Abstract: In a panel survey of online firms, we find that the ability to correctly forecast sales is highly correlated with firm performance. Despite its apparent importance, firms are remarkably bad at forming accurate predictions – if firms simply accurately reported their sales over the past 3-months as their prediction they would perform twice as well. We posit that simply encouraging them to review the financial data already easily available to them would dramatically improve their prediction performance and therefore impact their business decisions. We aim to run an RCT testing exactly that and show a causal pathway from monitoring business financials, to prediction performance, to overall business performance. Separately, we also show our estimates of the impact on businesses from the COVID-19 pandemic.

JEL Codes: L2, M2, O32, O33

Keywords: management, uncertainty, sales, COVID

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a Stanford University
b Fintech
1. Introduction

While firm expectations have long been theoretically important in Economics as a determinant of investment and production, empirical research on the expectations of firm managers has been more limited. By and large economists assumed firm managers had rational expectations and so sidestepped the issue until recent growing concerns about assuming rationality (Gennaioli et al. 2015).

In response to these concerns, a great deal of progress has been made over the past decade on assessing the rationality of managers expectations as a number of studies have begun collecting survey data with expectations data (e.g. Bachman and Elstner (2015), Altig et al. (2020a)). They have indeed pointed to a number of failures of rationality, such as the systematic overconfidence of managers in their own predictions of business outcomes (Barrero 2020). However, fundamental questions remain unresolved about how forecasting performance impacts realized economic outcomes.

In an attempt to answer this question, we have gathered data on manager expectations for future sales using an ongoing triannual survey of online firms in partnership with a large an online payment processing company, which we will refer to as Fintech. In each round of the survey managers are asked to predict future sales, which we can compare directly with their actual account data. We are now preparing a financial monitoring RCT that we believe will significantly improve their forecasts and allow us to study the causal relationship between manager forecast performance and realized firm performance.

From our survey, we find that the ability to correctly forecast sales is highly correlated with firm performance, even when controlling for other management scores. This indeed suggests that forecasting accuracy plays a large role in firm performance. This result is similar to the results found Tanaka et al. (2019), with the notable difference that they concentrate on the connection between macro forecast accuracy and firm performance, while the managers in our sample are predicting their own performance. They likewise find a strong relationship between forecast accuracy and firm performance.

Other studies have attempted to causally estimate the impact of forecast accuracy on firm performance using models with adjustment costs following inaccurate forecasts (e.g. Asker, Collard-Wexler, and de Loecker (2014), David and Venkateswaran (2019), Ma, Ropele, Sraer, and Thesmar (2020)). These works have found generally positive though more mixed results as in some cases the effects are likely negligible. At present we remain agnostic about the pathways that connect forecasting ability and performance. With our planned RCT, we would be the first, to our knowledge, to provide experimental results on this subject.

Despite the apparent importance of forecasting accuracy, firms are remarkably bad at forming accurate predictions. As an illustration, we find that if firms simply accurately reported their sales over the past 3-months as their prediction they would perform twice as well. This suggests that forecasting accuracy is not as important as the results above would suggest, managers are unaware of the importance, or managers are aware but do not know how to improve their forecasts. While previous works have been able to assess overall forecast error levels, other
papers have instead focused on the costs of non-rational expectation formation, focusing on some combination of over/under-optimism and over/under-confidence (i.e. bias in estimates of the first moment vs. the second moment) (e.g. Barrero (2020)).

Given our findings of large forecasting errors we suggest that even with rational expectation formation, firms may still be underperforming if they are able to easily improve their predictions but fail to do so. This could be either because they underinvest in forming accurate predictions (e.g. time, effort, or capital), or because they under-adopt tools and techniques to aid in their predictions.

Our particular context allows us to speak uniquely to this question. Fintech provides financial dashboards to all of the users in our sample. These dashboards are the front page of their account and clearly display financial metrics, most notably past sales. Given that firms could double their prediction performance by simply accurately reporting their past sales on Fintech, it’s clear that these dashboards could be a useful tool. The fact that only 40% of them are able to accurately report their past revenue suggests they aren’t using it.

Hence, we believe that we can easily and effectively increase the accuracy of their forecasts by introducing and encouraging dashboard usage among managers with and RCT. If successful, this will allow us to directly measure the causal impact of forecast accuracy on firm performance\(^1\) as well as provide suggestive evidence of the causal pathways involved.

