and cleaning up any major outliers. While the latter helps to reduce survey measurement error, the data do have certain limitations. Most notably, we are only able to observe the revenue that occurs on TechCo, which represents $52 \%$ of our sample's business revenue on average, according to the survey data (Table 1). This also means that we cannot observe revenue before the business joins TechCo, or easily distinguish between a business leaving TechCo and a business closing ${ }^{3}$. On the other hand, compared to administrative data we can observe businesses before they formalize, so are able to capture information on very early-stage entrepreneurship. The TechCo transactions data is also direct revenue data, rather than data reported to tax, accounting or statistical authorities, so is less susceptible to measurement error.

## 3. Results

In this section we present results on the large, negative, and heterogenous impacts of the crisis.

[^2]
### 3.1. Measuring the Impact of COVID-19

The impact of COVID-19 was collected in two-parts. First, respondents were asked to identify for a given quarter whether they were negatively impacted, positively impacted, or not impacted at all by COVID-19 (Figure A9a). For example:

What was the impact of COVID-19 on your firm's sales revenue over Quarter 1, 2020?

- Lower
- No Effect
- Raise

If they suggest that their sales were lowered or raised, they are asked to specify the magnitude of the impact (Figure A9b). For example:
"By what percentage did the impact of COVID-19 (raise/lower) your firm's sales over Quarter 1 (January 2020 through Match 2020)?"

This two-part structure was developed after piloting to avoid recording errors for negative numbers. Many business owners are familiar with brackets (that is the "( )" symbol) being used to denote negative numbers as these are the default indicators for negative values in Excel and other accounting software packages. As a result they were sometimes confused by a negative sign (that is the "-" symbol) in testing. Given the large negative impact of COVID correctly identifying negative versus positive impacts was essential, so this two-part question structure was required.

We then convert these impact it $^{\text {values to a percentage over the average baseline and use this to }}$ calculate the arc-percentage change following Davis, Haltiwanger and Schuh (1996), which is often called the "DHS change" measure. This DHS change measure compares the COVID sales (100+ the impact growth rate of COVID) against the baseline sales (100) and divides by the average of the two.

We use this DHS growth measure ${ }^{4}$ rather than the raw percentage change to allow for firms with zero sales in some quarters (those going from zero to positive sales receive $a+2$ and those from positive to zero a-2).

As one basic check on the survey reliability we compare firms' responses on the impact of COVID on their sales over 2020 Q2 and Q3 versus the change in revenue on TechCo between 2019 Q2 and Q3 and 2020 Q2 and Q3. We find an extremely tight relationship, for both positive and negative values, indicating a very close correspondence between survey responses and actual transaction data for the corresponding period (see Appendix Figure A8).

### 3.2. The Overall Impact of COVID

The impact of COVID on our sample has been large and negative as shown in Figure 1. Firms on average saw their sales drop $29 \%$ over 2020 Q2 and Q3. The mean, however, masks significant heterogeneity in the impact on firms with $43 \%$ of firms reporting a zero or positive impact of the pandemic compared to $57 \%$ of firms reporting a negative impact. This highlights not only the large negative mean impact of the pandemic but also the huge dispersion in effect across firms.

We plot in Figure 2 the time series of the reported impact of COVID by quarter, from 2020 Q1 to 2021 Q2, noting that while results for 2020 are mostly known at the point of the November 2020 survey the values for 2021 are forecasted. We see an extremely persistent impact of the COVID pandemic with again evidence of a wide dispersion of impact. In quarter 2 of 2020, the bottom 5\% of firms, in terms of impact, have had their sales completely wiped out, while the top $5 \%$ experienced a $50 \%$ or greater growth in sales. Firms at the 25 th percentile lost $60 \%$ of their sales, while those at the 75th percentile were not impacted at all.

These varied effects are expected to persist well into 2021. The firms which experienced increased sales, however, maintained the sales bump with very little to no tapering of the effects. A year after the peak of the economic impact, quarter 2 of 2021, firms in the bottom at the 5 th percentile still expect to have lost $75 \%$ of their sales while those in the 75 th percentile expect to have lost $10 \%$.

[^3]Those in the top 5\% expect to fully maintain their $50 \%$ gain in sales, a trend that is seen across the board for the upper half of the distribution. These divergent trajectories are in line with what is commonly referred to as a "K-shape" recovery where some firms and industries recover while others do not.

### 3.3. Online Vs. Offline

A huge factor in explaining why firms experienced such different impacts is the degree to which their businesses were online. Sales impacts of COVID have been and likely will continue to be far worse for offline firms than online firms.

