# Why did Firms Draw Down their Credit Lines during the COVID-19 Shutdown?*


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**Abstract**

The economic shutdown associated with the COVID-19 pandemic witnessed a dramatic surge in drawdowns on pre-existing credit lines. This paper examines how this liquidity was used by firms. Drawdowns were associated with an accumulation of liquid assets, suggesting a precautionary motive to mitigate future liquidity risk. We do not find strong evidence that drawdowns were associated with greater levels of investment on average. However, we find evidence that firms in industries that were less affected by the shutdown, such as professional services that can be performed remotely, were more likely to use drawdowns to maintain investment. On the intensive margin, this is especially true for firms in such industries that drew a relatively small amount of funds. These results suggest that a firm's incentive to draw down its credit lines during an aggregate liquidity shock can depend on its idiosyncratic exposure to the shock.



**Keywords: credit lines, COVID-19, liquidity, investment**

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# 1 Introduction

Credit lines, or contracts that allow firms to draw funds from their bank, comprise a substantial fraction of bank lending to businesses (Shockley and Thakor (1997)). The literature has generally established that firms are more likely draw down their credit lines when liquidity is scarce, but there are conflicting perspectives about why. On the one hand, Holmstrom and Tirole (1998) argue that credit lines help firms to manage their liquidity so that they can maintain investment.[1] On the other hand, Ivashina and Scharfstein (2010) find that firms drew down their credit lines during the global financial crisis as a precaution against the possibility that their lenders could become unable to provide liquidity in the future.

This paper investigates this question within the context of the shutdown associated with the COVID-19 pandemic. During March of 2020, the U.S. introduced social distancing restrictions in response to the COVID-19 pandemic, resulting in the suspension of non-essential economic activities involving in-person interactions. Businesses faced sharply declining profits, especially in industries with less flexibility for working at home (Figure 1).[2] During this time, firms drew a substantial amount of cash from pre-existing credit lines with their banks (Li, Strahan and Zhang (2020), Acharya and Steffen (2020)). To determine why firms drew down their credit lines during the COVID-19 shutdown, it is important to consider how they used the resulting liquidity.

This paper investigates three hypotheses to explain the increase in credit line drawdowns during the COVID-19 shutdown:

H1: Firms used the drawdowns to pay for immediate expenses.

H2: Firms accumulated liquidity as a precaution against future liquidity risk.

H3: Firms used the drawdowns to maintain investment during the shutdown.

We investigate this question using data on credit line drawdowns from S&P's Leveraged Commentary & Data and balance sheet data from Compustat. To try to best isolate

[1] Campello et al. (2012) and Berrospide and Meisenzahl (2015) find empirical evidence in support of this role during the global financial crisis.

[2] Papanikolaou and Schmidt (2020) find that such industries also experienced greater declines in employment, expected revenue growth, stock market performance, and creditworthiness.

the effect of credit line drawdowns on changes in liquidity and investment from immediately before the crisis in 2019Q4 through the start of the crisis in 2020Q1, we implement a difference-in-difference specification comparing firms that drew from a credit line relative to firms that did not. Although drawdowns are not randomly distributed across firms, we mitigate endogeneity by controlling for observable factors that could be jointly correlated with a firm's motivation to draw from a credit line and other adjustment strategies affecting the dependent variables, such as a firm's liquidity position and industry. We also instrument credit line drawdowns with a firm's predetermined level of undrawn credit commitments. Although a firm's level of undrawn commitments could be chosen partly in anticipation of adverse shocks in general, it is arguably less likely to have been chosen in anticipation of a shock like the COVID-19 shutdown, which was unique in its abruptness and magnitude.

Another unique feature of the COVID-19 shutdown was its heterogeneous effect across industries based on their ability to be performed remotely and whether they were designated as essential. Motivated by this observation, we further examine how the use of funds from credit line drawdowns varied with these industry characteristics. Finally, we also examine the intensive margin to see how the motivation behind credit line drawdowns was correlated with the size of the drawdowns.

We find that drawdowns were strongly associated with increased liquidity, consistent with hypothesis H2. We do not find evidence that drawdowns were on average associated with greater levels of investment, as measured by capital expenditure. However, we find some evidence that, within industries that were less affected by the shutdown, firms that drew modest amounts of funds were more likely maintain investment. A general conclusion supported by these results is that a firm's incentive to draw down its credit lines during an aggregate liquidity shock can depend on its idiosyncratic exposure to the shock.

## 2 Literature Review

This paper contributes to two strands of recent work examining the economic effects of the COVID-19 pandemic. First, it relates to papers showing a significant increase in credit line drawdowns during the COVID-19 shutdown. Acharya and Steffen (2020) find evidence that this may have been driven by a precautionary motive by firms trying to avoid credit rating downgrades. Li, Strahan and Zhang (2020) and Federal Reserve (2020) remark that banks have managed to accommodate these drawdowns thanks to inflows of deposits as well recent regulations that have strengthened their balance sheets compared to the global financial crisis.

Second, this work relates to papers illustrating the heterogeneous effects of the COVID-19 shutdown across industries. Papanikolaou and Schmidt (2020) finds that industries with fewer opportunities to work from home performed worse as measured by declines in employment, expected revenue growth, stock market performance, and expected likelihood of default. By contrast, Barrero, Bloom and Davis (2020) and Hassan et al. (2020) show that the shutdown provided expansion opportunities for some firms, such as those specialized in essential services.

This paper is also related to a more general literature on credit lines. Firms apply for credit lines to mitigate liquidity risk (Holmstrom and Tirole (1998), Acharya et al. (2014)). During the global financial crisis, firms used their credit lines to maintain investment (Campello, Graham and Harvey (2010), Campello et al. (2011), Campello et al. (2012), Berrospide and Meisenzahl (2015)). There is also evidence that firms drew down their credit lines during the crisis as a precautionary measure due to fears that their lenders would be unable to provide liquidity in the future (Ivashina and Scharfstein (2010), Montoriol-Garriga and Sekeris (2009), Huang (2010)).

# 3 Data

We obtain data on credit line drawdowns from Leveraged Commentary & Data, a subsidiary of S&P Global Market Intelligence. We construct a firm-level cross-section by computing the sum of drawdowns in March 2020. We merge this with balance sheet data from Compustat, which includes the percentage of liquid assets (which consists of cash and short-term investments) to total assets, capital expenditure to total assets, the logarithm of total assets, SIC industry indicators, and a measure of liquidity stress, which is defined as

$$stress = 100 * \frac{\text{lag short-term debt - lag liquid assets - net income}}{\text{lag total assets}} \tag{1}$$

In particular, liquidity stress is intended to measure a firm's short-term obligations relative to existing resources that can be used to meet those obligations, which includes the stock of liquid assets as of the last filing date as well as the flow of net income in the current period. A 95% winsorization is applied variables to mitigate the effect of outliers. Summary statistics are included in Table 1.

# 4 Methodology

We examine the effect of credit line drawdowns on firm characteristics during the COVID-19 shutdown by estimating the regression

$$\Delta Y_{ij} = \beta D_{ij} + \gamma X_{ij} + \alpha_j + \epsilon_{ij} \tag{2}$$

where $\Delta Y_{ij}$ is the difference from 2019Q4 to 2020Q1 of either the ratio of liquid assets to total assets or the ratio of capital expenditure to total assets for firm $i$ in 2-digit NAICS industry $j$, $D_{ij}$ is a dummy indicating whether a firm drew funds from a credit line in March 2020, $X_{ij}$ is a set of controls, and $\alpha_j$ represents industry fixed effects. The control variables include the logarithm of total assets in 2019Q4 and liquidity stress in 2020Q1 as defined in equation (1). T-statistics computed using heteroskedasticity-robust standard errors are reported in parentheses.