Separately from our forecast accuracy analysis, we also show our estimates of the impact on businesses from the COVID-19 pandemic. We were perfectly positioned to survey firms throughout the onset of the COVID-19 pandemic and were able to directly solicit their forecasts for the impact of COVID-19 on their businesses. We find large negative effects with substantial heterogeneity. Our results provide suggestive evidence of which firms likely escaped the brunt of the crisis and which will recover quickest.

Section 2 gives an overview of the survey and Fintech’s administrative data used in the analysis. Section 3 presents the results of our analyses. Broadly it covers the relationship between management practices and firm performance, prediction accuracy and firm performance, and dashboard use and prediction accuracy. We also include results on the impact of COVID-19. Section 4 concludes.

2. Data

2.1. Survey Design and Details

The Study of Internet Entrepreneurship survey is a panel survey of business founders in the United States using Fintech’s online payment services. To be eligible for the survey, businesses had to have had at least three transactions on Fintech. 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

\(^1\) It’s possible that the impact may not be immediate if firms forecasts improve rapidly but firms require time before they trust and put weight on these forecasts in their decision making.
were sampled. Businesses had to be for-profits, and the emails that Fintech 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 the 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 Fintech 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 big non-funded. Funded firms were those known to have VC-backing. Non-funded firms were then split into small and large based on the amount of revenue they had on Fintech in the prior year. Firms with below $10,000 in revenue the previous year were labeled small and firms above $10,000 were labeled big. Our sample is made up of 1/3 funded, 1/3 small, and 1/3 big.

We sampled a total of 22,403 firms. Firms were contacted with an invitation e-mail and three follow-ups spaced approximately a week apart. Firms were given $50 for 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 bonus for their Fintech revenues forecasts for the next quarter that came within 10% of their realized Fintech revenue.

Firms who did not respond were then contacted again in the following round of the panel and re-invited to participate with an invitation and two reminder emails. A total of 5,299 firms responded, for a response rate of 23.7%.

We sampled and contacted the first set of 18,000 businesses in 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. Those who had still not replied were dropped at this point and no longer contacted for further rounds.

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 4,405 businesses at this point, giving us the full sample of 22,403.

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.

2.2. Founder and Business Characteristics

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2 These rules apply to the largest waves of the survey – waves 3 and 4 which account for 18,405. Those in waves 1 and 2 which account for around 1,000 firms had slightly less strict selection criteria.

3 Waves 1 and 2 receive two reminders only.
From the baseline survey, we collected a number of characteristics on the founder and their business. Table 1 and Figure A3 provides some basic demographics on our survey. The average online entrepreneur is 39 years old, younger than the 42 years of the average US entrepreneur (from the Census Annual Survey of Entrepreneurs), with 95% of online businesses leaders more than 25 years old. We also see that 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.

Figure A3 compares select characteristics against data of businesses in the US from the Annual Survey of Entrepreneurs. There are some notable differences in the sampling frame that may account for some of the differences.

2.3. Payment Data

We observe each payment that a business receives through Fintech, allowing us to track revenue directly. While this allows us to avoid measurement error, it does have certain limitations. Most notably, we are only able to observe the revenue that occurs on Fintech, which only represents 50% of a business’s revenue on average according to the survey data (Table 1). This also means that we cannot observe revenue before the business joins Fintech, or easily distinguish between a business leaving Fintech and a business closing.

Second, Fintech accounts are not always uniquely matched to businesses. For instance, 40% of businesses have multiple accounts. Some of these accounts may be used for testing purposes while the businesses join Fintech, while others may correspond to individual establishments owned by the business. Ideally, we could aggregate accounts, however it is not always clear which accounts belong to the same business. In some cases, founders may have multiple accounts with the same email that actually correspond to different businesses which adds additional complication.

2.4. Management

In the second round of the survey (Summer 2019), firms were asked to respond to a module on management practices. The questions were copied with minor adjustments from the Management and Organizational Practices Survey (MOPS) and the Annual Survey of Entrepreneurs (ASE). In total, we used 7 questions, listed in appendix A1 along with their scoring. The questions cover personnel practices, the use key performance indicators, the use of targets, and the handling of issues that arise for the business.