Our primary measure of how online businesses perform is self-reported data on the percent of their revenue that they received online over the last 12 months. We find that fully online firms saw an average impact of $-23 \%$ in 2020, while firms with less than $15 \%$ of their revenue online saw an average impact of $-39 \%$ (Figure 3). This difference is extremely persistent as well (see Appendix Figure A4 for details). One year after the peak of the economic impact, quarter 2 of 2021, firms with at least $85 \%$ of their revenue online expect a $-6.6 \%$ impact on their sales while firms with at least $85 \%$ of their revenue offline expect a $-18.4 \%$ impact.

We verify our results using a second, less direct measure of how online businesses are. For a subset of firms we asked whether they considered themselves to be an online business only, a physical business only, or a combination of both. This breakdown shows a very similar result (see Appendix Figure A5). Businesses that are fully offline or partially offline report a $36.4 \%$ drop in sales, while fully online businesses report only a $23.3 \%$ drop.

### 3.4. Business Size

While the degree to which a business is online heavily determines the impact of COVID-19 on sales, effects vary widely by size and industry as well. Large businesses experience smaller impacts overall, with non-employer businesses bearing the worst of the crisis (figure 4). As a particularly dramatic example of the heterogeneity, primarily offline non-employee businesses lost $45.0 \%$ of their business over 2020 Q2 and Q3, while primarily online businesses with 20 or more employees only lost $10.7 \%$, a four-fold difference. One possible explanation is management practices, since larger firms tend to be better managed (e.g. Appendix Figure A6 and Bloom et al.
2019) and may also be better able to cope with the pandemic recession. Another possible explanation is financial position, as larger firms typically have better access to credit so may be more able to weather a period of losses.

These effects persist, as well. Businesses with 20 or more employees forecast a full recovery on average by quarter 2 of 2021, while non-employers forecast that they will still be losing $16.4 \%$ of their sales a full year after the peak (Appendix Figure A7).

We also see that industry plays an important role in firm performance (details in Appendix Figure A3). Digital businesses (i.e. producers of software and digital content) fare substantially better than travel (a $56 \%$ decline) or clothing (a $37 \%$ decline). Artists and photographers, a group in our data that largely consists of wedding and event photographers, experienced a $45 \%$ loss in sales.

### 3.5. Demographics - gender, race and education

Beyond which businesses are being impacted, we are also able to say something about which groups of people are bearing the brunt of the impact. We find that Black and female business owners are the worst impacted. Within demographic groups, there is still substantial variation by whether or not a business is mostly online. Differences in impact by gender are seemingly explained by differences in business characteristics.

Figure 5 shows that businesses owned by women are impacted harder than businesses owned by men. This is true regardless of whether or not they are online. Table 2 shows that female-owned businesses experienced $8 \%$ greater impacts on sales in column (1). Notably, however, these differences are largely explained by business characteristics. In particular when including a full set of industry controls (fixed effects) in column (2), the size of the business (the log of number of employees) in column (3), and the percent of their revenue that is online in column (4) the difference in impact between male and female-owned businesses drops. When we include all three of these factors in column (5) - industry, size and share of sales online - the female gap falls by three quarters and is no-longer significant. As such, we can largely account for the worse performance of female owned businesses during the pandemic in our sample by these firm characteristics.

There is also notable racial heterogeneity in the impact of the COVID-19 pandemic. Black-owned businesses are the most negatively impacted, as shown in Figure 6. Here we show the impact on businesses by quarter, with black owned business showing a particularly large drop in the first three quarters of the pandemic. In Table 3 we evaluate this result in regression format. In column (1) we see that black-owned businesses on average had an $8 \%$ worse impact from COVID-19 than white owned businesses (the omitted base-line category). But this result is not statistically significant because of the relatively small number of black businesses in the sample. Nevertheless, this potential gap is investigated further in the rest of the regression table. We include controls for industry, firm size and online revenue share individually in columns (2) to (4), and collectively in column (5). We see that the coefficient on black owned businesses remains large and relatively unchanged by these controls, suggesting that industry, firm size or online share does not explain the majority of the black greater sales loss under COVID-19. ${ }^{5}$ One possible explanation is that the black community has been (medically and economically) worse hit by the virus, and if blackowned businesses have greater sales among this community, it may have left them more exposed to the pandemic downturn.