To investigate potential differences in the use of credit line drawdowns across industries that were differentially affected by the shutdown, we also estimate variations of this specification that include the interactions of drawdowns with an indicator for industries that were relatively exposed to the shutdown and an indicator for industries that were relatively unexposed. To determine exposure, we consider the fact that the shutdown restricted non-essential economic activities involving in-person interactions. Specifically, we classify an industry as relatively exposed to the crisis if it is not deemed essential and a large fraction of jobs cannot be done at home, and we classify an industry as relatively unexposed to the crisis if it is essential or if a large fraction of jobs can be done at home. We determine essential industries at the 4-digit NAICS code level based on the classification in Papanikolaou and Schmidt (2020), which is a modified version of the guidance provided by the Cybersecurity and Infrastructure Security Agency (CISA). Some essential industries include food and beverage production, utilities, transportation, and medical services.

We determine the degree to which work in an industry can be done at home at the 2-digit NAICS code level based on the classification in Dingel and Neiman (2020). Specifically, we classify an industry as having a low fraction of jobs that can be done at home if no more than 25% of jobs can be done at home, which includes accommodation and food services; agriculture, forestry, fishing, and hunting; retail trade; construction; transportation and warehousing; manufacturing; health care and social assistance; and mining, quarrying, and oil and gas extraction. We classify an industry as having a high fraction of jobs that can be done at home if at least 75% of jobs can be done at home, which includes education services; professional, scientific, and technical services; management of companies and enterprises; and finance and insurance.

We also estimate the intensive margin of the effect of credit line drawdowns by estimating a similar regression as in equation (2) except restricting to the subsample of firms that drew funds from a credit line and using the logarithm of total credit line drawdowns $Log(drawdown)_{ij}$ rather than the indicator variable $D_{ij}$ as the treatment variable. It is useful to also consider the intensive margin because the amount that a firm draws from a credit line could depend on the intended use of the funds. For example, a firm seeking to accumulate a precautionary buffer of liquidity due to anticipation of losses for a long period of time may be more likely to draw a larger volume of funds compared to a firm seeking to finance current investment opportunities.

# 5 Identification

The regression in equation (2) includes industry fixed effects and other control variables to help uniquely identify the effect of credit line drawdowns on firm characteristics. In particular, the control variables address the concern that credit line drawdowns could have been correlated with other firm decisions affecting these characteristics. As an example in the case where the response variable is the ratio of liquid assets to total assets, firms that had weaker liquidity positions at the start of the crisis or that were in industries with greater exposure to the shutdown could have had a higher incentive to both draw funds from a credit line and reduce cash outflows in order to increase their liquidity, resulting in an upward bias of the coefficient $\beta$ in the absence of controlling for these factors.

To show the correlates of credit line drawdowns, Table 2 compares firms that drew funds from a credit line to firms that did not.[3] Firms that drew funds from a credit line were relatively large and illiquid. They also had higher rates of investment and were more likely to be in industries that were relatively exposed to the shutdown. However, they did not exhibit a statistically significant different degree of liquidity stress at the onset of the shutdown. Table 3 shows a similar set of statistics for the subsample of firms in industries that were relatively exposed to the COVID-19 shutdown, and Table 4 does so for the subsample of firms in industries that were relatively unexposed to the shutdown. Drawdowns are consistently associated with size and illiquidity, whereas the correlation with investment and immediate liquidity stress varies with the subsample.

It is possible that credit line drawdowns could have also been correlated with unobserved factors affecting the response variables. To sharpen the identification, the regression in equation (2) can be interpreted as a difference-in-differences design. The difference-in-differences design identifies the causal effect of drawdowns on liquidity under the assumption that firms that drew funds from a credit line and firms that had no drawdowns would have experienced parallel trends in the liquid assets to total assets ratio in the absence of the drawdown. In the results (Section 6), we assess the validity of this assumption for each variable by checking for the presence of pre-existing differential trends between the two groups.

As an additional measure to sharpen identification, we also estimate a version of equation (2) except instrumenting the use of a credit line with a firm's pre-existing level of undrawn revolving credit commitments in 2019Q4, which can be interpreted as a limit on the amount of credit a firm can draw during the COVID-19 shutdown. Data on un-

[3]Note that the number of firms with a drawdown is greater than the number of firms with data on drawdown volume in Table 1 because a small number of observations report that there was a drawdown but do not report the amount.

drawn credit is from Capital IQ. Table 5 shows in a first-stage regression that undrawn credit in 2019Q4 is a significant predictor of credit line drawdowns in March 2020, with an F-statistic of greater than 10 in both the extensive margin specification where the dependent variable is a dummy indicating a credit line drawdown and in the intensive margin specification where the dependent variable is the logarithm of total drawdowns on the subset of firms with a positive drawdown.

Instrumenting with undrawn commitments could mitigate endogeneity because it is predetermined. A potential caveat is that some firms could choose to maintain higher undrawn commitments in anticipation of shocks. In particular, such firms could also have a higher likelihood of implementing complementary adjustment strategies in response to shocks that could affect the response variables. However, it is less likely that firms would have chosen their level of undrawn commitments in anticipation of a shock like the COVID-19 shutdown, which was unique in its speed and severity.

# 6 Results

This section presents results illustrating how credit line drawdowns affected liquidity and investment during the COVID-19 shutdown.

## 6.1 Liquid assets

This section presents results illustrating how credit line drawdowns affected liquidity on the extensive margin and the intensive margin.

### 6.1.1 Extensive margin

Figure 2 shows the mean liquid assets to total assets ratio for firms that drew down their credit lines compared firms with no recorded drawdowns starting from one year before the COVID-19 pandemic, normalizing each series relative to its level in 2019Q4. Panel A shows this comparison for all industries, Panel B restricts to industries that were relatively exposed to the shutdown, and Panel C restricts to industries that were relatively unexposed to the shutdown. In each case, fluctuations in the relative trend between the two groups of firms before 2019Q4 are small compared to the sharp relative increase in liquidity for the firms that drew from a credit line in 2020Q1.

Table 6 presents corresponding cross-sectional evidence from estimating equation (2). In the baseline regression reported in Column (1), credit line drawdowns were positively and significantly associated with increases in the ratio of liquid assets to total assets. The estimate indicates that drawdowns were associated an increase in the liquid assets to total assets ratio of around 4.5 percentage points, which is substantial relative to the mean ratio of around 9.1% for the subsample of firms that drew funds from a credit line. The remaining columns show that this result is robust to variations of the specification. Column (2) shows that the result is qualitatively robust when the drawdown dummy is instrumented by the logarithm of undrawn credit commitments as of 2019Q4. Column (3) shows that the result is robust when estimated as the average treatment effect using a 1-nearest neighbor matching estimator with an exact match on industry and matching via Mahalanobis distance on the characteristics in $X_{ij}$. Column (4) shows the result when including a dummy for industries that were relatively exposed to the COVID-19 shutdown, a dummy for industries that were relatively unexposed to the COVID-19 shutdown, and their interactions with the drawdown dummy and the controls. The estimates for the interaction terms are insignificant, suggesting that the effect of drawdowns on liquid assets did not appear to vary with the degree of exposure to the shutdown.