Each question was scored on a scale of 0 to 1. The response which is associated with the most structured management practice is normalized to one, and the one associated with the least structured practices is normalized to zero. The composite management score used throughout this paper is then the simple average of those scores. Unless otherwise noted, the results

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4 We address this with survey data as best we can in the results section, however, there are concerns about what fraction of businesses that close ultimately chose to reply to our survey after they have closed and report their closure to us.
presented in this paper exclude the use of the two question on personnel practices as the majority of firms did not have enough personnel to warrant a discussion of their personnel practices.

2.5. Prediction Competition

In each round of the survey, respondents were asked to predict their revenue on Fintech over the next three months and the next twelve months. We restricted the predictions to revenue on Fintech so that we could check their predictions directly rather than rely on reported revenue from the survey.

For each survey, respondents were promised an additional $25 Amazon gift card if their 3-month prediction was within 10% of their actual revenue. Surprisingly, accuracy was quite low as is discussed further in the results.

2.6. Fintech Dashboard Usage

As part of using Fintech to process their payments, businesses are given access to a financial dashboard. This dashboard, shown in appendix Figure A4, appears immediately when users open their account. The dashboard allows users to easily see various financial metrics, including past revenue which they may reference while taking the survey and in particular while reporting past sales and predicting future sales.

We are able to observe dashboard usage passively, as each time a user accesses the dashboard it is recorded. This allows us to observe how often users access the dashboard in general, as well as see if they accessed the dashboard at the time of the survey. Despite the potential usefulness of the dashboard, there is large variation in the amount that businesses use it, as seen in Figure A5A, which shows the number of days in 2019 that businesses used their dashboard. The average user accesses their account approximately once per month. Dashboard usage is highly correlated with size as shown in figure A5B with a binned scatterplot of revenue versus the number of days businesses looked at their dashboard in 2019.

3. Results

3.1. Management and Firm Performance

Finding results similar to the management literature (e.g. Bloom and Van Reenan (2007)), we find that management performance is highly positively correlated with firm performance. We show results for three separate measures of firm performance: Revenue, Growth, Survival.

First, better managed firms are bigger. Figure 1A shows this with a binned scatterplot of Revenue versus composite management score\(^5\). We measure size with revenue, which is calculated as their total revenue on Fintech in 2019. We find that a one standard deviation change in management is associated with a 57% change in Revenue (Table 3). It is worth noting that our measure of revenue is revenue on Fintech only. In the appendix figure (APPENDIX

\(^5\) Binned scatter plots group the x-axis into quantiles and then plot the average of the y-variable in each quintile.
FIGURE) we perform a similar analysis with total revenue and estimated using their reports of the fraction of their revenue that occurs on Fintech and find similar results.

Second, better managed firms grow more. We find that a one standard deviation change in management is associated with 8.5% higher growth (Table 3). At present, we calculate growth using their 2019 revenue on Fintech versus their 2018 revenue on Fintech. We use the DHS formula of growth (Davis, Haltiwanger, and Schuh (1996)) which allow for firms to have zero revenue in 2018 or 2019 without being undefined, unlike with the standard growth rate formula. This accommodates firm entrance, firm exit, and other volatility in firm revenue that causes businesses to have periods with zero sales. Going forward, we hope to use growth following their response to the management questions on the survey so that we are purely testing the predictiveness of management scores, rather than the correlation with past growth.

Third, better managed firms are more likely to survive. As discussed in section 1, survival is hard to measure because we cannot perfectly distinguish between firms who close and firms who choose to no longer use Fintech. As a proxy of survival, we use whether or not a firm has had sales in the last 6 months. Using this measure, we find that a one standard-deviation change in management is associated with a 5% change in survival rate.

3.2. Forecasting and Firm Performance

We find that forecasting is significantly associated with business performance on all three metrics: revenue, growth, and survival. Despite the strong association between forecast accuracy and performance, we find that firms are remarkably bad at forecasting their revenue. In part this may because they have poor sales tracking.

Forecast error is measured using the percent difference between the predicted revenue and the actual revenue. In the denominator we use the average of the predicted and actual revenue as follows:

\[
\text{Forecast Error}_{it} = \frac{(\text{Predicted}_{it} - \text{Actual}_{it})}{(\text{Predicted}_{it} + \text{Actual}_{it})}
\]

We use this average to allow for cases where either the predicted revenue or actual revenue is zero without the error being undefined. In the case where they predict having positive revenue, but the realized revenue is 0, the forecast error is 1. In the case where they predict having zero revenue but end up having positive revenue, the forecast error is -1.