We also see that Asian-owned businesses appear to be less impacted than White-owned businesses. These differences disappear, however, when controlling for business characteristics, in particular industry, reflecting their relatively greater representation in digital and medical industries.

Last of all, we turn to area of education. In Figure 7 we see that businesses run by individuals with degrees in the humanities are the worst hit, particularly those that are offline, which lose on average $43 \%$ of their sales. On the opposite end of the spectrum, STEM businesses which are primarily online lose $19 \%$ of their business. As with previous results, the differences in impacts persist strongly over time. As we show in Table 4, however, once you control for business characteristics of industry, size, and share online this humanities gap falls significantly, suggesting these businesses tend to be in more impacted industries, smaller and more off-line. Interestingly, businesses owned by founders with a business or economics degree also perform less well (than STEM businesses which are the omitted category), but this is not well explained by their industry, size, or online composition.

[^4]
## 4. Conclusions

We use survey data on a panel of around 2,500 US small businesses to assess the impact of COVID-19. We find a significant negative sales impact that peaked in Quarter 2 of 2020, with an average loss of $29 \%$ in sales. The large negative impact masks significant heterogeneity, with over $40 \%$ of firms reporting zero or a positive impact, while almost a quarter report losses of more than $50 \%$. These impacts also appear to be persistent, with firms reporting the largest sales drops in mid-2020 still seeing large sales loses a year later in mid-2021. In terms of business types, we also find the smallest offline firms experienced sales drops of $45 \%$ compared to $10 \%$ for the largest online firms. Finally, in terms of the owners we find female and black owners reported significantly larger drops in sales. Owners with a humanities degree also experienced far larger losses, while those with a STEM degree saw the least impact.

## References

Alekseev, Georgij, Safaa Amer, Manasa Gopal, Theresa Kuchler, J. W. Schneider, Johannes Stroebel, and Nils Wernerfelt. "The Effects of COVID-19 on US Small Businesses: Evidence from Owners, Managers, and Employees." Managers, and Employees (September 10, 2020) (2020).

Adams-Prassl, Abi, Teodora Boneva, Marta Golin, and Christopher Rauh. 2020 "Inequality in the Impact of the Coronavirus Shock: Evidence from Real Time Surveys." CEPR Discussion Paper 14665.

Altig, D., Barrero, J. M., Bloom, N., Davis, S. J., Meyer, B. H., \& Parker, N. (2020), "Surveying business uncertainty", Journal of Econometrics (Forthcoming).

Balla-Elliott, Dylan, Zoë B. Cullen, Edward L. Glaeser, Michael Luca, and Christopher T. Stanton. Business reopening decisions and demand forecasts during the COVID-19 pandemic. No. w27362. National Bureau of Economic Research, 2020.
Baker, Scott R., Nicholas Bloom, Steven J. Davis, Kyle J. Kost, Marco C. Sammon, and Tasaneeya Viratyosin (2020). "The unprecedented stock market impact of COVID-19." No. w26945. National Bureau of Economic Research.

Barrero, Jose Maria, Nicholas Bloom, and Steven J. Davis (2020a). "Covid-19 is also a reallocation shock." No. w27137. National Bureau of Economic Research.

Barrero, Jose Maria, Nicholas Bloom, and Steven J. Davis (2020b). "Why working from home will stick." Stanford mimeo.

Bartik, Alexander W., Marianne Bertrand, Zoë B. Cullen, Edward L. Glaeser, Michael Luca, and Christopher T. Stanton (Forthcoming). "The Impact of COVID-19 on Small Business Outcomes and Expectations." Proceedings of the National Academy of Sciences.

Bloom, Nicholas, Erik Brynjolfsson, Lucia Foster, Ron Jarmin, Megha Patnaik, Itay SaportaEksten and John Van Reenen, 2019, "What drives differences in management practices", American Economic Review, volume 109(5), pp1648-1683.

Buffington, Catherine, Carrie Dennis, Emin Dinlersoz, Lucia Foster, and Shawn Klimek, (2020). Measuring the effect of covid-19 on us small businesses: The small business pulse survey. Discussion paper.