Various additional specifications are reported in Table 7. Column (1) shows that the result is robust to modifying the dependent variable to mitigate seasonality. In particular, instead of using the difference from 2019Q4 to 2020Q1, it subtracts out the average difference from Q4 to Q1 during 2010-2019. Column (2) shows that the result is robust to estimation of equation (2) via median regression to reduce the influence of outliers. Column (3) shows that the result is qualitatively robust to using the growth of liquid assets rather than the difference in the ratio of liquid assets to total assets. Column (4) shows that the result is robust to using the marginal expected shortfall (MES) as defined in Acharya et al. (2017) as a measure of tail-risk in place of liquidity stress as defined in equation (1). The MES for a firm is computed as its average stock return in the 5% of days in 2019 where the market achieved its lowest return. Data on stock prices for individual firms is obtained from CRSP, and data on the S&P 500 as a measure of market returns is obtained from FRED.

#### 6.1.2 Intensive margin

Panel A of Figure 3 shows the difference in the liquid assets to total assets ratio from 2019Q4 to 2020Q1 for firms that drew down their credit lines relative to the magnitude of the drawdown after partialling out the control variables specified in equation (2). The figure indicates a positive relationship between the magnitude of credit line drawdowns and liquidity. Panel B shows this relationship for firms in relatively exposed and unexposed industries. Both industry groups exhibit a positive association between drawdown magnitudes and liquidity, although the association appears to be somewhat stronger for the exposed industries.

Table 8 presents corresponding cross-sectional evidence from estimating equation (2) except using the volume of drawdown funds. The baseline specification in Column (1) and the instrumental variable specification in Column (2) indicate that credit line drawdowns were positively and significantly correlated with changes in the liquid assets to total assets ratio. Column (3) shows that this result is robust to using the fraction of a firm's drawdown to its credit line. Column (4) shows that the positive association between drawdowns and liquidity is somewhat stronger for more strongly exposed firms, but the estimates are insignificant. Various additional extensions are reported in Table 9.[4] The results are qualitatively consistent with the baseline specification.

#### 6.1.3 Interpretation of findings

Overall, the results in this section provide robust evidence for the hypothesis that firms drew down their credit lines as a precautionary measure to safeguard against future liquidity risk (see hypothesis H2 from Section 1).

### 6.2 Investment

This section presents results illustrating how credit line drawdowns affected investment on the extensive margin and the intensive margin.

[4]The specifications are described in the review of Table 7 as described in Section 6.1.1.

### 6.2.1 Extensive margin

Figure 4 shows the mean capital expenditure to assets ratio for firms that drew down their credit lines compared to firms with no recorded drawdowns, normalizing each series relative to its level in 2019Q4.[5] Fluctuations in the relative trend between the two groups of firms before 2019Q4 are small compared to the decrease in 2020Q1 for the full sample and the subsample of exposed firms, although there appear to be more notable preceding fluctuations in the subsample of unexposed firms. For the sample of all firms and the subsample of exposed firms, the firms that drew funds from a credit line appear to exhibit a slightly more severe decline in investment compared to the other firms.

Table 10 and Table 11 present corresponding cross-sectional evidence from estimating equation (2).[6] The estimate in the baseline specification is insignificant. The results vary across specifications, as there is a positive and significant estimate in the matching specification, a negative and significant estimate in the median regression, and insignificant estimates for the remaining specifications. The interaction with exposed industries is generally negative, and it is significant at 10% in the specification with a correction for seasonality. The interaction with unexposed industries is generally positive, and it is significant at the 10% level in the interactions specification.

### 6.2.2 Intensive margin

Panel A of Figure 5 Panel A shows the difference in the capital expenditure to assets ratio from 2019Q4 to 2020Q1 for firms that drew down their credit lines relative to the magnitude of the credit line drawdown after partialling out the control variables specified in equation (2). The figure does not indicate a strong relationship between the magnitude of credit line drawdowns and increased investment. Panel B shows that the size of credit line drawdowns were slightly more associated with lower investment for firms in industries that were relatively exposed to the COVID-19 shock compared to firms in unexposed industries.

Table 12 and Table 13 present corresponding cross-sectional evidence from estimat-

[5] As in Figure 2, Panel A shows this comparison for all industries, Panel B restricts to industries that were relatively exposed to the shutdown, and Panel C restricts to industries that were relatively unexposed to the shutdown.

[6] The specifications are described in the review of Table 6 and Table 7 in Section 6.1.1.

ing equation (2) except using the volume of drawdown funds.[7] In the intensive margin, the estimate in the baseline specification is insignificant. The results vary across specifications, as there is a positive and significant estimate in the growth specification, a negative and significant estimate in the median regression and instrumental variable regression, and insignificant estimates for the remaining specifications. In the majority of the specifications, the size of credit line drawdowns were more negatively associated with investment for firms in unexposed industries, which is significant in the first interactions specification and the specification using the MES as a measure of liquidity stress during the shutdown.

### 6.2.3 Interpretation of findings

Overall, the results in this section do not provide robust evidence that drawdowns were used to maintain investment during the shutdown on average (see hypothesis H3 from Section 1). However, the extensive margin analysis provides some evidence that firms in relatively unexposed industries were more likely to use some of the funds from drawdowns to maintain investment. Moreover, the intensive margin analysis suggests that this was more common among firms that drew a modest amount of funds. This last point is consistent with the explanation that firms with large drawdowns were more likely to accumulate liquidity as a precaution against long-term liquidity risks, whereas firms with smaller drawdowns were more likely to use it to finance current investment opportunities.

## 7 Conclusion

This paper examines how firms used credit line drawdowns during the COVID-19 shutdown. Drawdowns were strongly associated with increased cash holdings, consistent with the interpretation that firms sought to reduce future liquidity risk. We do not find strong evidence that, on average, firms used credit line drawdowns to maintain investment during the shutdown. However, there is some evidence that firms in industries that were relatively unexposed to the economic restrictions associated with the shutdown

[7] The specifications are described in the review of Table 8 and Table 9 in Section 6.1.2.

were more likely to use their credit lines to maintain investment during the shutdown, especially if they drew a modest amount of funds. These results suggest that a firm's incentive to draw down its credit lines during an aggregate liquidity shock can depend on its idiosyncratic exposure to the shock.

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# A Figures

Figure 1: The top panel shows the median net income to assets ratio. The bottom panel shows the median ratio of net income to assets relative to the 2019Q4 level for three industry groups: all firms, firms in industries that were relatively exposed to the COVID-19 shutdown, and firms in industries that were relatively unexposed to the COVID-19 shutdown (see Section 4 for a more detailed description of the industry groups).