We then define forecast accuracy as the absolute value of forecast error.

\[
\text{Accuracy}_{it} = 1 - |\text{Forecast Error}_{it}|
\]

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6 We ask firms to report whether or not they have closed in the survey, but there is likely much larger attrition from the survey for closed firms which would bias survival estimates downwards.

7 Some firms also go through long periods of time greater than 6 months with no sales before they reemerge with sales, so this does falsely estimate some firms as closed when they are still alive.

8 Adapted from the DHS growth rates used above
Figure 2A shows that firms with higher accuracy are bigger.

Figure 2B shows that firms with higher accuracy grow faster. As a reminder, we are at present calculating growth using their 2019 revenue on Fintech versus their 2018 revenue on Fintech. Going forward, we hope to use growth measured after the prediction period of the survey so that we are purely testing the predictiveness of accuracy, rather than the correlation of accuracy with past growth.

Figure 2C shows that firms with higher accuracy are more likely to survive. As a proxy of survival, we again use whether or not a firm has had sales in the last 6 months. Given that forecast accuracy is so positively associated with business performance, even while controlling for management, it seems that businesses should aim to perform well at it. Figure 3 shows the remarkable difficulty that firms experience in forming accurate predictions. As shown by the grey bar, only 14.3% of respondents are able to successfully forecast their sales over a 3-month period to within 10% of their actual sales over that period. This is despite firms being given a $25 reward for forecast accuracy, which given this question takes less than one minute to complete would appear to be a reasonable incentive for accurate forecasting.

What is more surprising is that if firms had simply accurately reported their revenue over the past three months as their prediction for the next 3 months, their predictions would have performed twice as well. That is, while 14.3% of firms accurately predict sales within 10% of realizations, if firms had simply used their last 3 months of sales as their prediction (so just copied the number from their dashboard) they would have increased forecast accuracy on average to 23.8%. This suggests one reason for firm’s inaccurate forecasts is they are not very aware of their current revenues. Figure 4 confirms this, as when asked to report their revenue over the past 3-months, only 40% are able to do so within 10%.

### 3.3. Dashboard use and Forecasting Accuracy

As mentioned in section 1, using the dashboard is an easy way for businesses to consult their financial data for the purposes of reporting revenue and forecasting future sales. Given that users are able to easily consult their past revenue, it begs the question why respondents are performing so poorly in reporting their past revenue and forecasting their future revenue.

Certainly, our results appear to show that dashboard can be very useful. Figure 5A shows a binned scatterplot of forecast errors versus the number of times that firm used the dashboard in 2019. We indeed see that daily users of the dashboard perform better.

Beyond general use of the dashboard and general awareness of financials, we can also zero in on dashboard use during the survey. Figures 5B and 5C replicate Figures 3 and 4, only the results are shown by whether or not individuals viewed their dashboard the day that they completed the survey. In figure 5B we see that forecast errors are much smaller when respondents view the...
dashboard. The difference is even more striking when it comes to reporting past revenue accurately (Figure 5C). Firms that use the dashboard are significantly more likely to accurately report their revenue.

3.4. The Impact of COVID

While the forecasting results from the primary part of our analysis, we also were perfectly positioned to ask firms about the impact of the COVID-19 pandemic on their businesses throughout the onset of the pandemic. In light of this, we are able to present results on large, negative, and very heterogenous impacts of the crisis.

Overall, when we asked firms to forecast the impact of the COVID-19 pandemic on their sales, we found strikingly negative results. Figure 6a (top left) shows the 3-month forecasts, which cover the months of May, June, and July. In these forecasts, we see that firms are expecting on average a 30% drop in sales solely as a result of COVID-19. The effect, shown in Figure 6c (bottom left), is a drop in the firms’ forecasted quarterly growth rates from 2% in January to -14% in April. There is also a huge dispersion showing - while 6% of firms report COVID will drive their sales to zero (-100%) another 15% of firms report a positive impact on sales. Over the 1-year horizon Figure 6b (top right) shows firms are less pessimistic, predicting an 13% drop in yearly sales. These figures are similar to others on the impact of COVID on US firms sales, with for example Bartik et al. (2020) reporting a 40% reduction in employment and Altig et al. (2020b) reporting a 23.3% reduction in full year 2020 sales.