Cajner, Tomaz, Ryan A. Crane, Leland D. and Decker, John Grigsby, Adrian Hamins-Puertolas, Erik Hurst, Christopher Kurz, and Ahu Yildirmaz. 2020. "The U.S. Labor Market during the Beginning of the Pandemic Recession." NBER Working Paper 27159
Chetty, R., Friedman, J. N., Hendren, N., \& Stepner, M. (2020). How did covid-19 and stabilization policies affect spending and employment? a new real-time economic tracker based on private sector data (No. w27431). National Bureau of Economic Research.
Davis, S. J., Haltiwanger and Scott Shuh (1996), "Job Creation and Destruction", MIT Press.
Gourinchas, P. O., Kalemli-Özcan, Ṣ., Penciakova, V., \& Sander, N. (2020). Covid-19 and SME Failures (No. w27877). National Bureau of Economic Research.
Hupkau, Claudia, and Barbara Petrongolo. 2020, October. "Work, Care and Gender during the Covid-19 Crisis." CEPR Discussion Paper No. 15358.
Kahn, Lisa B., Fabian Lange, and David G. Wiczer (2020). Labor Demand in the time of COVID19: Evidence from vacancy postings and UI claims. No. w27061. National Bureau of Economic Research.
Mongey, Simon, Laura Pilossoph, and Alex Weinberg. 2020. "Which Workers Bear the Burden of Social Distancing Policies?" NBER Working Paper 27085.
Papanikolaou, Dimitris, and Lawrence D. W. Schmidt. 2020. "Working Remotely and the Supplyside Impact of Covid-19." NBER Working Paper 27330

Figure 1: The COVID-19 Impact on Sales was $17 \%$ on Average, but Extremely Varied


Note: Data for 2,393 firms in the Stanford-Stripe survey from OctoberNovember 2020.

Figure 2: The COVID-19 Impact Was Worst In Quarter 2 of 2020


Note: Data for 2,393 firms in the Stanford-Stripe survey from OctoberNovember 2020. 2020 quarter 1, 2, and 3 data is reported, while 2020 quarter 4 and 2021 data is forecasted. Purple shading is darkest for 45 to $55-$ percentile band, and gets lighter for deciles moving outwards from the center (e.g. the 40 to 44 and 56 to 60 is the next shade lighter etc.).

Figure 3: The Impact of COVID-19 Was Worse for Offline Firms


Note: Data for 2,393 firms in the Stanford-Stripe survey from October-November 2020. Figure shows the impact on 2020 Q2 and Q3 sales

Figure 4: The Impact of COVID-19 was Worse for Smaller Firms


Note: Data for 2,393 firms in the Stanford-Stripe survey from OctoberNovember 2020. Online firms $=(>50 \%$ of revenue online). Figure shows the impact on 2020 Q2 and Q3 sales

Figure 5: The Impact of COVID-19 was Worse for Female Owned Firms


Figure 6: Impact of COVID-19 was Worse for Black Owned Firms


Note: Data for 2,393 firms in the Stanford-Stripe survey from OctoberNovember 2020. 2020 quarter 1, 2 , and 3 data is reported, while 2020 quarter 4 and 2021 data is forecasted.

Figure 7: The Impact of COVID-19 was Worse for Owners with Humanities Degrees


Note: Data for 2,393 firms in the StanfordStripe survey from October-November 2020. Online firms $=(>50 \%$ of revenue online). Figure shows the impact on 2020 Q2 and Q3 sales

## Table 1: Descriptive Statistics

|  | N | Mean | Median | SD | Min | Max |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Age | 2380 | 38.80 | 37 | 10.20 | 16 | 72 |
| Hours Per Week | 2259 | 37.06 | 40 | 22.00 | 0 | 100 |
| Businesses Owned | 2252 | 1.47 | 1 | 0.79 | 1 | 5 |
| Other Employment | 2266 | 0.23 | 0 | 0.42 | 0 | 1 |
| Previous Founding Experience | 2252 | 0.95 | 1 | 1.25 | 0 | 5 |
| Annual Income (\$ '000s) | 2265 | 58.93 | 30 | 85.81 | 0 | 560 |
| Number of Founders |  |  |  |  |  |  |
| Number of Employees | 2252 | 1.54 | 1 | 0.84 | 1 | 5 |
| \% Revenue Online | 2282 | 8.04 | 2 | 34.56 | 0 | 1025 |
| \% Revenue Fintech | 2267 | 72.15 | 95 | 36.55 | 0 | 100 |
| \% Revenue International | 2320 | 52.34 | 50 | 38.55 | 0 | 100 |
|  | 1906 | 8.76 | 0 | 19.01 | 0 | 100 |

Observations
2393

Note: Data for firms in the Stanford-Stripe survey from January 2019-November 2020. Number of employees includes owners, and part-time employees are counted as 0.5 (including owners if they are part-time). Hours per week is the number of hours spent on the business they founded