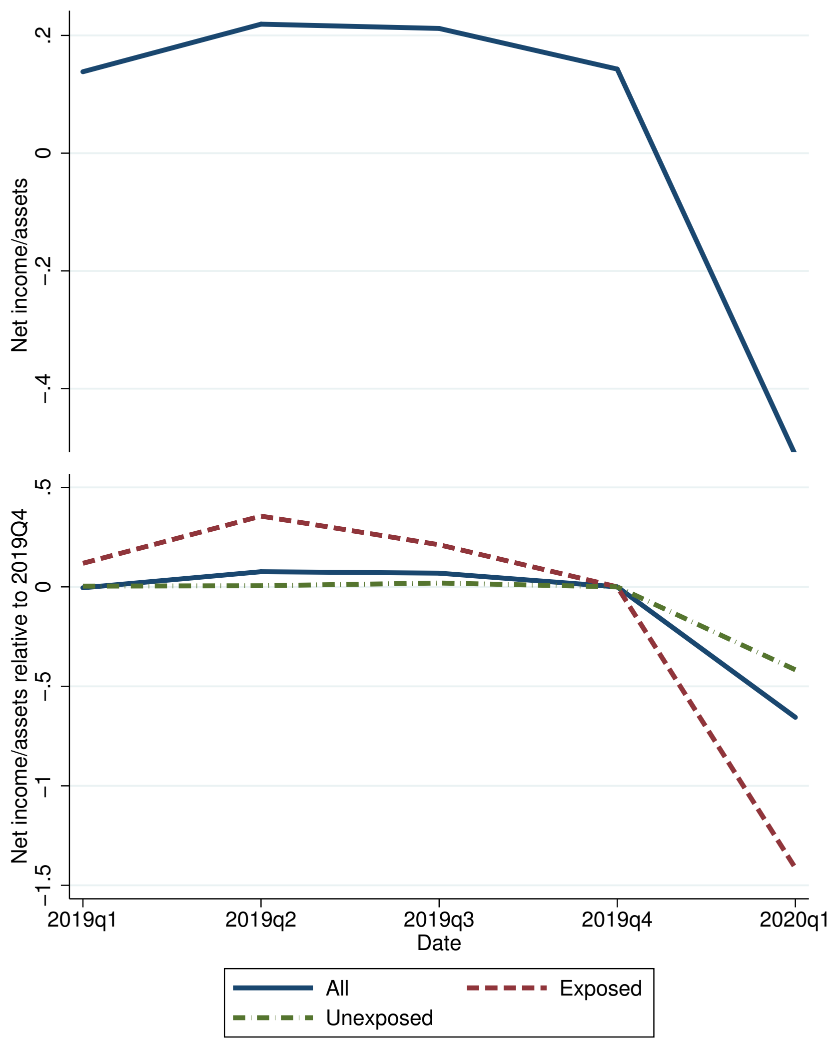


Figure 2: The left panel shows the mean ratio of liquidity (cash and short-term investments) to assets relative to the 2019Q4 level for firms that drew funds from a credit line and for firms that did not. The middle panel shows the same within the subset of industries that were strongly exposed to the COVID-19 shutdown. The right panel shows the same within the subset of industries that were relatively unexposed to the COVID-19 shutdown (see Section 4 for a more detailed description of the industry groups).

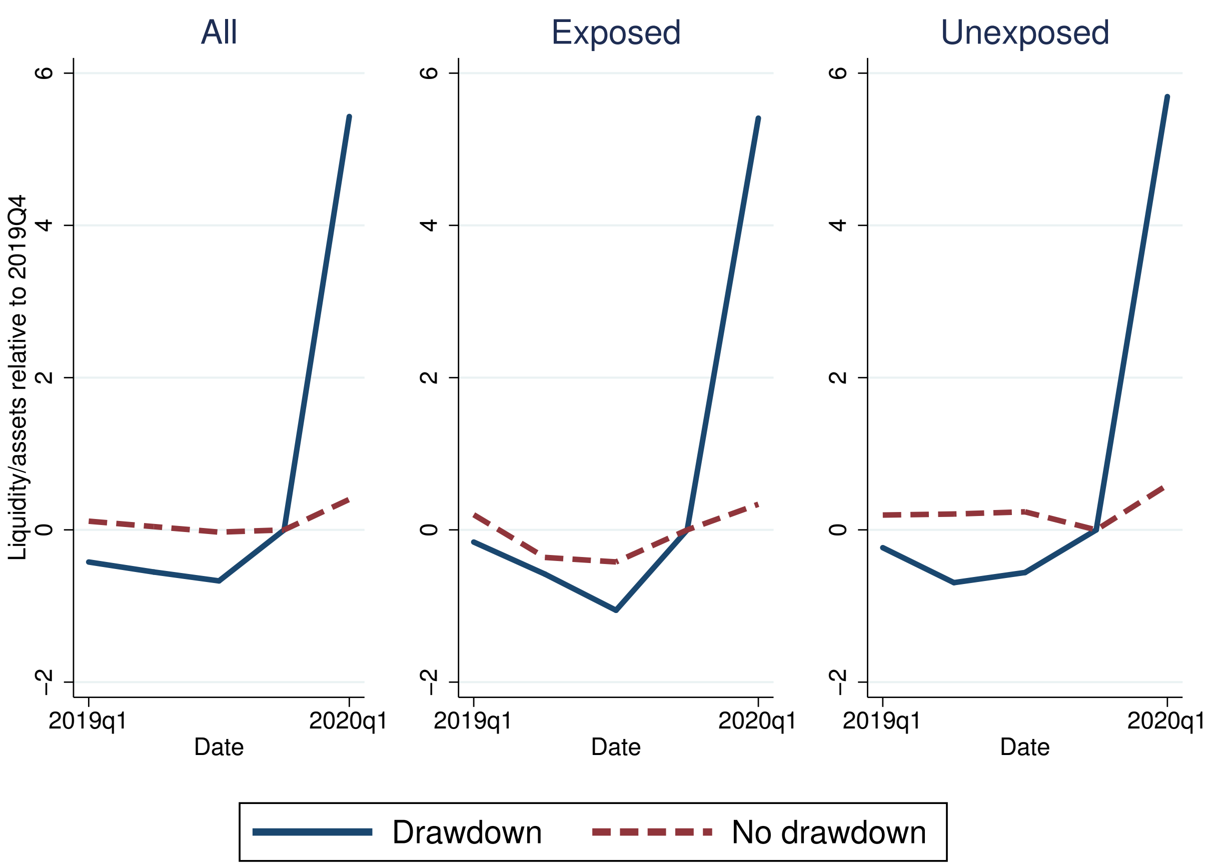


Figure 3: The left panel shows a binned scatterplot of the difference in the ratio of liquidity (cash and short-term investments) to assets from 2019Q4 to 2020Q1 for firms that drew from a credit line on the y-axis and the logarithm of total funds acquired through a credit line drawdown during March 2020 on the x-axis. The right panel shows the same within the subset of industries that were strongly exposed to the COVID-19 shutdown and the subset of industries that were relatively unexposed to the COVID-19 shutdown (see Section 4 for a more detailed description of the industry groups).