COVID-19 has also created massive “uncertainty” for firms, with 64% reporting that COVID-19 is one of the top 3 biggest sources of uncertainty for their firms. One possible factor driving some of the negative projections is the temporary shut-down of businesses across the US. Figure 6d (bottom left) shows that 18% of the firms in our sample are experiencing a temporary closure, mostly due to mandated government closure. Interestingly, these firms do not all forecast a total loss of revenue over the next three months, indicating that many are predicting restrictions will be lifted before the end of June.

Even firms that operate entirely online are not immune from the economic impact. Figure 7a shows average forecasted impacts of COVID-19 for businesses that have a physical location, operate online only, or do both. Firms with physical locations are experiencing the brunt of the impact, with massive projected losses of over half of their sales. Online businesses experience roughly half of the impact, which although much better, still reflects losses of over a quarter of their sales. Businesses with both online and offline sales experience an impact roughly similar to businesses that are offline.

Despite the fact that businesses with physical locations are worse off, this does not imply that home businesses are able to fare any better. In our business survey, we had previously asked firms about their primary workspace - at home, in an office, or in a shared office space. We see in Figure 7b that firms in all locations have been heavily hit by COVID-19, suggesting that even firms already operating from home are still seeing drastic falls in revenue.
Figure 7c shows the impact varies heavily by product group/industry. Using the product codes provided by Fintech we group firms into industries/product groups. Firms in clothing have been the hardest hit while other retail and services are impacted almost as much.

Figure 8a shows founders with humanities degrees report the largest negative impact while those with STEM the smallest impact, reflecting the greater hi-tech share of firms founded by STEM degree holders. In Figure 8b we see that female company founders report a larger negative impact (-34% compared to -28% for males). A primary reason appears to be industry mix - a higher percentage of male founders are operating firms in software, while a higher percentage of female founders are operating firms in Clothing.

4. **Conclusions**

We have gathered data on manager expectations for future sales using an ongoing triannual survey of online firms in partnership with Fintech, an online payment processing company. Each round of the survey, managers are asked to predict future sales, which we can compare directly with their actual account data. We are now preparing a financial monitoring RCT that we believe will significantly improve their forecasts and allow us to study the causal relationship between manager forecast performance and realized firm performance.

Preliminary results from the panel survey suggest that manager ability to correctly forecast sales is highly correlated with firm performance. Despite its apparent importance, firms are remarkably bad at forming accurate predictions – if firms simply accurately reported their sales over the past 3-months as their prediction they would perform twice as well. We posit that simply encouraging them to review the financial data already easily available to them would dramatically improve their prediction performance and therefore impact their business decisions.

Separately, we also show our estimates of the impact on businesses from the COVID-19 pandemic. We found that Online businesses are sheltered, though not immune from the impacts of the COVID-19 pandemic. Female entrepreneurs are also impacted more heavily than male entrepreneurs largely because they are in industries that are more heavily impacted and have degrees in fields that are more affected.
Bibliography

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Barrero, Jose Maria, Nicholas Bloom, and Ian Wright. “Short and Long Run Uncertainty,” n.d., 55.


Appendix

A1. Management Questions

In the second round of the survey (Summer 2019), firms were asked to respond to a module on management practices. The questions were copied with minor adjustments from the Management and Organizational Practices Survey (MOPS) and the Annual Survey of Entrepreneurs (ASE).

1. How many key performance indicators (KPIs) are monitored at your business?
2. How frequently are KPIs typically reviewed at your business?
3. What did you do when a service or production problem arises in your business?
4. What describes the time frame of your service/production targets?
5. How easy or difficult is it to achieve service, or production targets?
6. What are the primary ways employees are promoted in your business?
7. When is an under-performing employee reassigned or dismissed?