## Table 2: The More Negative Female Impact is Accounted for By

 Industry, Firm Size and Share Online|  | Sales Impact | Sales Impact | Sales Impact | Sales Impact | Sales Impact |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Female | $-0.078^{* * *}$ | -0.042 | -0.040 | $-0.071^{* *}$ | -0.009 |
|  | $(0.029)$ | $(0.031)$ | $(0.030)$ | $(0.029)$ | $(0.031)$ |
| Log Employees |  |  | $0.094^{* * *}$ |  | $0.093^{* * *}$ |
|  |  | $(0.014)$ |  | $(0.014)$ |  |
| \% Rev. Online |  |  |  | $0.002^{* * *}$ | $0.002^{* * *}$ |
|  |  |  |  | $(0.000)$ | $(0.000)$ |
| Industry FEs |  | Yes |  |  | Yes |
| Dep. Mean | -0.320 | -0.320 | -0.320 | -0.320 | -0.320 |
| \# Obs | 2083 | 2083 | 2083 | 2083 | 2083 |

Note: Data for 2,393 firms in the Stanford-Stripe survey from October-November 2020. Standard errors are robust.

Table 3: The More Negative Impact on Black Owned Firms is Not Accounted for by Industry, Size or Share of Sales Online

|  | Sales Impact | Sales Impact | Sales Impact | Sales Impact | Sales Impact |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Asian | $0.125^{* *}$ | $0.093^{*}$ | 0.084 | $0.100^{*}$ | 0.029 |
|  | $(0.055)$ | $(0.054)$ | $(0.055)$ | $(0.055)$ | $(0.053)$ |
| Black | -0.079 | -0.081 | -0.054 | -0.093 | -0.074 |
|  | $(0.080)$ | $(0.082)$ | $(0.079)$ | $(0.079)$ | $(0.080)$ |
| Hispanic | 0.014 | 0.011 | 0.019 | 0.019 | 0.020 |
|  | $(0.058)$ | $(0.058)$ | $(0.057)$ | $(0.059)$ | $(0.057)$ |
| Log Employees |  | $0.090^{* * *}$ |  | $0.090^{* * *}$ |  |
|  |  |  | $(0.015)$ |  | $(0.015)$ |
| \% Rev. Online |  |  |  | $0.002^{* * *}$ | $0.002^{* * *}$ |
|  |  | Yes |  | $(0.000)$ | $(0.000)$ |
| Industry FEs |  | -0.319 | -0.319 |  | Yes |
| Dep. Mean | -0.319 | 1906 | 1906 | -0.319 | -0.319 |
| \# Obs | 1906 |  |  | 1906 | 1906 |

Notes: White owned businesses are the omitted category. Data for 2,393 firms in the Stanford-Stripe survey from October-November 2020. Standard errors are robust.

Table 4: Negative Humanities Effect Accounted for Mainly by Industry, Size and Share Online

|  | Sales Impact | Sales Impact | Sales Impact | Sales Impact | Sales Impact |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Degree Humanities \& Arts | $-0.111^{* * *}$ | $-0.092^{* *}$ | $-0.074^{*}$ | $-0.105^{* * *}$ | -0.056 |
|  | $(0.039)$ | $(0.040)$ | $(0.039)$ | $(0.039)$ | $(0.039)$ |
| Degree Econ \& Bus | $-0.089^{* *}$ | $-0.083^{* *}$ | $-0.106^{* * *}$ | $-0.085^{* *}$ | $-0.095^{* * *}$ |
|  | $(0.035)$ | $(0.035)$ | $(0.035)$ | $(0.035)$ | $(0.035)$ |
| Degree Other | $-0.075^{*}$ | -0.056 | -0.044 | -0.064 | -0.021 |
|  | $(0.039)$ | $(0.039)$ | $(0.039)$ | $(0.039)$ | $(0.039)$ |
| Degree Social Sciences | -0.017 | -0.030 | 0.001 | -0.003 | -0.006 |
|  | $(0.043)$ | $(0.044)$ | $(0.044)$ | $(0.043)$ | $(0.044)$ |
| Log Employees |  |  | $0.099^{* * *}$ |  | $0.096^{* * *}$ |
|  |  | $(0.015)$ |  | $(0.015)$ |  |
| \% Rev. Online |  |  | $0.002^{* * *}$ | $0.002^{* * *}$ |  |
|  |  |  |  | $(0.000)$ | $(0.000)$ |
| Industry FEs |  |  |  | Yes |  |
| Dep. Mean | -0.319 | -0.319 | -0.319 | 1919 |  |
| \# Obs | 1946 | 1946 | 1946 |  |  |

Notes: STEM is the omitted category. Data for 2,393 firms in the Stanford-Stripe survey from October-November 2020. Standard errors are robust.