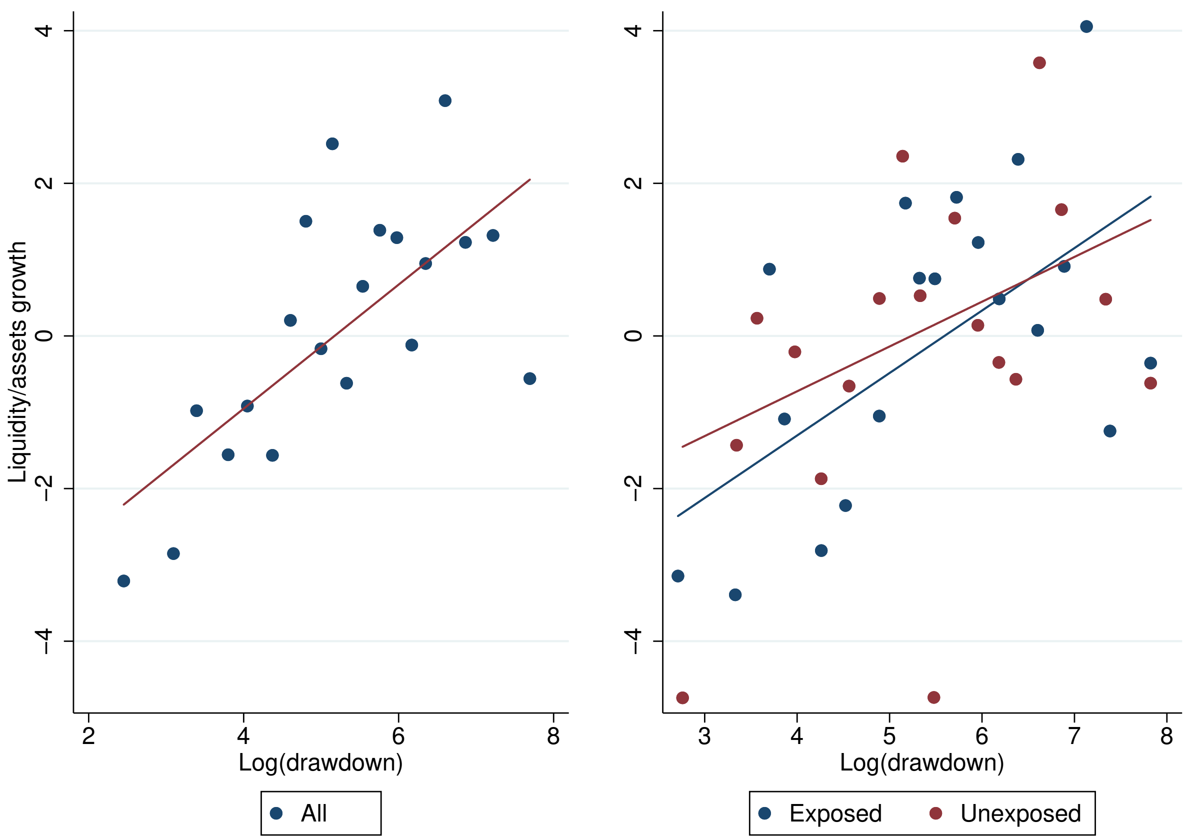
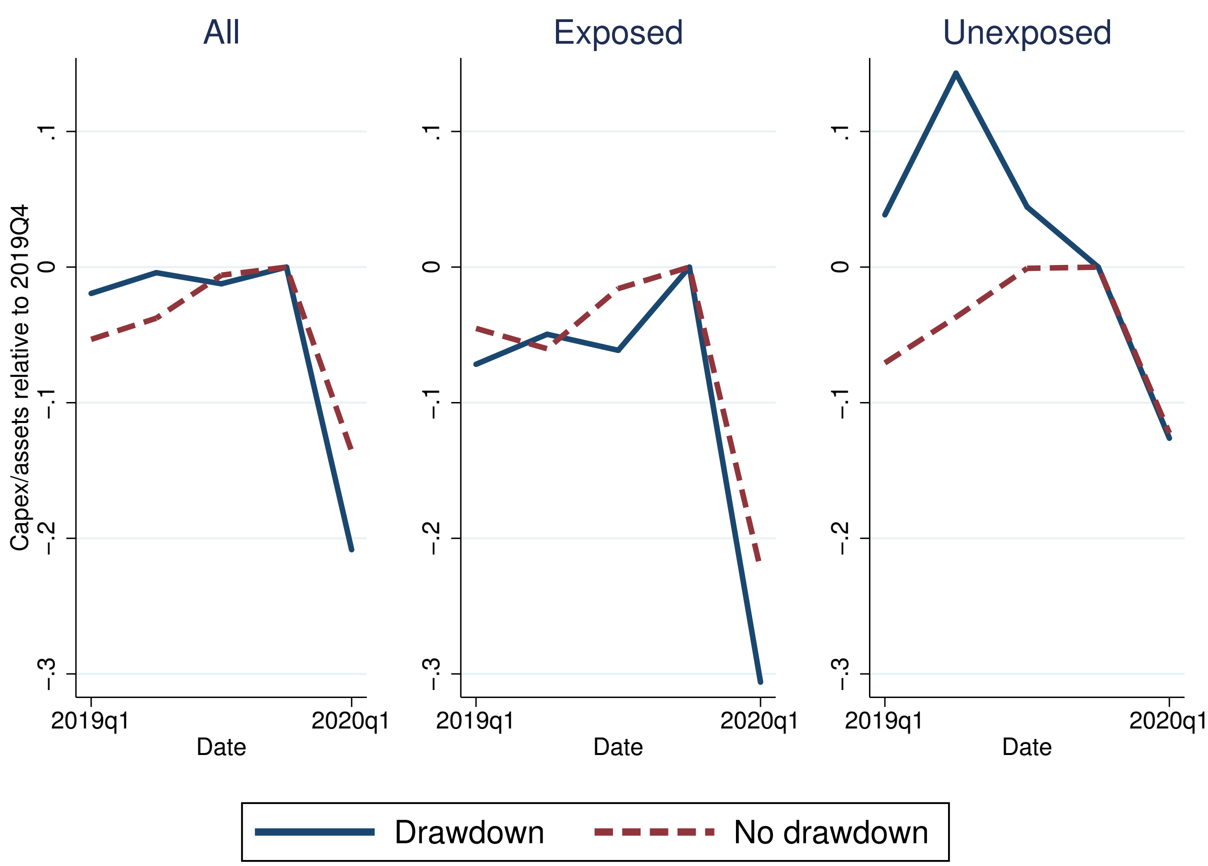


Figure 4: The left panel shows the mean ratio of capex (capital expenditure) to assets relative to the 2019Q4 level for firms that drew funds from a credit line and for firms that did not. The middle panel shows the same within the subset of industries that were strongly exposed to the COVID-19 shutdown. The right panel shows the same within the subset of industries that were less exposed to the COVID-19 shutdown (see Section 4 for a more detailed description of the industry groups).



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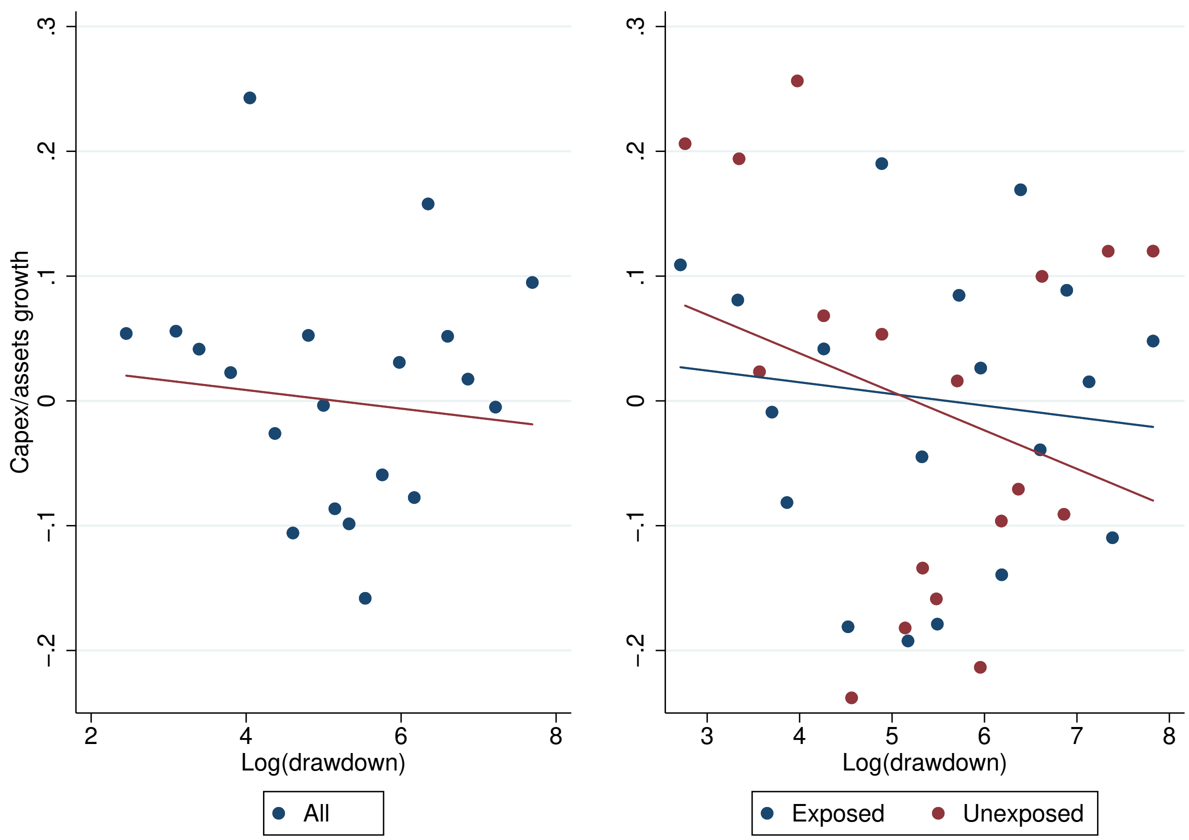