A2. Prediction Competition

A3. Dashboard
# Table 1: Summary Statistics

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**Business Characteristics**

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Notes: Data for online firms comes from 5,300 survey responses on the Stanford-Stripe Study of Internet Entrepreneurship.
### Table 2: Management Score and Firm Revenue

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Notes: Personality Measurements were collected in the third wave, approximately four months after the management measurements were collected in wave 2.
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<td>(0.020)</td>
<td>(0.006)</td>
<td>(0.006)</td>
</tr>
<tr>
<td><strong>Forecast Error</strong></td>
<td>-1.175***</td>
<td>-0.244***</td>
<td>-0.174***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.092)</td>
<td>(0.041)</td>
<td>(0.012)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>9.783***</td>
<td>10.550***</td>
<td>0.037</td>
<td>0.183***</td>
<td>0.913***</td>
<td>1.026***</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
<td>(0.076)</td>
<td>(0.019)</td>
<td>(0.031)</td>
<td>(0.006)</td>
<td>(0.010)</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>2050</td>
<td>2050</td>
<td>1842</td>
<td>1842</td>
<td>2050</td>
<td>2050</td>
</tr>
</tbody>
</table>

Notes: Data for online firms comes from 5,300 survey responses on the Stanford-Stripe Study of Internet Entrepreneurship.
Figure 1: Managed and Firm Performance

Notes: 2,207 survey responses from the second wave of the Stanford-Stripe Study of Internet Entrepreneurship.
Figure 2: Accuracy and Performance

Notes: 2,044 survey responses from the second wave of the Stanford-Stripe Study of Internet Entrepreneurship. Forecast Error is the difference between the forecasted and actual revenue divided by their average. As examples: overestimating by 100% = .66, overestimating by 200% = 1, overestimating by 1000% = 1.66
Figure 3: Firms Forecast Poorly

Notes: Data for firms comes from 2,400 survey responses on the Stanford Study of Internet Entrepreneurship. Predictions were gathered in the Summer of 2019, prior to the COVID-19 pandemic, in responses to the question “What do you predict your revenue on Fintech will be over the next three months?” Forecast error was then calculated by comparing their predictions with sales data recorded by Fintech.
Figure 4: Firms have Poor Sales Tracking

Notes: Data for firms comes from 2,400 survey responses on the Stanford Study of Internet Entrepreneurship. Predictions were gathered in the Summer of 2019, prior to the COVID-19 pandemic, in responses to the question “What was your revenue on Fintech over the last three months?” Forecast error was then calculated by comparing their predictions with sales data recorded by Fintech.
Figure 5: Dashboard Use Associated with Greater Accuracy

Notes: Data for firms comes from 2,400 survey responses on the Stanford Study of Internet Entrepreneurship. Predictions were gathered in the Summer of 2019, prior to the COVID-19 pandemic, in responses to the question “What do you predict your revenue on Fintech will be over the next three months?” Forecast error was then calculated by comparing their predictions with sales data recorded by Fintech. Dashboard usage was calculated based on the number of times they viewed their Fintech Account.
Figure 6: COVID Impact on Firms Expected Sales

Notes: Data for firms comes from 2,400 survey responses on the Stanford Study of Internet Entrepreneurship.
Figure 7: COVID Expected Impact by Firm Type

By what percentage will COVID-19 raise/lower your firm's 2020 Q2 sales?

- Home: -30%
- Office: -30%
- Co-Working Space: -24%

By what percentage will COVID-19 raise/lower your firm's 2020 Q2 sales?

- Physical: -38%
- Both: -39%
- Online: -21%

Notes: Data for firms comes from 2,400 survey responses on the Stanford Study of Internet Entrepreneurship
Figure 8: COVID Expected Impact by Founder Degree and Gender

Notes: Data for firms comes from 2,400 survey responses on the Stanford Study of Internet Entrepreneurship.
Figure A1: Survey Firms Location

Notes: Data for online firms comes from 5,300 survey responses on the Stanford-Stripe Study of Internet Entrepreneurship.
Notes: Data for online firms comes from 5,300 survey responses on the Stanford-Stripe Study of Internet Entrepreneurship.
Figure A3: Demographics of Online businesses

Gender
- Male
- Female

Education
- Masters+
- Bachelors
- 2-Year Degree
- Some College
- High School
- < High School

Founder Age
- 65+
- 55 to 64
- 45 to 54
- 35 to 44
- 25 to 34
- < 25

Firm Age (Years)
- 41+
- 26 to 40
- 21 to 25
- 16 to 20
- 11 to 15
- 6 to 10
- 5
- 4
- 3
- 2
- 1
- 0

Notes: Data for online firms comes from 5,300 survey responses on the Stanford-Stripe Study of Internet Entrepreneurship. Data for all US firms is from the Annual Survey of Entrepreneurs, 2016 (ASE)
Figure A4: Dashboard Example

Note: Source https://stripe.com/docs/dashboard
Figure A5: Dashboard Views 2019