Figure A1: Demographics of Online businesses


Figure A2: Average Impact of COVID-19 by State
Average Impacts of COVID-19 on 2020 Q2 \& Q3 Sales By State
 October-November 2020. States with fewer than 12 observations are marked as not having enough data.

Figure A3: Average Impact of COVID-19 By Industry


Figure A4: Impact over time by \% of Revenue online


Note: Data for 2,393 firms in the StanfordStripe survey from October-November 2020. Categories are Offline ( $<15 \%$ of revenue online), Mostly offline ( $>15 \%$ and $<50 \%$ ), Mostly online ( $>50 \%$ and $<85 \%$ ), and Online (>85\%)

Figure A5: Average Impact of COVID-19 By Online Vs. Offline


Note: Data for 2,393 firms in the
Stanford-Stripe survey from OctoberNovember 2020. Figure shows the impact on 2020 Q2 and Q3 sales

## Figure A6: Better Managed Firms are Bigger



Notes: 2,207 survey responses from the second wave of the Stanford-Stripe Study of Internet Entrepreneurship. The management scores are based on the Bloom et al. (2019) management scoring approach applied to this sample of firms.

Figure A7: : Impact over time by Employment


Note: Data for 2,393 firms in the Stanford-Stripe survey October-November 2020.

Figure A8: Reported Impact of COVID-19 Correlates with Sales Growth


Note: Data for 2,393 firms in the StanfordStripe survey from October-November 2020. Figure shows the impact on 2020 Q2 and Q3 sales plotted against the average growth of transactions revenue in Fintech between 2019 Q2 and Q3 vs 2020 Q2 and Q3.

Figure A9: Reported Impact of COVID-19 Correlates with Sales Growth
We would like you to consider the recent impact of COVID-19 in the following questions.

What was the impact of COVID-19 on your firm's sales revenues over:
Lower No Effect Raise

Quarter 1, 2020 (Jan. 2020 - Mar. 2020)?
Quarter 2, 2020 (Apr. 2020 - Jun. 2020)?
$\bigcirc \bigcirc$

Quarter 3, 2020 (Jul. 2020 - Sep. 2020)?

$\bigcirc$$\bigcirc$

By what percentage did the impact of COVID-19 lower your firm's sales over Quarter 1 (January 2020 through March 2020)? Must be between 0\% and 100\%.
$\qquad$
\%

By what percentage did the impact of COVID-19 lower your firm's sales over Quarter 2 (April 2020 through June 2020)? Must be between 0\% and 100\%.
$\qquad$
\%

By what percentage did the impact of COVID-19 lower your firm's sales over Quarter 3 (July 2020 through September 2020)? Must be between 0\% and 100\%.
$\qquad$
$\square \%$

## Table A1: Response rates by Firm Characteristics

|  | Survey Not Completed. |  | Survey Completed. |  |  |  |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: |
|  | Mean | Std. Dev. |  | Mean | Std. Dev. | t-stat | Norm. Diff.

Notes: Data from full-sample 26,403 firms in the Stanford-Stripe.

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[^0]:    ${ }^{1}$ The company is Stripe, which employs one co-author. To facilitate this research, Stripe allowed the authors to communicate with its customers to request their survey participation and limited, anonymized access to data from users that granted permission and opted-in to the study.

[^1]:    ${ }^{2}$ While this $23.7 \%$ response rate may seem low, it is high for firm surveys, especially during the pandemic. Prior COVID-19 firms surveys obtained response rates that were substantially lower, for example $0.017 \%$ for Bartik et al. (2020) and $1.5 \%$ in Alekseev et al. (2020, while pre-pandemic US firm surveys typically obtained response rates between $10 \%$ to $30 \%$ (e.g. see Altig et al. 2020).

[^2]:    ${ }^{3}$ We address this with survey data as best we can in the results section, however, there may be bias in the fraction of closed businesses that respond to our survey after they have closed.

[^3]:    ${ }^{4}$ Careful readers will note this is numerically the same as impact $_{i t} /\left(0.5 *\right.$ impact $\left._{i t}+100\right)$

[^4]:    ${ }^{5}$ With the same caveats for small sample sizes and statistically insignificant results.