## B Tables

Table 1: Summary statistics. D is a dummy indicating whether a firm drew funds from a credit line in March 2020, Drawdown is the sum of drawdowns in millions of USD for firms that drew funds from a credit line, Liquid assets/assets is the percentage of cash and short-term investments to total assets in 2019Q4, Capex/assets is the percentage of capital expenditure to total assets in 2019Q4, Total assets is total assets in millions of USD, Stress is liquidity stress in 2020Q1 as defined in equation (1), Exposed is a dummy indicating whether a firm was in an industry that was relatively exposed to the COVID-19 shutdown, and Unexposed is a dummy indicating wheth a firm was in an industry that relatively unexposed to the shutdown (see Section 4 for a more detailed description of the industry groups).

| | N | Mean | SD | P25 | P75 |
|---|---|---|---|---|---|
| D | 5386 | 0.07 | 0.25 | 0.00 | 0.00 |
| Drawdown ($ m) | 362 | 396.04 | 530.66 | 60.00 | 500.00 |
| Liquid assets/assets (%) | 5386 | 20.53 | 26.41 | 2.49 | 26.83 |
| Capex/assets (%) | 5386 | 0.89 | 1.22 | 0.04 | 1.23 |
| Total assets ($ m) | 5386 | 6932.90 | 17690.04 | 56.99 | 3882.08 |
| Stress | 5386 | -3.92 | 41.67 | -18.20 | 3.21 |
| Exposed | 5386 | 0.18 | 0.39 | 0.00 | 0.00 |
| Unexposed | 5386 | 0.51 | 0.50 | 0.00 | 1.00 |

Table 2: This table compares firms that drew funds from a credit line to firms with no recorded drawdowns. The first row presents the number of observations in each group, and the remaining rows present the mean in the first two columns. The last column presents the t-statistic from a difference in means test. Liquidity stress is as of 2020Q1. The remaining variables are as of 2019Q4.

| | Drawdown | No drawdown | T-statistic |
|---|---|---|---|
| N | 370 | 5,016 | |
| Liquid assets/assets | 9.094 | 21.38 | -20.796 |
| Capex/assets | 1.041 | 0.882 | 3.194 |
| Log(assets) | 7.903 | 5.957 | 22.422 |
| Stress | -3.688 | -3.933 | .281 |
| Exposed | 0.314 | 0.172 | 5.734 |
| Unexposed | 0.249 | 0.525 | -11.729 |

Table 3: This table compares firms that drew funds from a credit line to firms with no recorded drawdowns for firms in industries that were relatively exposed to the COVID-19 shutdown. The first row presents the number of observations in each group, and the remaining rows present the mean in the first two columns. The last column presents the t-statistic from a difference in means test. Liquidity stress is as of 2020Q1. The remaining variables are as of 2019Q4.

| | Drawdown | No drawdown | T-statistic |
|---|---|---|---|
| N | 116 | 862 | |
| Liquid assets/assets | 7.927 | 13.26 | -5.696 |
| Capex/assets | 1.202 | 1.473 | -2.72 |
| Log(assets) | 8.287 | 5.612 | 15.573 |
| Stress | 0.219 | 6.373 | -3.489 |

Table 4: This table compares firms that drew funds from a credit line to firms with no recorded drawdowns for firms in industries that were relatively unexposed to the COVID-19 shutdown. The first row presents the number of observations in each group, and the remaining rows present the mean in the first two columns. The last column presents the t-statistic from a difference in means test. Liquidity stress is as of 2020Q1. The remaining variables are as of 2019Q4.

| | Drawdown | No drawdown | T-statistic |
|---|---|---|---|
| N | 92 | 2,633 | |
| Liquid assets/assets | 7.944 | 24.09 | -15.629 |
| Capex/assets | 0.956 | 0.805 | 1.716 |
| Log(assets) | 8.038 | 6.153 | 10.852 |
| Stress | -3.703 | -7.443 | 2.624 |

Table 5: First stage. This table presents results from estimating the equation $Y_{ij} = \beta Log(undrawn\ credit)_{ij} + \gamma X_{ij} + \alpha_j + \epsilon_{ij}$, where $Y_{ij}$ is either a dummy indicating whether firm $i$ in 2-digit NAICS industry $j$ drew funds from a credit line in March 2020 (Column (1)) or the logarithm of total drawdowns (Column (2)), $Log(undrawn\ credit)_{ij}$ is the logarithm of undrawn credit commitments as of 2019Q4, $X_{ij}$ is a set of controls (including the logarithm of total assets in 2019Q4 and liquidity stress in 2020Q1 as defined in equation (1)), and $\alpha_j$ represents industry fixed effects. Column (2) restricts to the subset of a firms with a positive drawdown.

| | (1) | (2) |
|---|---|---|
| | D | Log(drawdown) |
| Log(undrawn credit) | 0.019*** | 0.478*** |
| | (5.12) | (8.76) |
| Observations | 3123 | 354 |
| $R^2$ | 0.086 | 0.817 |
| Controls | Yes | Yes |
| Industry FE | Yes | Yes |

Table 6: Effect of credit line drawdowns on liquid assets to total assets (extensive margin). This table presents results from estimating variations of the equation $\Delta Y_{ij} = \beta D_{ij} + \gamma X_{ij} + \alpha_j + \epsilon_{ij}$, where $\Delta Y_{ij}$ is the difference from 2019Q4 to 2020Q1 of liquid assets to total assets for firm $i$ in 2-digit NAICS industry $j$, $D_{ij}$ is a dummy indicating whether a firm drew funds from a credit line in March 2020, $X_{ij}$ is a set of controls (including the logarithm of total assets in 2019Q4 and liquidity stress in 2020Q1 as defined in equation (1)), and $\alpha_j$ represents industry fixed effects. T-statistics computed using heteroskedasticity-robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Column (1) shows the results from the baseline specification. Column (2) shows the results when $D_{ij}$ is instrumented by the logarithm of undrawn credit commitments as of 2019Q4. Column (3) shows the average treatment effect using a 1-nearest neighbor matching estimator with an exact match on industry and matching via Mahalanobis distance on the characteristics in $X_{ij}$. Column (4) shows the result when including a dummy for industries that were relatively exposed to the COVID-19 shutdown, a dummy for industries that were relatively unexposed to the COVID-19 shutdown, and their interactions with the drawdown dummy and the controls (see Section 4 for a more detailed description of the industry groups).

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Baseline | IV | Matching | Interactions |
| D | 4.475*** | 12.951*** | 6.853*** | 4.588*** |
| | (16.78) | (3.34) | (10.05) | (11.16) |
| D x Exposed | | | | -0.370 |
| | | | | (-0.57) |
| D x Unexposed | | | | -0.023 |
| | | | | (-0.04) |
| Observations | 5386 | 3123 | 5293 | 5386 |
| $R^2$ | 0.071 | -0.184 | | 0.074 |
| Controls | Yes | Yes | | Yes |
| Industry FE | Yes | Yes | | Yes |

Table 7: Effect of credit line drawdowns on liquid assets to total assets (extensive margin): extensions. This table presents results from estimating variations of the equation $\Delta Y_{ij} = \beta D_{ij} + \gamma X_{ij} + \alpha_j + \epsilon_{ij}$, where $\Delta Y_{ij}$ is the difference from 2019Q4 to 2020Q1 of liquid assets to total assets for firm $i$ in 2-digit NAICS industry $j$, $D_{ij}$ is a dummy indicating whether a firm drew funds from a credit line in March 2020, $X_{ij}$ is a set of controls (including the logarithm of total assets in 2019Q4 and liquidity stress in 2020Q1 as defined in equation (1)), and $\alpha_j$ represents industry fixed effects. It also includes a dummy for industries that were relatively exposed to the COVID-19 shutdown, a dummy for industries that were relatively unexposed to the COVID-19 shutdown, and their interactions with the drawdown dummy and the controls (see Section 4 for a more detailed description of the industry groups). T-statistics computed using heteroskedasticity-robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Column (1) shows the results when the dependent variable is the difference from 2019Q4 to 2020Q1 of liquid assets to total assets minus the average difference from Q4 to Q1 from 2010 to 2019 to mitigate seasonality. Column (2) shows the results when estimating via median regression. Column (3) shows the results when using the growth of liquid assets rather than the difference in liquid assets to total assets. Column (4) shows the result when using the marginal expected shortfall (MES) as defined in Acharya et al. (2017) as a measure of tail-risk instead of liquidity stress.

| | (1)<br>Seasonality | (2)<br>Median | (3)<br>Growth | (4)<br>MES |
|---|---|---|---|---|
| D | 5.163*** | 4.541*** | 112.344*** | 4.793*** |
| | (11.09) | (11.84) | (6.22) | (10.93) |
| D x Exposed | -0.521 | -0.096 | -41.682 | -0.701 |
| | (-0.73) | (-0.13) | (-1.32) | (-1.02) |
| D x Unexposed | -0.638 | -0.069 | 8.648 | 0.046 |
| | (-0.95) | (-0.13) | (0.26) | (0.07) |
| Observations | 5386 | 5386 | 5320 | 3496 |
| $R^2$ | 0.059 | | 0.090 | 0.081 |
| Controls | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |

Table 8: Effect of credit line drawdowns on liquid assets to total assets (intensive margin). This table presents results from estimating variations of the equation $\Delta Y_{ij} = \beta Log(drawdown)_{ij} + \gamma X_{ij} + \alpha_j + \epsilon_{ij}$, where $\Delta Y_{ij}$ is the difference from 2019Q4 to 2020Q1 of liquid assets to total assets for firm $i$ in 2-digit NAICS industry $j$, $Log(drawdown)_{ij}$ is the logarithm of total credit line drawdowns in March 2020, $X_{ij}$ is a set of controls (including the logarithm of total assets in 2019Q4 and liquidity stress in 2020Q1 as defined in equation (1)), and $\alpha_j$ represents industry fixed effects. T-statistics computed using heteroskedasticity-robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Column (1) shows the results from the baseline specification. Column (2) shows the results when $Log(drawdown)_{ij}$ is instrumented by the logarithm of undrawn credit commitments as of 2019Q4. Column (3) shows the results when using the ratio of total drawdowns to the credit limit instead of the logarithm of total drawdowns. Column (4) shows the result when including a dummy for industries that were relatively exposed to the COVID-19 shutdown, a dummy for industries that were relatively unexposed to the COVID-19 shutdown, and their interactions with drawdown volume and the controls (see Section 4 for a more detailed description of the industry groups).

| | (1)<br>Baseline | (2)<br>IV | (3)<br>Limit | (4)<br>Interactions |
|---|---|---|---|---|
| Log(drawdown) | 3.927*** | 4.139*** | | 3.940*** |
| | (13.28) | (7.66) | | (8.62) |
| Drawdown/limit | | | 3.711*** | |
| | | | (4.46) | |
| Log(drawdown) x Exposed | | | | 0.491 |
| | | | | (0.67) |
| Log(drawdown) x Unexposed | | | | -0.351 |
| | | | | (-0.46) |
| Observations | 361 | 354 | 354 | 361 |
| $R^2$ | 0.463 | 0.450 | 0.167 | 0.499 |
| Controls | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |

Table 9: Effect of credit line drawdowns on liquid assets to total assets (intensive margin): extensions. This table presents results from estimating variations of the equation $\Delta Y_{ij} = \beta Log(drawdown)_{ij} + \gamma X_{ij} + \alpha_j + \epsilon_{ij}$, where $\Delta Y_{ij}$ is the difference from 2019Q4 to 2020Q1 of liquid assets to total assets for firm $i$ in 2-digit NAICS industry $j$, $Log(drawdown)_{ij}$ is a dummy indicating whether a firm drew funds from a credit line in March 2020, $X_{ij}$ is a set of controls (including the logarithm of total assets in 2019Q4 and liquidity stress in 2020Q1 as defined in equation (1)), and $\alpha_j$ represents industry fixed effects. It also includes a dummy for industries that were relatively exposed to the COVID-19 shutdown, a dummy for industries that were relatively unexposed to the COVID-19 shutdown, and their interactions with drawdown volume and the controls (see Section 4 for a more detailed description of the industry groups). T-statistics computed using heteroskedasticity-robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Column (1) shows the results when the dependent variable is the difference from 2019Q4 to 2020Q1 of liquid assets to total assets minus the average difference from Q4 to Q1 from 2010 to 2019 to mitigate seasonality. Column (2) shows the results when estimating via median regression. Column (3) shows the results when using the growth of liquid assets rather than the difference in liquid assets to total assets. Column (4) shows the result when using the marginal expected shortfall (MES) as defined in Acharya et al. (2017) as a measure of tail-risk instead of liquidity stress.

| | (1)<br>Seasonality | (2)<br>Median | (3)<br>Growth | (4)<br>MES |
|---|---|---|---|---|
| Log(drawdown) | 3.831*** | 4.010*** | 115.565*** | 3.461*** |
| | (7.72) | (10.98) | (3.48) | (7.01) |
| Log(drawdown) x Exposed | 0.775 | 1.016* | 13.988 | 1.076 |
| | (1.00) | (1.87) | (0.26) | (1.39) |
| Log(drawdown) x Unexposed | -0.078 | 0.227 | -66.187 | 0.125 |
| | (-0.09) | (0.44) | (-1.12) | (0.17) |
| Observations | 361 | 361 | 361 | 335 |
| $R^2$ | 0.449 | | 0.301 | 0.408 |
| Controls | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |

Table 10: Effect of credit line drawdowns on capital expenditure to total assets (extensive margin). This table presents results from estimating variations of the equation $\Delta Y_{ij} = \beta D_{ij} + \gamma X_{ij} + \alpha_j + \epsilon_{ij}$, where $\Delta Y_{ij}$ is the difference from 2019Q4 to 2020Q1 of capital expenditure to total assets for firm $i$ in 2-digit NAICS industry $j$, $D_{ij}$ is a dummy indicating whether a firm drew funds from a credit line in March 2020, $X_{ij}$ is a set of controls (including the logarithm of total assets in 2019Q4 and liquidity stress in 2020Q1 as defined in equation (1)), and $\alpha_j$ represents industry fixed effects. T-statistics computed using heteroskedasticity-robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Column (1) shows the results from the baseline specification. Column (2) shows the results when $D_{ij}$ is instrumented by the logarithm of undrawn credit commitments as of 2019Q4. Column (3) shows the average treatment effect using a 1-nearest neighbor matching estimator with an exact match on industry and matching via Mahalanobis distance on the characteristics in $X_{ij}$. Column (4) shows the result when including a dummy for industries that were relatively exposed to the COVID-19 shutdown, a dummy for industries that were relatively unexposed to the COVID-19 shutdown, and their interactions with the drawdown dummy and the controls (see Section 4 for a more detailed description of the industry groups).

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Baseline | IV | Matching | Interactions |
| D | -0.028 | -0.550 | 0.112*** | -0.059 |
| | (-0.98) | (-1.03) | (2.48) | (-1.35) |
| D x Exposed | | | | -0.009 |
| | | | | (-0.12) |
| D x Unexposed | | | | 0.114* |
| | | | | (1.80) |
| Observations | 5386 | 3123 | 5293 | 5386 |
| $R^2$ | 0.019 | -0.029 | | 0.021 |
| Controls | Yes | Yes | | Yes |
| Industry FE | Yes | Yes | | Yes |

Table 11: Effect of credit line drawdowns on capital expenditure to total assets (extensive margin): extensions. This table presents results from estimating variations of the equation $\Delta Y_{ij} = \beta D_{ij} + \gamma X_{ij} + \alpha_j + \epsilon_{ij}$, where $\Delta Y_{ij}$ is the difference from 2019Q4 to 2020Q1 of capital expenditure to total assets for firm $i$ in 2-digit NAICS industry $j$, $D_{ij}$ is a dummy indicating whether a firm drew funds from a credit line in March 2020, $X_{ij}$ is a set of controls (including the logarithm of total assets in 2019Q4 and liquidity stress in 2020Q1 as defined in equation (1)), and $\alpha_j$ represents industry fixed effects. It also includes a dummy for industries that were relatively exposed to the COVID-19 shutdown, a dummy for industries that were relatively unexposed to the COVID-19 shutdown, and their interactions with the drawdown dummy and the controls (see Section 4 for a more detailed description of the industry groups). T-statistics computed using heteroskedasticity-robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Column (1) shows the results when the dependent variable is the difference from 2019Q4 to 2020Q1 of capital expenditure to total assets minus the average difference from Q4 to Q1 from 2010 to 2019 to mitigate seasonality. Column (2) shows the results when estimating via median regression. Column (3) shows the results when using the growth of capital expenditure rather than the difference in capital expenditure to total assets. Column (4) shows the result when using the marginal expected shortfall (MES) as defined in Acharya et al. (2017) as a measure of tail-risk instead of liquidity stress.

| | (1)<br>Seasonality | (2)<br>Median | (3)<br>Growth | (4)<br>MES |
|---|---|---|---|---|
| D | 0.024 | -0.055*** | -2.995 | -0.048 |
| | (0.39) | (-3.94) | (-0.52) | (-1.03) |
| D x Exposed | -0.237** | -0.030 | -5.936 | 0.039 |
| | (-2.15) | (-0.74) | (-0.79) | (0.46) |
| D x Unexposed | 0.026 | 0.001 | 8.986 | 0.078 |
| | (0.29) | (0.03) | (1.02) | (1.14) |
| Observations | 5269 | 5386 | 4619 | 3496 |
| $R^2$ | 0.013 | | 0.022 | 0.036 |
| Controls | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |

Table 12: Effect of credit line drawdowns on capital expenditure to total assets (intensive margin). This table presents results from estimating variations of the equation $\Delta Y_{ij} = \beta Log(drawdown)_{ij} + \gamma X_{ij} + \alpha_j + \epsilon_{ij}$, where $\Delta Y_{ij}$ is the difference from 2019Q4 to 2020Q1 of capital expenditure to total assets for firm $i$ in 2-digit NAICS industry $j$, $Log(drawdown)_{ij}$ is the logarithm of total credit line drawdowns in March 2020, $X_{ij}$ is a set of controls (including the logarithm of total assets in 2019Q4 and liquidity stress in 2020Q1 as defined in equation (1)), and $\alpha_j$ represents industry fixed effects. T-statistics computed using heteroskedasticity-robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Column (1) shows the results from the baseline specification. Column (2) shows the results when $Log(drawdown)_{ij}$ is instrumented by the logarithm of undrawn credit commitments as of 2019Q4. Column (3) shows the results when using the ratio of total drawdowns to the credit limit instead of the logarithm of total drawdowns. Column (4) shows the result when including a dummy for industries that were relatively exposed to the COVID-19 shutdown, a dummy for industries that were relatively unexposed to the COVID-19 shutdown, and their interactions with drawdown volume and the controls (see Section 4 for a more detailed description of the industry groups).

| | (1)<br>Baseline | (2)<br>IV | (3)<br>Limit | (4)<br>Interactions |
|---|---|---|---|---|
| Log(drawdown) | -0.037 | -0.121** | | 0.036 |
| | (-1.14) | (-2.04) | | (0.69) |
| Drawdown/limit | | | -0.052 | |
| | | | (-0.69) | |
| Log(drawdown) x Exposed | | | | -0.105 |
| | | | | (-1.31) |
| Log(drawdown) x Unexposed | | | | -0.183** |
| | | | | (-2.28) |
| Observations | 361 | 354 | 354 | 361 |
| $R^2$ | 0.130 | 0.110 | 0.121 | 0.156 |
| Controls | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |

Table 13: Effect of credit line drawdowns on capital expenditure to total assets (intensive margin): extensions. This table presents results from estimating variations of the equation $\Delta Y_{ij} = \beta Log(drawdown)_{ij} + \gamma X_{ij} + \alpha_j + \epsilon_{ij}$, where $\Delta Y_{ij}$ is the difference from 2019Q4 to 2020Q1 of capital expenditure to total assets for firm $i$ in 2-digit NAICS industry $j$, $Log(drawdown)_{ij}$ is a dummy indicating whether a firm drew funds from a credit line in March 2020, $X_{ij}$ is a set of controls (including the logarithm of total assets in 2019Q4 and liquidity stress in 2020Q1 as defined in equation (1)), and $\alpha_j$ represents industry fixed effects. It also includes a dummy for industries that were relatively exposed to the COVID-19 shutdown, a dummy for industries that were relatively unexposed to the COVID-19 shutdown, and their interactions with drawdown volume and the controls (see Section 4 for a more detailed description of the industry groups). T-statistics computed using heteroskedasticity-robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Column (1) shows the results when the dependent variable is the difference from 2019Q4 to 2020Q1 of capital expenditure to total assets minus the average difference from Q4 to Q1 from 2010 to 2019 to mitigate seasonality. Column (2) shows the results when estimating via median regression. Column (3) shows the results when using the growth of capital expenditure rather than the difference in capital expenditure to total assets. Column (4) shows the result when using the marginal expected shortfall (MES) as defined in Acharya et al. (2017) as a measure of tail-risk instead of liquidity stress.

| | (1)<br>Seasonality | (2)<br>Median | (3)<br>Growth | (4)<br>MES |
|---|---|---|---|---|
| Log(drawdown) | 0.058 | -0.048** | 115.565*** | 0.033 |
| | (0.97) | (-1.98) | (3.48) | (0.68) |
| Log(drawdown) x Exposed | -0.173 | 0.084 | 13.988 | -0.111 |
| | (-1.64) | (1.15) | (0.26) | (-1.40) |
| Log(drawdown) x Unexposed | -0.096 | 0.007 | -66.187 | -0.209*** |
| | (-1.14) | (0.10) | (-1.12) | (-2.60) |
| Observations | 356 | 361 | 361 | 335 |
| $R^2$ | 0.158 | | 0.301 | 0.156 |
| Controls | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |