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The COVID-19 Impact on Corporate Leverage and Financial Fragility

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Abstract

We study the impact of the COVID-19 recession on capital structure of publicly listed U.S. firms. Our estimates suggest leverage (Net Debt/Asset) decreased by 5.3 percentage points from the pre-shock mean of 19.6 percent, while debt maturity increased moderately. This de-leveraging effect is stronger for firms exposed to significant rollover risk, while firms whose businesses were most vulnerable to social distancing did not reduce leverage. We rationalize our evidence through a structural model of firm value that shows lower expected growth rate and higher volatility of cash flows following COVID-19 reduced optimal levels of corporate leverage. Model-implied optimal leverage indicates firms which did not de-lever became over-leveraged. We find default probability deteriorates most in large, over-leveraged firms and those that were stressed pre-COVID. Additional stress tests predict value of these firms will be less than one standard deviation away from default if cash flows decline by 20 percent.

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1 Introduction

The COVID-19 pandemic and associated efforts to combat its spread, caused a rapid and unprecedented slowdown in the global economy, including a record drop in U.S. GDP during 2020:Q2 (Hotchkiss et al., 2020).[1] Cash flows were heavily impaired in many industries, with adverse implications for corporate solvency. Recent research on the corporate sector shows that flow of credit to non-financials remained robust through drawdowns on existing credit lines (e.g. Deghi et al. (2021); Acharya and Steffen (2020)) and policy support from the Federal Reserve (Gilchrist et al. (2020); Haque and Varghese (2021)), allowing most companies to remain operational. While these facilities may have averted or delayed bankruptcies, in the face of structural changes viability assessments remain fraught with difficulties. Therefore, the full impact of the recession on corporate financial health requires a comprehensive examination of firm leverage, optimal capital structure and default risk. We fill this gap in the literature.

Specifically, we ask three questions. First, how did firms' capital structures (leverage and debt maturity) evolve after the onset of the COVID-19 shock? Did all firms adjust their capital structures or only those firms (i) highly exposed to financial risks pre-COVID, and (ii) whose businesses were at greatest risk from social distancing? Finally, given firms' capital structure choices in response to the pandemic recession, how were default probabilities affected? Our paper examines the interconnected relationships between the choice of leverage, growth expectation, firm risk and default probability in the context of an unprecedented public health crisis. To the best of our knowledge this is the first paper to (i) document how heterogeneity in firm risk influenced capital structure adjustments following the onset of COVID, (ii) structurally estimate optimal leverage, allowing us to identify if firms became "over-leveraged" during the recession and (iii) estimate probability of default.[2]

[1] U.S. GDP dropped by 9.5 percent quarter-over-quarter.

[2] Following much of the literature, we identify a firm as "Over-Leveraged" if its actual leverage is higher than model-implied optimal leverage. See for instance, Korteweg (2010). It is also worth noting most

In this paper, our focus is on *net debt* as a share of total assets for *publicly listed U.S. companies* only. Net debt, which is debt net of cash, allows us to better capture cash flow shortfalls or if companies are over-leveraged. We recognize, however, there are alternate measures of leverage. For example, defining leverage as debt to income, IMF (2021) document an increase in corporate leverage in both advanced and emerging economies with a sample that aggregates information of both publicly active and *private* firms. We focus on publicly listed firms because our structural model of a firm's value-maximising level of leverage, described subsequently, is more applicable for firms that have easy access to secondary equity markets. Thus, our analysis is intended to complement existing studies by offering an alternate way of examining leverage for publicly listed firms.

Our benchmark regressions show that firm leverage (Net Debt/Asset) declined by 5.3 percentage points due to Covid-related lockdowns.[3] This is substantial considering pre-crisis mean leverage in our sample is 19.6 percent. Moreover, we find debt maturity increased marginally. Our regression specification controls for firm size, asset tangibility, growth prospects, profitability and time-invariant firm-level factors that can affect leverage. Both the de-leveraging effect and rise in maturity are stronger among firms that were already exposed to high financial risks pre-COVID, measured through the variation in firms' need to rollover the current portion of long-term debt.[4] Strikingly, businesses most severely affected by social distancing did not reduce leverage any more than those less vulnerable, although they shortened their debt maturity structure. For ease of exposition,

existing studies on optimal capital structure rely on the concept of target debt using regressions rather than firm value maximization (see Flannery and Rangan, 2006; Cook and Tang, 2010; Oztekin and Flannery). However, as Haque (2021) and He and Yang (2021) argue, firm value maximization is central to capturing the trade-off theory of debt (Kraus and Litzenberge, 1973).

[3]Note, by definition, we are measuring the share of firm value financed with debt adjusted for cash, while widespread reports and other studies have documented that the *supply* of overall debt financing has been unaffected because of policy support. Additionally our sample focuses on publicly listed firms in the US only. Thus our results are not necessarily contradictory to studies suggesting overall corporate leverage has increased.

[4]First introduced by Almeida et al. (2009), the current portion of long-term debt provides an exogenous measure of rollover risk since the decision to issue long-term debt is typically made years in advance. In contrast, other measures of rollover risk such as short-term debt suffer from standard endogeneity problems. We elaborate more on this measure subsequently.

we label this risk as "business risk." Our benchmark result is robust to a battery of robustness checks including alternate measures of leverage (Gross Debt/Asset) and variation in liquidity.

We find that a standard model of optimal capital structure estimated separately in the pre-COVID and post-COVID samples is consistent with our benchmark results. The model predicts a decline in the optimal level of corporate leverage driven by a deterioration in expected growth rate of cash flows and spike in asset risk. However, comparing optimal leverage post-COVID with the data shows firms exposed to business risk have become over-leveraged.

Our structural estimates of distance-to-default (DTD) reveals firms that became over-leveraged, i.e. those exposed to high business risk, experienced the sharpest deterioration in credit risk.[5] These effects are particularly concentrated among firms in the bottom quartile (sorted on distance-to-default) as well as the largest firms. Simulated stress tests confirm that these over-leveraged firms are most likely to default if growth slows down or if they experience further spikes in risk. Our results, which are novel in the growing COVID-19 literature, raises implications for financial stability and build up of systemic risk.

We begin our analysis by building a large sample of firm-quarter level data of U.S. publicly active firms from North America Compustat.[6] Consistent with the large body of literature on U.S. public firms that document debt and equity have an approximate 30:70 split, we show that mean Gross Debt/Asset is 33.43 percent in our pre-COVID sample.[7] Next, we trace out the rising pattern in leverage, measured by Net Debt/Asset, since the Global Financial Crisis. Median leverage ratio rose from 10 percent in early 2007 to 21 percent in 2019:Q4, followed by a decline beginning 2020:Q1. This decline is confirmed in

[5]Distance-to-default can be interpreted as the number of standard deviations between current asset value and the insolvency point.

[6]Reliance on firm-level data is important because aggregate country-level data can mask underlying heterogeneity in risk exposure that can drive the overall trends.

[7]See for example Axelson et al. (2013)

a standard pre-post regression controlling for capital structure determinants advocated by Rajan and Zingales (1995).

We introduce two types of plausibly exogenous firm risk. First, we measure financial risk by establishing a causal liquidity channel during the COVID-19 pandemic, by exploiting plausibly exogenous cross-sectional variation in the level of firm exposure to liquidity shocks. More specifically, we utilize heterogeneity in firms' need to rollover current portion of long-term debt during the COVID shock to show that firms with higher refinancing needs contract leverage levels more than similar firms that do not need to rollover long-term debt. As Almeida et al. (2009) argue, the exogeneity of this measure allow us to estimate the causal effect of being exposed to financial risk, emanating from an unanticipated liquidity shock. Second, for business risk, we compute growth in sales in 2020:Q2, and classify firms in the bottom quartile as exposed to business risks from social distancing. For robustness, we repeat this exercise with Return on Assets. The exogeneity in this measure comes from the unanticipated nature of the pandemic.

A set of carefully specified difference-in-differences regressions reveal financial risks played a key role in our benchmark de-leveraging effect. Firms with large share of long-term debt maturing in the post-COVID sample reduced leverage by approximately 4 percentage points more than less-exposed firms. We document these firms also raised their maturity structure consistent with the fact that they had lower share of long-term debt pre-COVID, thus reducing refinancing risk. Our main surprising result is that we fail to document any such de-leveraging among firms most seriously affected by the drop in demand from social distancing, compared to firms less affected by shutdowns. While these findings are novel, they do not shed light on whether firms are now closer or further away from their value-maximizing level of leverage.

Consequently, the second part of the paper centers around computing optimal leverage and default probability using structural models. We employ the structural model of Leland and Toft (1996) (henceforth, the LT model). As summarised in Bartram et al. (2015), the

LT model builds upon the observation made by Black and Scholes (1973) and Merton (1974) that the equity of a firm resembles a call option on the firm's assets. The LT Model generalizes the Merton model, in several ways. Bankruptcy can occur anytime (similar to Black and Cox (1976)). In addition, bankruptcy is endogenously triggered by equity holders to maximize equity value. In short, the Leland and Toft (1996) model embeds both the trade-off theory and agency theory. The model is estimated, separately for the pre-COVID and post-COVID samples, by minimizing the squared deviation of predicted equity volatility from actual volatility. Not surprisingly, our estimates show the level of optimal leverage decreased by 13 percent driven primarily by significant reductions in expected growth and rise in asset return volatility, both of which we estimate directly from the data. While the reduction in optimal leverage is consistent with the de-leveraging effect we document in our benchmark regressions (for all firms and firms exposed to financial risk), our model identifies firms that were most exposed to lockdown risks became over-leveraged following the onset of the pandemic. This is intuitive since they do not de-lever based on the differential impact on their cash flows from lockdowns compared to those less affected.

A natural implication of becoming over-leveraged relates to change in default risk. We estimate default probabilities using a canonical Merton (1974) credit risk model, which is considered the benchmark starting point to evaluate distress risk. We rely on an iterative algorithm introduced by Vassalou and Xing (2004) to estimate unobservable asset drift and volatility, the key challenge in estimating structural credit risk models. We estimate DTD and find significant deterioration in credit risk for firms exposed to business risk, i.e., those that did not de-lever based on business risks and allowed actual debt to exceed optimal leverage. When we restrict our analysis to only large firms, defined as firms with an average size of at least USD 1 billion, we observe the deterioration in credit risk is greater for those that were most impacted by social distancing. Among large firms exposed to business risk, the $25th$ percentile value of DTD is 1.22 which is the lowest in all the sub-samples we investigate. This subset of firms experienced a 50 percent deterioration in distress risk.

We conclude by simulating two stress tests: we impose (i) a 20 percent decline in expected growth rate of cash flows and (ii) a 20 percent rise in cash flow return volatility. Since we impose these restrictions for all firms, in principle, our simulation can be viewed as an aggregate economic shock. We re-estimate the model with each of these stress scenarios and find, among companies exposed to business risk, $25th$ percentile DTD is 0.86. In other words, the asset value of the bottom quartile of these firms is less than one standard deviation away from reaching insolvency.

Related Literature: While our findings exploit the COVID-19 shock as a natural laboratory, our methodology is broadly applicable to any recessionary episode. We contribute to several strands of literature. First, we contribute to the literature on the impact of recessions on capital structure. Demirguc-Kunt et al. (2020) assessed the impact on capital structure following the global financial crisis in 75 countries. They found evidence of deleveraging and maturity reduction, which were particularly significant for non-listed firms, including both SMEs as well as large non-listed companies. Relatedly, our paper belongs to the growing literature on corporate debt in U.S. firms following the onset of the COVID-19 shock. Hotchkiss et al. (2020) show that capital raising was particularly strong among firms most affected by the pandemic, confirming that much of the new issuance reflects demand for capital to replace cash flows lost to the economic disruption from the pandemic. The extension to this observation relates to firms becoming over-leveraged which we identify in this paper. Deghi et al. (2021) find that, among listed firms, entities with weaker liquidity or solvency positions before the onset of COVID-19, as well as smaller firms, suffered relatively more financial stress in some economies in the early stages of the crisis. Acharya and Steffen (2020) document a mad "dash-for-cash" in response to the crisis. To the best of our knowledge, our paper is the first to arrive at a simple firm-level measure of risks due to social distancing which plays a key role in our analysis.

Next, the paper relates to the vast literature on optimal capital structure based on structural models. Merton (1974), Leland (1994) and Leland and Toft (1996) pioneer this literature and we make two contributions: we identify the impact on model-implied optimal leverage following the coronavirus shock and we are able to use our analysis to identify over-leveraged firms. As such our paper applies standard capital structure model in the context of a recession shedding new light on our understanding of the dynamics of optimal leverage as a function of external conditions. Finally, we contribute to the large literature on structural estimation of credit risk. We contribute to this literature by documenting the impact of the COVID-19 shock on default risk and identifying heterogeneity across firms based on the type of risk they are exposed to.

Paper Roadmap: The rest of the paper proceeds as follows. Section 2 discusses the data and the empirical strategy. Section 3 reports the benchmark regressions. Section 4 outlines the theoretical model used to solve for companies' optimal leverage. Section 5 presents quantitative analysis of the model and identifies over-leveraged firms. Section 6 estimates default probability and the impact from stress tests. Finally, section 7 concludes.

2 Data and Methodology

2.1 Data Source and Summary Statistics

Our sample construction begins with publicly-held active firms that have accounting data in the U.S. Compustat Quarterly Database till 2020Q4. To mitigate confounding effects from other local and global shocks we begin our sample from 2018Q1. Following Bartram et al. (2015) we exclude utilities and financial services companies since these firms are regulated and may have different risk-taking incentives. In addition, we apply a variety of screens to our sample. First, we exclude firms whose asset value is negative. Since we seek to understand optimal choice of debt, we also exclude companies that do not hold any debt in any firm-quarter during the sample period. [8] We require that our sample has observations for all variables of interest in the post-COVID period, 2020Q2-2020Q4. Finally, we winsorize our variables at the 1 percent and 99 percent respectively to mitigate effects from outliers. After this filtering process, we are left with approximately 40,000 firm-quarter observations and approximately 3,100 unique firms.

The advantage of detailed balance sheet and income statement data at the firm level is the information it provides on a number of variables, such as sales, profitability, debt and assets. In addition, debt is broken down into short and long-term debt as well as the amount of long-term debt due in the next 12 months. Each unit of observation includes firm name, the year-quarter, accounting data for a number of variables which will be listed in Table 2 and 6-digit North American Industry Classification. The data includes firms from a wide range of industries including mining, basic manufacturing, accommodation, airlines and other types of transportation, retail stores and energy distribution. We use the firm-quarter variables to construct our measures of financial risk and business risk.

Our database allows us to construct several standard firm-level determinants of capital structures that have been well established in the literature (see Rajan and Zingales, 1995; Booth et al. 2001; Demirguc-Kunt and Maksimovic, 1996). These variables aim to capture various factors underpinning firms' capital structures that are related to agency models of conflicts between insiders and outside financiers as in Klaus and Litzenberger (1973), Jensen and Meckling (1976), Bradley et al. (1984), Hart and Moore (1995), Diamond (2004) and asymmetric information models of external financing as in Myers and Majluf (1984). Demirguc-Kunt et al. (2020) suggest that firm size is expected to have a positive impact on firm's capital structures since larger firms tend to have higher survival rates than smaller firms, are generally less risky and more diversified, and hence less likely to default on their debt obligations. Firms with good growth opportunities, are more likely to forego profitable investment opportunities if they are more indebted and rely more on longer

[8] This is 2.5 percent of the sample. In unreported robustness checks, we confirm our results are not affected by exclusion of "debt-free" firms.

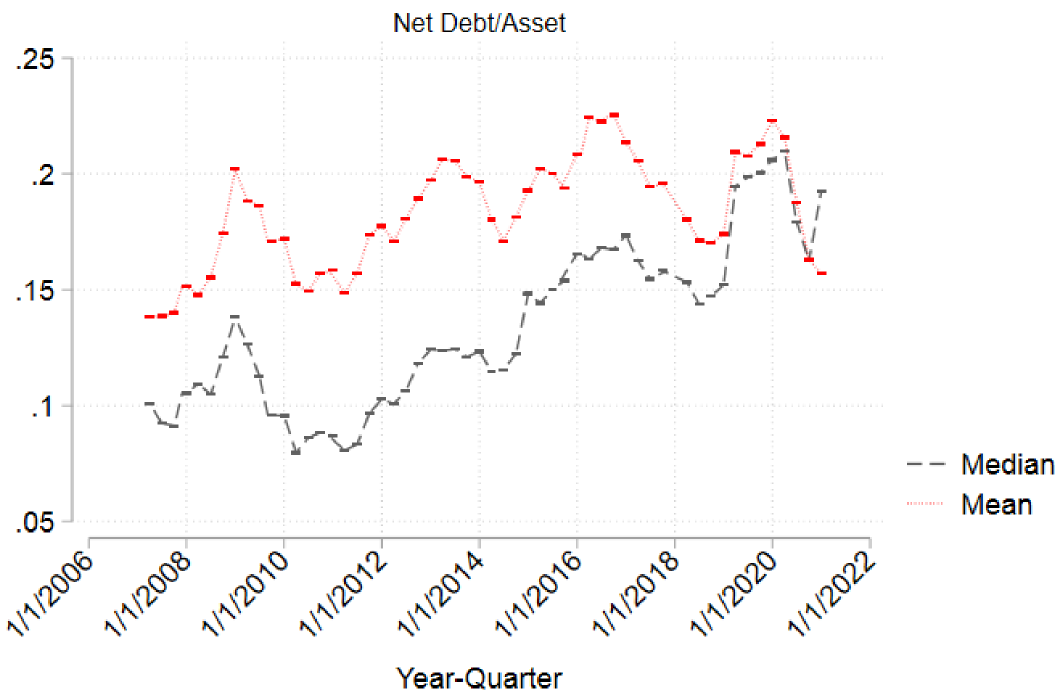
maturity debt. This is due to the fact that the benefits from new investments financed with risky debt accrue largely to existing debt holders rather than shareholders (Myers, 1977). More profitable firms may be able to grow from retained earnings and would require less external finance than other firms, according to the pecking order view (Myers and Majluf, 1984.

Table A2 in the Appendix shows the summary statistics for the selected firm-level variables for the full sample. We report debt-related outcomes in Table 1 (presented subsequently) and focus only on measures related to asset size, sales and growth in this table. As documented widely, the size of public firms in the U.S. is quite large. The median firm has total assets of USD 1.3 billion. We also observe that firm size is highly skewed: the mean firm size of USD 9.48 billion is higher than the $75th$ percentile value of USD 5.53 billion. We note similar patterns in profitability which we proxy with Earnings Before Interest Taxes Depreciation and Amortization (EBITDA) scaled by operating revenue. The median firm has an EBITDA margin of 15.46 percent while the sample also includes some highly unprofitable firms.

2.2 Empirical Fact: Rising Trend in Leverage post-GFC

Figure 1 presents quarterly trend in leverage post-GFC. We observe median Net Debt/Asset has risen from 10 percent in 2007:Q1 to 22 percent in 2020:Q1. The trend in mean leverage is similar, albeit marginally less pronounced, and exhibits a cyclical behavior since the GFC. These patterns are consistent with widespread reports of rising corporate debt. For example, the IMF (2019) cautioned that easy financial conditions have extended the corporate credit cycle, with further financial risk-taking by firms and continued buildup of debt. It is also worth noting that both the mean and median dropped sharply beginning 2020:Q1, co-inciding with the onset of the pandemic. The drop in mean leverage is perhaps more pronounced than previous cycles of de-leveraging.

Figure 1: Rising Trend in Leverage Post-GFC



The chart above reports mean and median leverage ratio defined as Net Debt/Asset. We winsorize our data at the 1 and 99 percent level and aggregate across firms by each year-quarter.

2.3 Empirical Strategy

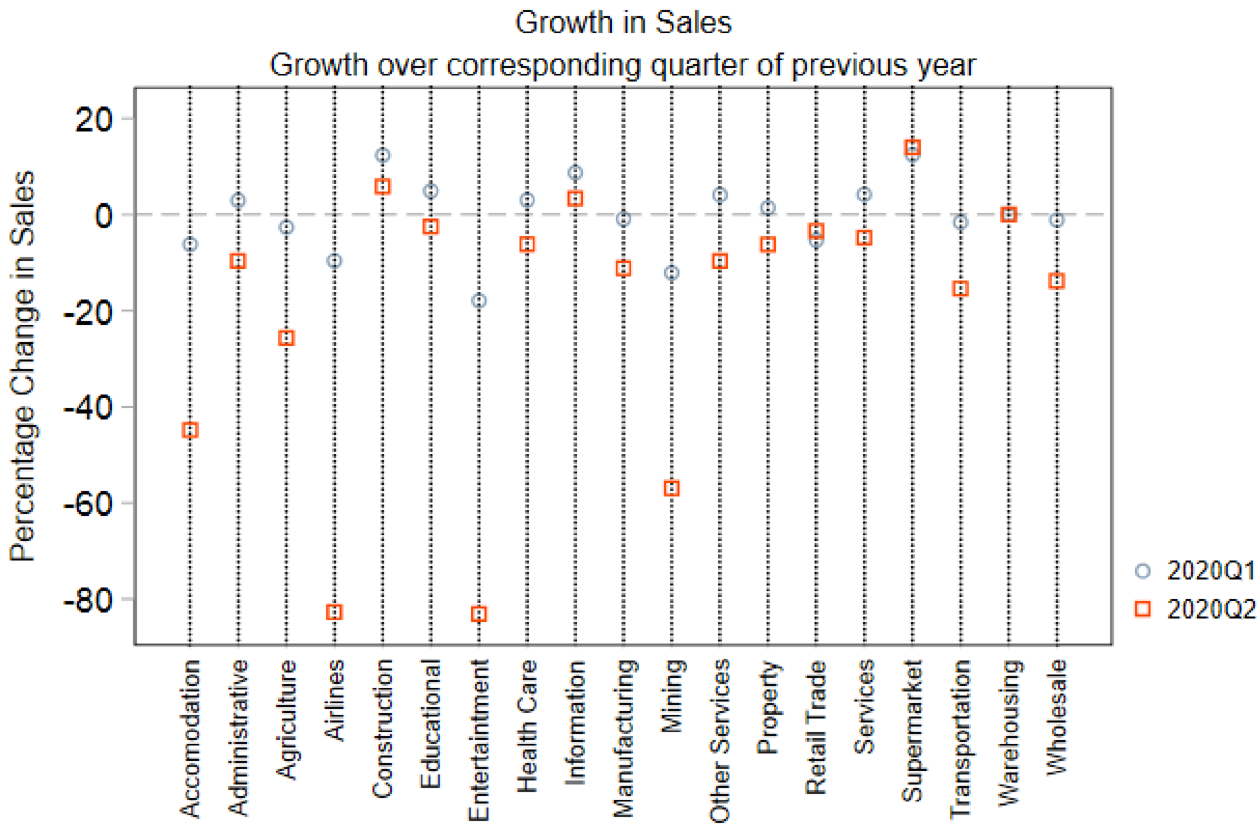
A visual inspection of debt levels suggests that following the onset of the pandemic, debt levels may have come down. To formally examine the significance of the patterns observed in Figure 1, we first test whether leverage levels decreased following the onset of the pandemic. We consider this our baseline analysis. The literature on capital structure typically models leverage as a function of observable firm characteristics. Following Rajan and Zingales (1995) and numerous other studies our baseline leverage determinants include: firm size proxied by log (Assets), Tangibility, Market/Book value of Equity and Profitability proxied by EBIT/Asset. Larger firms and those with more tangible assets may find it easier to borrow and therefore would tend to have higher debt since their expected cost of distress is likely to be lower. Firms with higher profits may have higher retained earnings and hence lower debt. Faster-growing firms, ceteris paribus, may need to raise more external capital in the form of either debt or equity (Flannery et al. (2020)). To avoid using information not yet known at the time of the adjustment decision, all traditional capital structure determinants are lagged by one quarter. We begin with the following benchmark specification:

$$Y_{it} = \beta_1 Post_t + \gamma' \mathbf{X}_{it-1} + \alpha_i + \delta_y + \lambda_{jt} + \epsilon_{it} \tag{1}$$

Observations are at the firm-quarter level. The dependant variables are (i) Net Debt/Asset, (ii) Net Long-term Debt/Asset and, to proxy maturity, Long-term Debt/Total Debt, following Demirguc-Kunt et al. (2020). The vector $X_{i,t-1}$ includes controls outlined above. The variable of interest is $Post_t$ which takes a value of 1 for the three complete quarters in our sample following the onset of the pandemic: 2020:Q2-2020:Q4. A negative coefficient suggests a decline in leverage following the recessionary shock. We include firm α_i, year δ_y, and sector-time λ_{jt} fixed effects.

Defining Exposure to Business Risk and Financial Risk: Next, in order to gain a more granular understanding of how pre-shock exposure to different risks affects capital structure post-COVID, we introduce two types of risk: (i) business-risk from social distancing and (ii) financial risk. First, to identify firms whose businesses were most impacted by social distancing, we define business risk based on a firm's realized sales growth in 2020Q2 relative to 2019Q2. Specifically, we consider firms in the lowest quartile of sales growth in 2020Q2 exposed to "business risk". Since COVID-19 was an exogenous shock in demand, the drop in sales in 2020Q2 should not be confounded by any other effect that systematically affected the same industries. We choose only 2020Q2 instead of aggregating over 2020Q2-Q4 to avoid any anticipation effects confounding our measure. To check the validity of our measure, Figure 2 plots growth in sales in the first two quarters of 2020 aggregated across 2-digit NAICS industries. Since industries such as Airlines were particularly affected, we plot this sector separately. The figure shows that sales growth

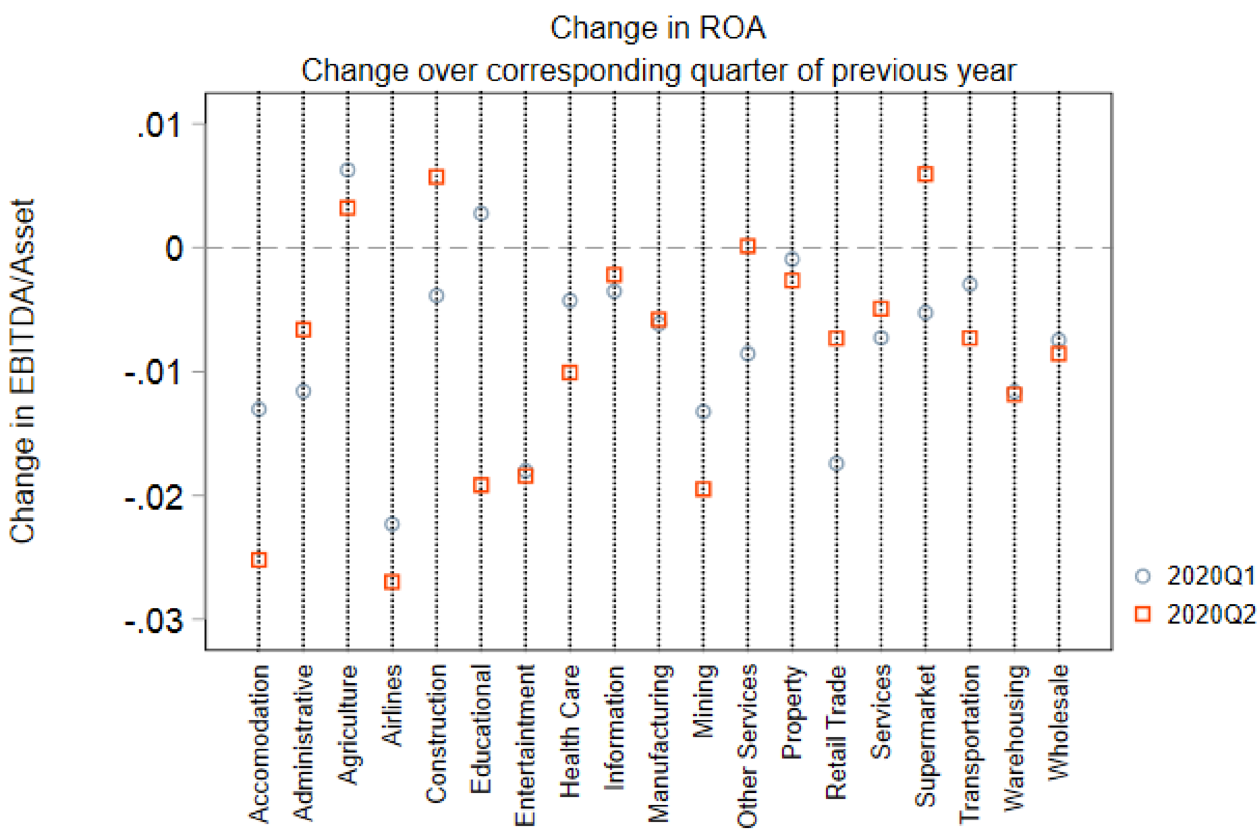
Figure 2: *Exposure to Business Risk based on Sales Growth*



Notes: Firm-level growth in sales, aggregated to the industry-level in 2020:Q1 and 2020:Q2 compared to 2019:Q1 and 2019:Q2 respectively.

is capturing industries that have been widely documented as those worst hit by COVID. For example, we see an 80 percent drop in sales in Airlines and a 10 percent increase in sales for supermarkets, likely reflecting the increase in demand for online shopping. We also see significant drop in sales in the sector classified as "Accommodation", reflecting the drop in demand for hotels, Airbnbs etc which is also consistent with conventional wisdom. As robustness we also utilize the change in Return on Assets: firms with change in ROA in the lowest quartile in 2020Q2 relative to 2019Q2 are now classified as exposed to high Business Risk. Figure 3 documents similar patterns for ROA. We are reassured of the accuracy of our measure since the patterns in sales and ROA are consistent with conventional wisdom regarding the type of firms most severely hurt by social distancing.

Figure 3: Exposure to Business Risk based on ROA Change



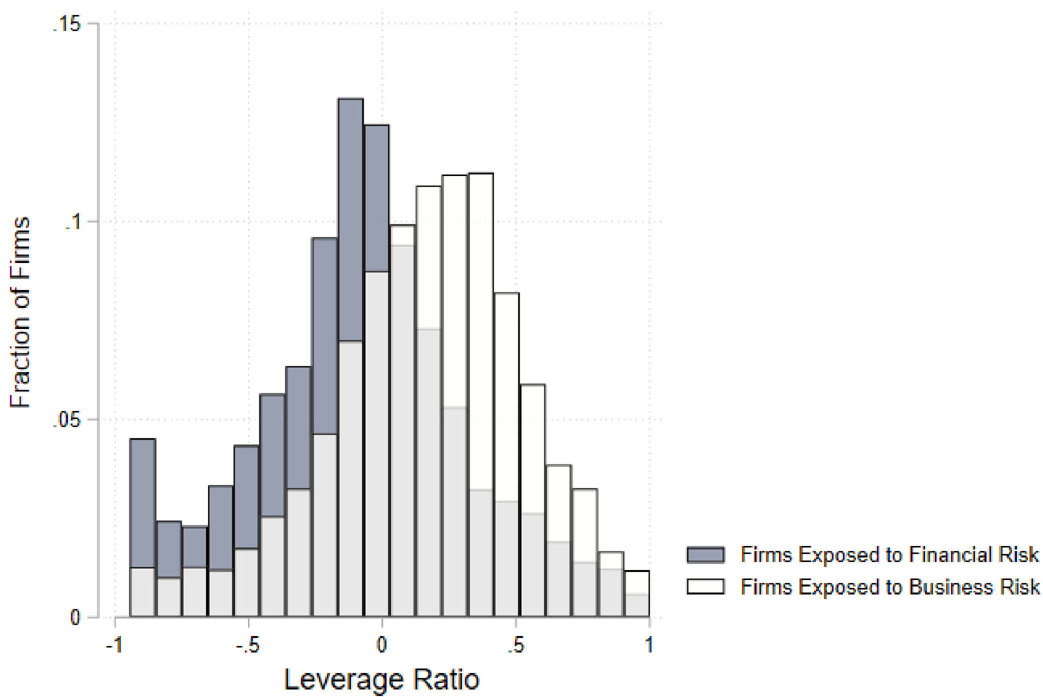
Notes: ROA change for each quarter relative to corresponding quarter of previous year. ROA is defined as EBITDA/Total Assets.

Second, to identify firms who were exposed to significant financial risk pre-COVID, we exploit heterogeneity in firms' need to rollover the current portion of long-term debt. Specifically, we sort firms based on their ratio of long-term debt due in one year over total debt. Firms in the top quartile are classified as exposed to financial risk.[9] Our hypothesis is that firms with large shares of long-term debt due in the next 12 months would need to retract debt levels more than the average firm due to much tighter liquidity conditions. As Gilchrist et al. (2020) note, the onset of the pandemic resulted in liquidity drying up and

[9]The cutoff at the 75th percentile is 20.1 percent meaning companies are exposed to financial risk if their share of the current portion of long-term debt in total debt is 20.1 percent or higher.

credit spreads surging amid a global flight to safety. The main advantage of this measure is that it is largely predetermined at the moment of debt issuance (potentially years in advance) and as such is less affected by recent developments. This is a key advantage in that it allows us to get around the issue of endogeneity that confounds most alternative measures of rollover risk such as share of short-term debt. Thus, this measure allows us to identify a causal liquidity shock on leverage. As already mentioned, we label this type of liquidity risk stemming from refinancing needs broadly as "financial risk."

Figure 4: Distribution of Leverage Ratio by Risk Exposure



Notes: The chart above plots leverage ratio (Net Debt/Asset) for companies exposed to financial risk and business risk for the overall sample period. Each type of risk is defined in Table A1 in the Appendix. We restrict the plot to companies with leverage ratios between -1 to +1 to reduce loss in visual clarity due to outliers.

Armed with these two measures, we estimate the following difference-in-differences (DiD) specification where $Exposed_i$ will alternatively take the value of 1 if a firm is exposed to these risks.

$$Y_{it} = \beta_1 Post_t + \beta_2 Post_t \times Exposed_i + \gamma' \mathbf{X}_{it-1} + \alpha_i + \delta_y + \lambda_{jt} + \epsilon_{it} \tag{2}$$

In Eq. (2) the coefficient of interest is β_2, the DiD estimate of the causal impact of exposure to business or financial risk on capital structure post-covid.

3 Benchmark Results

3.1 Impact of COVID-19 on Capital Structure

We begin by first tabulating sample means of leverage, gross debt and maturity for our entire sample, firms exposed to financial risk and those exposed to business risk. We summarize these in Table 1. While gross debt/asset does not reveal any significant de-leveraging, we note our primary variable of interest Net Debt/Asset reveals significant reduction in leverage post-COVID in firms exposed to financial risk. The difference between gross and net debt ratio is particularly pronounced for these subset of firms indicating they tend to hold large amount of cash. We also note the simple raw mean does not show any de-leveraging in firms exposed to business risk from social distancing. In fact, the Gross Debt/Asset measure suggests these firms increased their debt levels post-COVID. Observe that firms exposed to business risk, according to our definition, comprise a non-trivial 10.5 percent of total assets in U.S. publicly listed firms, as shown in Panel C. It is worth mentioning our measure of business risk is conceptually similar, though not identical, to Boyerchenko et al. (2020) who also measure firm-level stress due to COVID-19 using Compustat data. Figure 4 plots the cross-section in leverage by each firm type showing firms with rollover risk had lower leverage.

To formally examine the significance of these patterns observed in Table 1, we begin with our benchmark regression evaluating the systematic impact on debt due to the COVID-19 shock. Columns (1) to (3) of Table 2 summarize our initial results. On average,

Table 1: Capital Structure of U.S. Firms

Panel A: Pre-COVID	Gross Debt/Asset (%)	Net Debt/Asset (%)	Maturity
Full Sample	33.43	19.56	0.74
Firms Exposed to Financial Risk	29.28	2.92	0.52
Firms Exposed to Business Risk	38.65	23.32	0.77
Panel B: Post-COVID Onset			
Full Sample	33.91	16.99	0.77
Firms Exposed to Financial Risk	26.11	-5.79	0.56
Firms Exposed to Business Risk	43.37	23.75	0.75
Panel C: Share of Assets by Risk-type	(% of total assets)		
Firms exposed to Financial Risk	6.09	-	-
Firms exposed to Business Risk	10.48	-	-

Notes: This table reports capital structure before and after the onset of the COVID-19 Recession. All variables are defined in Table A1 in the Appendix. Pre-COVID sample is 2018:Q1-2020:Q1. Post-COVID sample is 2020:Q2-2020Q4. Debt Maturity is the share of long-term debt in total debt following Demirguc-Kunt et al. (2020). In panel C, we report the share of assets held by firms exposed to financial risk and firms exposed to business risk as a percentage of total assets in our full sample. Note in Panel C, we do not distinguish between pre and post-covid sub-samples and only highlight the relative importance of these subset of firms.

we observe a negative effect on leverage ratio. The effects are non-trivial. Our baseline specification suggests leverage ratio decreases by 5.3 percent, controlling for standard determinants of capital structure. This effect is non-trivial considering the pre-shock unconditional mean was 19.56 percent. Column (2) suggests a decline in long-term leverage of 2.6 percent. These results are consistent with Demirguc-Kunt et al. (2020). Turning to our measure of debt maturity, we observe that average maturity of outstanding debt increases after controlling for standard determinants and time-invariant unobservables. This is consistent with Diamond and He (2014) who show that borrowers should aim at lengthening debt maturity during period of financial crisis, because the rollover-costs of short-term debt increase. Demirguc-Kunt et al. (2015) on the other hand document a decline in debt maturity following the global financial crisis. [10] These results indicate the change in risk and growth profiles of companies due to COVID has an effect on both the level and maturity of debt, and is consistent with dynamic trade-off theory models such as Leland and Toft (1996), which is estimated subsequently in Section 5.

We also document that the de-leveraging effect we document in our benchmark results is much higher compared to the last two major recessions in the United States. Specifically, we find only a reduction of 1.5 percent in leverage following the global financial crisis and an insignificant change in leverage following the dotcom bubble. We find a less conclusive pattern when we investigate maturity. These results are reported in Appendix C.

Table 2: The COVID-19 Impact on Capital Structure

	$Leverage$	$Long-term\ Leverage$	$Debt\ Maturity$
$Post$	-0.053***	-0.026***	0.015***
	(0.005)	(0.003)	(0.004)
R^2	0.039	0.039	0.018
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Sector x Quarter FE	Y	Y	Y
Controls	Y	Y	Y
N	38520	41650	39257

This table summarizes results of OLS regressions on amount and maturity of leverage. $Post$ takes value 1 during the first three full-quarters following the onset of the pandemic (2020Q2-2020Q4). The baseline results are presented in Columns (1) to (3). Standard errors are clustered at the firm level.

Despite our rich set of controls, there could be concerns that we are capturing a spurious correlation since conventional wisdom is that debt and leverage has been rising for the past decade supported by easy financing conditions. We highlight one of the important ones in Table 3, and discuss the rest in Section 3.3 on robustness tests. Specifically we conduct a placebo analysis, which probes whether spurious trends rather than COVID-effect might explain the result. To do this we first drop our post-COVID sample. Next,

[10] Their primary sample centers around private firms and SMEs. They find weaker evidence of declines in debt maturity for listed firms that are larger and have easier access to capital market financing.

Table 3: Placebo Tests on Benchmark Specification

	Leverage		*Long − Term Leverage*		*Maturity*	
Post	-0.002	-0.002	0.001	0.004	0.010***	0.004
	(0.005)	(0.005)	(0.003)	(0.003)	(0.004)	(0.004)
R^2	0.044	0.044	0.054	0.054	0.022	0.022
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Sector x Quarter FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
N	28886	28886	31114	31114	28926	28926

This table summarizes results of OLS regressions of Placebo Tests on amount and maturity of leverage. We drop the post-COVID sample and randomly assign $Post = 1$ to different sub-samples in our time series. In the odd columns, $Post = 1$ in 2019:Q3-2020Q1. In the even columns, $Post = 1$ in 2019:Q4-2020Q1. All controls are identical to the benchmark specification. Standard errors are clustered at the firm-level.

we randomly set $Post = 1$ from 2019Q3-2020Q1 and, in another iteration this is set to 2019Q4-2020Q1. We hypothesize that if a spurious trend is driving our result we should see similar declines in leverage in pre-covid sample periods, when there is no systematic effect to induce de-leveraging. Table 3 presents these placebo estimates. We find a small and insignificant estimate for both leverage and long-term leverage. Importantly, we do not pickup a decline in leverage in the pre-COVID sample for randomly assigned values for $Post$. These results strongly indicate that our baseline result documenting a decline in leverage is not a spurious correlation and reflects the change in firm behavior post-COVID. On debt maturity, we note a significant coefficient in one of the randomly selected post-COVID samples, suggesting there may have been some rising trend in maturity before COVID.[11]

Table 4: Difference-in-Differences Regressions on Leverage

	Leverage			*Long − term Debt*		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.055***	-0.046***	-0.049***	-0.029***	-0.021***	-0.024***
	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
Post × *Business Risk*	0.010		0.012	0.010		0.010
	(0.010)		(0.010)	(0.006)		(0.006)
Post × *Financial Risk*		-0.039***	-0.037***		-0.025***	-0.024***
		(0.010)	(0.010)		(0.007)	(0.007)
R^2	0.037	0.042	0.042	0.041	0.040	0.042
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Sector x Quarter FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
N	36268	36538	34838	39379	39486	37773

This table summarizes results of within-firm Difference-in-Differences regressions on leverage ratio. Post takes value 1 during the first three full-quarters following the onset of the pandemic (2020Q2-2020Q4). Business Risk and Financial Risk are indicator variables that equal 1 based on definitions outlined in the text as well as Appendix Table A1. Standard errors are clustered at the firm level.

3.2 Risk-Exposure and Impact of COVID-19 on Capital Structure

Table 4 presents the results of estimating Eq. (2) that captures differential effect of being exposed to business risk and financial risk during the COVID shock. Our hypothesis is that exposure to financial risk will induce firms to de-lever more compared to firms that are not exposed to financial risk. Recall we exploit plausibly exogenous variation in firms' needs to rollover the current portion of long-term debt to measure exposure to financial risk. We also hypothesize firms most severely affected by the pandemic are likely to reduce their leverage ratios faced with greater uncertainty in expected payoffs. We begin by looking at the impact on leverage in columns (1) and (3).

Column (1) suggests firms exposed to the unanticipated business risk from social dis-

[11]Our focus in Table 3 is on ensuring robustness of the primary de-leveraging effect since media reports document increase in debt levels for much of the post-GFC period, while there is less conclusive trend on maturity.

Table 5: Difference-in-Differences Regression on Debt Maturity

Y_{jt} : *Debt Maturity*	(1)	(2)	(3)
Post	0.026***	0.002	0.011**
	(0.004)	(0.004)	(0.005)
Post × *Business Risk*	-0.038***		-0.030***
	(0.007)		(0.007)
Post × *Financial Risk*		0.034***	0.037***
		(0.009)	(0.009)
R-squared	0.020	0.012	0.014
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Sector x Quarter FE	Y	Y	Y
Controls	Y	Y	Y
N	37733	33847	32480

* $p < .10$, ** $p < .05$, *** $p < .01$

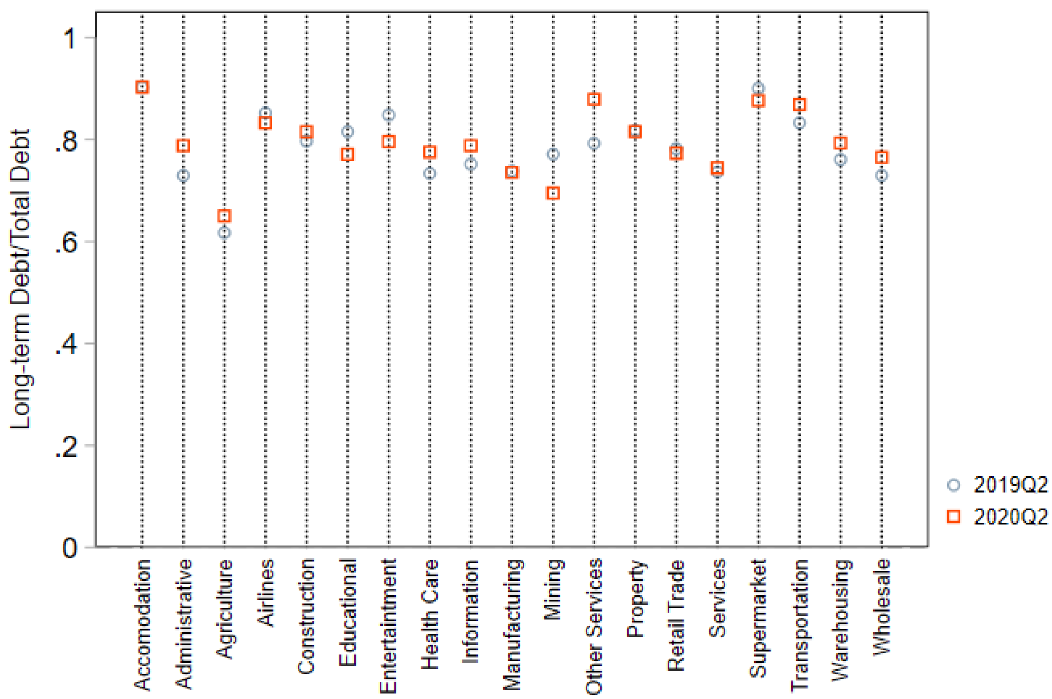
Notes: This table summarizes results of within-firm Difference-in-Differences regressions on debt maturity proxied by the share of long-term debt in total debt. Post takes value 1 during the first three full-quarters following the onset of the pandemic (2020Q2-2020Q4). Business Risk and Financial Risk are indicator variables that equal 1 based on definitions outlined in the text as well as Appendix Table A1. Standard errors are clustered at the firm level.

tancing did not change their debt levels controlling for standard capital structure determinants.[12] This was surprising at least to us since the risk-return profile of these companies are most severely affected. As will be shown in the subsequent section, in the absence of additional de-leveraging relative to less exposed firms, these companies run the risk of becoming over-indebted since their optimal levels of leverage are likely to decline due to the shock.

Next, we turn to column (2) to examine the impact on companies exposed to financial risk. There is a large, economically and statistically significant effect of exposure to financial or rollover risk during the shock from the pandemic. Looking at the coefficients, we observe leverage is lower by 3.9 percent in response to the shock for companies exposed to financial risk. Combined with the -4.6 percent coefficient on *Post*, these findings

[12]Note this difference-in-differences interpretation is only relative to firms less exposed, since we indeed document that *Post* is statistically significant and negative.

Figure 5: Debt Maturity by Sector



Notes: This chart plots debt maturity by sector in 2019Q2 and 2020Q2. Debt Maturity is proxied by the share of long-term debt in total debt.

indicate a total reduction in leverage of approximately 8.5 percent for companies exposed to financial risk.

We then turn to column (3) to jointly test the effect on financial and business risk. We again find there is no differential effect from being exposed to risks from social distancing but the large negative effect from financial risk persists. Taken together our findings suggests financial risks tend to matter more for capital structure adjustment decisions. Next, we repeat the exercise with long-term leverage in columns (4)-(6). The results display similar patterns though the magnitudes are relatively smaller.

We next turn to Table 5 to investigate the impact on debt maturity, proxied by share of long-term debt. Looking at column (1) in Table 5, we note that firms exposed to business risk lower their maturity structure. In contrast, we see in column (2) firms exposed to financial risk raised their maturity structure. We note similar patterns in column (3).

Naturally this raises the question why firms exposed to risks from social distancing display opposing patterns. One explanation offered by Leland and Toft (1996) is that firms with very high levels of risk find it optimal to shorten their maturity structure. This is because, for higher risk, the increase in value from optimally using long term versus short term debt falls, while the agency costs of using long term debt are greater. Figure 7, plots debt maturity in 2019Q2 and 2020Q2 by sector. We note that the sectors affected most severely from social distancing such as Education and Entertainment lower their maturity structure consistent with the theory proposed in the literature. An alternate explanation is that these firms chose to reduce interest costs by lowering their maturity structure.

3.3 Robustness Tests

In this section we explore alternative measures and robustness checks and their impact on capital structure.

Table 6: Alternate Tests on Leverage

	(1)	(2)	(3)	(4)
$Post$	-0.030***	-0.032***	-0.023***	-0.046***
	(0.004)	(0.006)	(0.006)	(0.007)
R-squared	0.052	0.053	0.124	0.037
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Sector x Quarter FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Additional Controls	N	Y	Y	N
N	42822	38475	35436	23868

Notes: The table above reports alternate tests on our baseline pre-post regression of the impact of COVID-19 on leverage. In column (1) the dependant variable is gross debt ratio defined as the sum of long-term and short-term debt scaled by assets. In column (2) we add the log of quarterly closing stock price to further control for valuation effects. In column (3) we add cash ratio defined in Table A1 in the Appendix. Finally, in column (4) we restrict the pre-COVID window to 2019Q1-2020:Q1. Standard errors are clustered at the firm level.

An Alternate Measure of Leverage: Gross Debt/Asset. First, we establish that the effect on leverage from the COVID-shock was not influenced by our measure of debt. We introduce Gross Debt/Total Assets, which is also a measure of leverage used in the capital structure literature, to see if the baseline results were driven merely by variation in cash holdings. Table 6, column (1) examines this issue using our baseline pre-post specification. We find gross debt, scaled by asset, declined by 3 percentage points post-COVID. Thus the impact on leverage is not sensitive to our choice of measure.

Control Variables. We have thus far used standard capital structure determinants widely used in the literature. We now add additional controls to our benchmark specification. Two factors that may lead to confounding effects are changing stock prices and corporate sector liquidity. Note, we already include Market/Book ratio in our benchmark specification. To further confirm our results are not confounded by rising valuations from low central bank interest rates, we include the log of quarterly stock prices in column (2). As can be seen, the results are nearly identical. Next, in column (3) we add cash ratio and find similar results. We note our point estimate is marginally smaller at this stage, but our overall qualitative result holds.

Sample Time-Frame. Since, by construction, our pre-post estimate is based on the history of information between 2018 to 2020:Q1, one concern can be that there can be unobserved time-series variation that we are unable to pick up that could affect our results. We believe this is unlikely considering that we are using both Year and Quarter fixed effects in addition to our time-varying control. Nevertheless, to minimize any remaining concern, we repeat the analysis using 2019:Q1-2020:Q1 as our pre-COVID window. We present these results in column (4). As can be seen, the point estimate is quite similar to our benchmark result.

Alternate measure for Business Risk from Social Distancing. We also repeat our analysis on exposure to business risk from social distancing using Return on Assets as mentioned previously. All of our primary results are unchanged. These regressions are available upon request.

4 A Model of Optimal Capital Structure

In this section we outline a model of optimal capital structure that will be used to explain the patterns documented thus far. We hypothesize that the reduction in leverage is consistent with a decline in the optimal level of leverage following the recessionary shock. Furthermore, since we documented that firms facing business risk did not alter their capital structure relative to those less exposed to business risk, an estimate of optimal leverage will allow us to determine if these companies have become over-leveraged post-COVID. Over-leveraged firms are naturally more vulnerable to financial shocks, debt-overhang and raise systemic economic risks.

Determining a firm's optimal capital structure is challenging. Most existing studies on optimal capital structure focus on the concept of a target debt level using predicted values from a regression rather than maximizing firm value with respect to leverage. However, firm value maximisation is central to the trade-off theory of capital structure. We thus estimate a structural model of optimal capital structure following Leland and Toft (1996).

4.1 Model Outline

The relation between risk stemming from an aggregate shock and capital structure is likely to be affected by the endogenous nature of financial decision-making (eg: firms with stable cash flows can afford higher debt levels). Studies by Kim, Ramaswamy, and Sundaresan (1993), Longstaff and Schwartz (1995), and Nielsen et al. (1993) assume bankruptcy occurs at an exogenously specified asset value, such as debt principal value or when cash flow fails to cover interest payments. Yet neither approach correctly describes bankruptcy as an optimal decision by equity holders to surrender control to bond holders (Leland, (1994)). Much of the recent capital structure literature emphasizes "endogenous default", where agents can decide default timing ex post. It is straight forward to see the appeal of this framework given that our sample covers public firms that can issue additional equity as long as it is optimal for equity-holders, despite a dilution of holdings. Detailed derivation of the model is outlined in Appendix B. We describe the essential elements of the model below:

All agents are risk-neutral. Consider a firm that has productive assets whose unleveraged value A_t, follows standard geometric brownian motion:

$$\frac{dA_t}{A_t} = [\mu_a(A,t) - \delta]dt + \sigma_a dB_t^A \tag{3}$$

where $\mu_a(A,t)$ is the total expected rate of return on asset value; δ is the constant fraction of value paid out to security holders; dB is the increment of the standard brownian motion. The stochastic process of A is assumed to be unaffected with the choice of leverage (eg: coupons after tax benefits). The continuously paid coupons C are tax-deductible at rate τ and the realized cost of financial distress amount to a fraction α of firm value. In this setting the value of the firm is shown below:

$$\begin{gathered} v(A) = A + TB(A) - BC(A) = \\ A + \frac{\tau C}{r}[1 - (\frac{A}{A_B})^{-x}] - \alpha A_B(\frac{A}{A_B})^{-x} \end{gathered} \tag{4}$$

Shareholders are residual claimants to the value of the firm and their payoffs are expressed by:

$$E(A;A_B;T) = v(A;A_B) - D(A;A_B;T) \tag{5}$$

where the value of debt is given by:

$$\begin{aligned} d(A;A_B;t) = \int_0^t e^{-rs}c(t)[1 - F(s;A;A_B)]ds + e^{-rt}\rho(t)[1 - F(t;A;A_B)] \\ + \int_0^t e^{-rs}p(t)A_B[1 - F(s;A;A_B)]ds \end{aligned} \tag{6}$$

The default A_B is chosen endogenously ex post to maximize the value of equity at

$A = A_B$, given the limited liability of equity and the debt structure. The public company chooses debt with face value P and default-triggering asset level to solve the following optimization problem:

$$\max_{P, A_B} v(A, A_B, P, T)\Big|_{A=A_0} \tag{7}$$

subject to the endogenous bankruptcy trigger and the return process of the fundamental value of the underlying asset.

4.2 Estimation Strategy

Estimation follows two steps. Parameters that do not require the model structure such as risk-free rate or tax rate are calibrated outside of the model or borrowed from the literature. We use the 20-year constant maturity U.S. Treasury yield (compiled by the Federal Reserve Board) as a proxy for the risk-free rate, r. For the corporate income tax rate, τ , we use 30 percent. Following Goldstein et al. (2001), we assume a value of 0.05 for α, the fraction of firm value lost in bankruptcy[13]. Second, we estimate key parameters using maximum likelihood directly from our firm-level data. We normalize our initial sample values to 100, which simplifies numerical estimation and inference.

Following Bartram et al. (2015) we estimate the model by minimizing the squared deviation of predicted equity volatility (σ_e) from actual volatility. We define equity volatility as $\sigma_e = l(\sigma_a) \times \sigma_a$, where $l(\sigma_a)$ transforms asset volatility to equity volatility.[14]. Equity and asset volatility are defined as the standard deviation of equity and asset returns

[13]We choose not to use the LT (1996) calibrated value for bankruptcy cost because it has been criticized in the literature as much higher than what is observed in the data.

[14]$l(\sigma_a)$ is also defined similar to Bartram et al. (2015). $l(\sigma_a) = [1 + D(A, A_b, \mathrm{T})/E(A, A_b, \mathrm{T})]^*(k(\sigma_a))$. This estimation procedure is consistent with the original LT model where asset risk value was chosen to achieve the equity volatility that is observed in the data.

respectively. We model firm asset volatility as a function of firm-level characteristics:

$$\sigma_a = exp(\beta_0 + \sum^n \beta_i X_i) \tag{8}$$

where X_i is a set of covariates including firm size, tangibility, profitability, liquidity and profit volatility; β_i are the estimated coefficients using maximum likelihood. The exponential function ensures positive values for σ_a. Next, debt maturity is parameterized between 1 and 10 years using the following expression:

$$T = 1 + 9\frac{Long\ term\ Debt}{Total\ Debt} \tag{9}$$

The face value of all outstanding debt is (P) is calculated as net book leverage. Similar to previous studies we proxy the drift rate with long-term risk-free rate under risk-neutral valuation and the payout rate δ at 0.5 percent. These observable variables allow for the calculation of all other variables in our optimization problem described in detail in Section B of the Appendix. As summarized in previous studies, this estimation procedure calibrates the model in a way that allows for the endogenous nature of the bankruptcy decision.

All calibrated and estimated parameter values are summarized in Table 7. We estimate the model separately for the pre and post-covid sample for three groups of firms: (i) all firms, (ii) firms exposed to financial risk and (iii) firms exposed to business risk from social distancing. Note that we retain the same values for tax rates, bankruptcy costs and dividend payouts rates for both periods. Since our focus is not on the determinants of firm risk we do not report individual coefficient estimates from Eq. (8) and instead focus on predicted values of σ_a.[15] It is worth noting that σ_a is much higher for firms exposed to high financial risk and this level rises further post-COVID. On the other hand, estimated risk for firms with business risk is closer to the overall sample means. Finally

[15]To compute predicted asset risk, we use only economic variables that are statistically significant. These estimates are available upon request.

we note that our estimate of σ_a of 0.31 for the full sample lies within the range of values used in previous studies. For example, Leland and Toft (1996) sets asset risk at 0.2, while Ju et al. (2005) sets asset risk at 0.38 (or 38 percent). Leland (1998) uses 0.2 and 0.3 to denote two different risk levels. We are thus reassured of our estimated parameter since the capital structure literature has established that volatility of the asset return process greatly influences estimates of optimal leverage.

Table 7: Model Parameter Values

	Pre-COVID	Post-COVID	Source
Panel A: Calibrated Values			
Risk-free Rate (%)	2.5	1.3	20-year Risk-free Rate
Tax Rate (%)	30	30	Standard
Payout Rate (%)	0.5	0.5	Standard
Bankruptcy Cost	0.05	0.05	Goldstein et al. (2001)
Panel B: Estimated Values	*Mean (Std. Dev)*	*Mean (Std. Dev)*	
σ_a, full sample	0.31 (2.39)	0.35 (2.31)	Estimated
σ_a, firms exposed to FR	0.42 (3.06)	0.52 (9.1)	Estimated
σ_a, firms exposed to BR	0.32 (1.3)	0.29 (0.67)	Estimated
Maturity, full sample	7.68 (2.88)	7.9 (2.5)	Estimated
Maturity, firms exposed to FR	5.66 (2.9)	6.0 (2.55)	Estimated
Maturity, firms exposed to BR	7.92 (2.7)	7.76 (2.6)	Estimated

Notes: This table reports calibrated and estimated parameters in Panels A and B respectively to compute optimal leverage following Leland and Toft (1996) model. σ_a is defined as the standard deviation of asset return and is estimated as outlined in the text. Panel B reports predicted values and standard deviations for σ and debt maturity. FR denotes Financial Risk, BR denote Business Risk. 20-year risk-free rate is retrieved from the Federal Reserve Bank of St. Louis.

5 Quantitative Analysis

5.1 Model-Implied Optimal Leverage

We summarize the preliminary findings of the model in Table 8 below. We observe a striking reduction in the level of optimal leverage following the onset of the COVID recession, consistent with our benchmark regressions. The model predicts a decline in the value-maximizing level of leverage of approximately 13 percent, from 31.50 to 18.73 percent. Both the rise in estimated volatility (standard deviation of asset return) and sharp decline in expected growth rate (proxied by the long-term risk-free rate) drove this decline. However, we also note that greater impact was attributable to the decline in expected growth rate, which is consistent with the idea that social distancing adversely impacted aggregate demand.

Table 8: Model Results: Optimal Leverage (%)

	Pre-Covid	Post-Covid	Over-Leveraged
Full Sample	31.50	18.73	No
Firms Exposed to Financial Risk	17.60	8.30	No
Firms Exposed to Business Risk	31.10	19.16	Yes

Notes: The table above reports estimated optimal leverage based on the structural Leland and Toft (1996) model under risk-neutral valuation. Optimal Leverage is defined as the payoff received by debt-holders (value of debt) over the value of the levered firm. A firm is classified as Over-Leveraged if its actual minus model-implied leverage is greater than 0, where actual leverage ratios are reported in Table 1.

Recall from Table 1 that leverage ratio pre-COVID was 19.56 percent followed by a decline to around 16.99 percent post-COVID for the full sample. Thus, the model predicts that firms, on average, were under-leveraged prior to the COVID-shock and the decline in optimal leverage greatly reduced this difference between actual debt and model-implied optimal debt. We note that model does a particularly good job of matching the data post-covid.

We have thus far established that the results from the benchmark regressions in section 3 are consistent with the view that firms experienced a decline in their optimal leverage ratios. We next evaluate patterns for firms exposed to business risk from social distancing, and those exposed to financial risk from rollover risk. We find companies exposed to financial risk also experienced a significant reduction in optimal leverage. In fact, the model predicts optimal leverage ratio declines by around 50 percent for this type of firms.

This is primarily driven by the large increase in estimated firm risk reported in Table 7, in addition to the decline in growth expectations. Companies exposed to financial risk tend to exhibit greater asset return volatility, leading to lower optimized leverage. Note that this finding is also consistent with the patterns documented in the benchmark regressions where the decline in leverage was greater for firms exposed to rollover risk.

Next, we turn to firms whose businesses were most severely impacted by COVID-19. The difference-in-differences regressions indicated these companies did not significantly adjust debt levels relative to non-exposed peers, and only shortened their maturity structure. In fact, raw means based on Gross Debt suggest these firms raised their debt level post-COVID as shown in Table 1. Not surprisingly though, the model however documents a large decline in optimal leverage for these companies as well. The decline is largely comparable to that for the entire sample with optimal leverage ratio of around 18.73 percent post-COVID. Regardless of the accounting measure of debt we use, it is straight-forward to see these companies have become over-leveraged following the onset of the COVID shock. We classify a firm as over-leveraged if their actual leverage exceeds model-implied optimal leverage. This finding has natural implications for corporate fragility and financial stability since over-leveraged firms are more vulnerable to future shocks and contribute to systemic risk in an economy. We look at this in more detail in the following section.

6 Structural Estimation of Default Probability

6.1 Methodology

In this section we outline the procedure to estimate Distance-To-Default (DTD) and probability of default. The structural approach to estimating default revolves around the intuition developed by Merton (1974), which is that a firm's securities can be priced as contingent claims on the value process of the firm. Merton (1977) points out the applicability of the contingent claims approach to pricing deposit insurance in the banking context.

The approach has been applied by Ronn and Verma (1986) and Duan (1994). Using the estimation procedure in Vassalou and Xing (2004) and Bharath and Shumway (2008), we use equity prices and balance sheet data from pre-COVID and post-COVID onset periods to infer the implied changes in default probabilities for companies[16].

Following Vassalou and Xing (2004) and Bharath and Shumway (2008), we use an iterative algorithm that requires making an initial guess of drift and volatility. Using the Black and Scholes (1973) option pricing formula, equity value can be calculated according to:

$$E = N(d_1)A + De^{-rT}N(d_2) \tag{10}$$

where $d_1 = \frac{\frac{A}{D}+(r+0.5\sigma_A^2 T)}{\sigma_A\sqrt{T}}$ and $d_2 = d_1 - \sigma_A\sqrt{T}$. As is well-known in the credit risk literature, D is the firm's debt, all of which is assumed to mature at the same time T, $N(\cdot)$ the cumulative distribution function of the standard normal under the risk neutral measure.

The default probability P_{def} is the probability that the firm's assets will be less than the book value of the firm's liabilities. In other words:

$$P_{def,t} = Prob(V_{A,t+T} \leq D_t|V_{A,t}) = Prob(ln(V_{A,t+T}) \leq ln(D_t|V_{A,t}) \tag{11}$$

We can then express the value of assets based on standard GBM process:

$$ln(V_{A,t+T}) = ln(V_{A,t}) + (\mu - \frac{\sigma_A^2}{2}T + \sigma_A\sqrt{T}\epsilon_{t+T}) \tag{12}$$

where $\epsilon_{t+T} \approx N(0,1)$. Let $V_{A,t} = A_t$, we can then express the DTD metric as follows:

$$DD = \frac{ln(\frac{A_t}{D}) + (u_A + 0.5\sigma_A^2)T}{\sigma_A\sqrt{T}} \tag{13}$$

[16] An alternative approach can be to estimate default probability from the Leland and Toft (1996) model. We choose to use the Merton (1974) framework since it is still the more popular approach in estimating credit risk in the literature. The main difference between the two models in terms of calculating default likelihood is the default barrier, in addition to the payout rate.

where u_A is used under the physical probability measure. We link equity values to asset values using the following expressions:

$$\sigma_E = \frac{A}{D} N(d_1)\sigma_A \tag{14}$$

Equity volatility is estimated as the standard deviation of equity value return for each company. The default barrier is again set net of cash and cash-like assets:

$$D = Short\ Term\ Debt + 0.5 * Long\ Term\ Debt - Cash\ and\ Cash\ Equivalents \tag{15}$$

Next, the iterative algorithm starts by guessing an initial value for σ_A , which we set equal to $\sigma_A^0 = \sigma_E \frac{\sigma_E}{E+D}$, where E is the book value of equity at the end of the year-quarter, and D is the book value of debt as defined earlier. Initial drift is proxied by 10-year constant treasury rate. Given these estimates and initial values, we can solve Eq. (14) for A to obtain the first iteration. We repeat this exercise until we achieve a standard convergence criterion. Defining $\epsilon < 0.001$, we stop the algorithm when we achieve this criterion shown in Eq. (16) and estimate Distance-To-Default, shown in Eq. (17). According to Vassalou and Xing, there are two main differences between this approach and the one used by KMV. KMV uses Bayesian adjustments for the country, industry, and size of the firm. Additionally, they also allow for convertibles and preferred stocks in the capital structure of the firm.

$$|\sigma_A^n - \sigma_A^{n-1} < \epsilon| \tag{16}$$

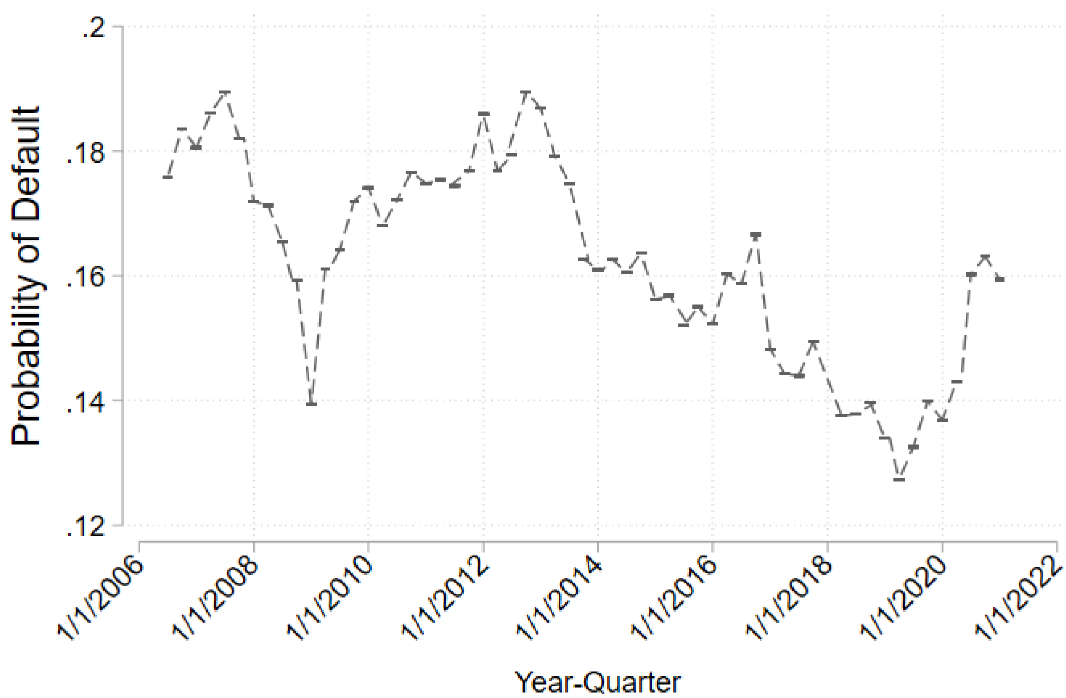
$$DTD = \frac{ln(\frac{A_t}{A_B}) + (\mu_A - \delta + 0.5\sigma_A^2)T}{\sigma_A\sqrt{T}} \tag{17}$$

$$P_{def} = N(-DTD) = N(-\frac{ln(\frac{A_t}{D}) + (\mu_A + 0.5\sigma_A^2)T}{\sigma_A\sqrt{T}}) \tag{18}$$

Finally we aggregate our estimates of default probability using a simple unweighted average by each year-quarter and plot a time-series to assess its consistency with the literature.

6.2 Structural Model Estimates: Default Risks Concentrated Among Larger Over-Leveraged Firms

Figure 6: Estimated Probability of Default



Notes: Expected Default Frequency estimated from the structural model of Merton (1974). For estimating the asset volatilities, the assumed maturity is 1 year, the default barrier is assumed to be short-term debt plus half of long-term debt minus cash and cash equivalents. Risk-free rate is proxied by the 10-year constant maturity treasury rate.

We begin by plotting default probability aggregated across firms by year-quarter starting from 2006. Figure 6 shows default probabilities were elevated around the financial crisis. We note a dip around 2009 before default probabilities picked up sharply again coinciding with the Eurozone sovereign debt crisis. Default probabilities declined since

Table 9: Structural Model Distance-To-Default Estimates

	All Firms		Firms with FR		Firms with BR	
	p(50)	p(25)	p(50)	p(25)	p(50)	p(25)
Panel A: All Firms						
Pre-COVID	9.76	1.76	7.76	1.43	9.34	1.88
Post-COVID	10.51	1.40	8.83	1.33	9.39	1.51
$\Delta(Post - Pre)$	0.75	-0.36	1.07	-0.10	0.05	-0.37
Panel B: Large Firms						
Pre-COVID	10.09	1.90	11.97	3.86	10.2	2.37
Post-COVID	10.77	1.52	13.15	2.81	9.14	1.22
$\Delta(Post - Pre)$	0.68	-0.38	1.18	-1.05	-1.06	-1.15

Notes: This table shows estimates of the distance to default metric using the asset volatility and implied asset values from the structural model for pre and post-COVID onset samples. FR denotes "Financial Risk", BR denotes "Business Risk". It shows how many standard deviations a company's asset value has to deviate from its mean before it defaults. For estimating the asset volatilities, the assumed maturity is 1 year, the default barrier is assumed to be short-term debt plus half of long-term debt minus cash and cash equivalents. Risk-free rate is proxied by the 10-year constant maturity treasury rate. Large firms are defined as those with average total asset value greater than USD 1 billion.

then somewhat until 2017 around the time of major unexpected political turbulence (e.g. Brexit). Finally, we see the sharpest single-quarter increase in default probability in 2020 coinciding with the onset of the COVID recession. These trends are consistent with conventional wisdom, reassuring us of the validity of our structural estimation.

We summarize our results on the impact of COVID-19 on default likelihood in Table 9. We rely on the DTD metric widely used in the credit risk literature. Column 1 in Panel A shows the median firm reduced default likelihood post-COVID consistent with the de-leveraging effect documented in the benchmark specifications. DTD rises by about 10 percent from 9.76, in other words the median firm is further away from default. However, we uncover an opposing trend when we focus on firms in the bottom quartile sorted on DTD. Specifically, the firm in the $25th$ percentile experiences a decline in DTD from 1.76 to 1.40, a deterioration by around 20.5 percent. Thus, firms which were already stressed pre-COVID became more vulnerable to bankruptcy. We observe similar trends for firms exposed to rollover risk and business risk. We note however that the change is highest for firms exposed to business risk: a decline of 0.37 to 1.51 as can be seen in Column (6).

Table 9, Panel B repeats the analysis for firms with asset value greater or equal to USD 1 billion, which we classify as $Large$ firms. We note that the patterns documented in Panel A are amplified for $Large$ firms. For example firms in the $25th$ percentile in the sample experienced a decline of 0.38. More crucially for our analysis we note the highest deterioration is associated with firms exposed to business risk originating from social distancing. Both in levels and change, we note these firms became the most vulnerable post-COVID. For example, the firm in the $25th$ percentile has a DTD value of 1.22, the lowest in all sub-samples reported. These patterns are reflective of the rise in default risk from becoming over-leveraged as shown in Section 5. Alfaro et al. (2019) argue large firms have the greatest potential to generate systemic risk. Our results raise important implications consistent with this view which show the largest firms exposed to risks from social distancing are much closer to default following the onset of the pandemic recession.

6.3 Stress Tests

The previous analysis reveals important patterns about the level and change in risk in US corporations following their capital structure decisions in response to the pandemic recession. From a regulatory perspective, it is also useful to gain an idea of the resilience of these companies to systemic downturns. In this section we ask, how resilient are companies if growth slowed down or asset risk increased, given leverage adjustments following the COVID-19 shock? To simulate stress tests, we re-estimate default probabilities using counterfactuals. Specifically, for each company, we add a 20 percent decline in expected growth rate and, for the second stress test, a 20 percent rise in cash flow volatility and trace out DTD pre and post-COVID. Note that these simulations are *over and above* the effect arising from the COVID recession or other macroeconomic effects. By design, it takes into account the fact that some firms adjusted leverage while others did not.

Table 10: Stress Tests on Distance-To-Default Estimates

	All Firms		Firms with FR		Firms with BR	
	p(50)	p(25)	p(50)	p(25)	p(50)	p(25)
	Shock 1: Growth Slowdown					
Panel A1: All Firms						
Pre-COVID	7.96	1.44	6.95	1.20	7.82	1.53
Post-COVID	8.76	1.01	7.23	1.01	7.95	1.06
$\Delta(Post - Pre)$	0.80	-0.43	0.28	-0.19	0.13	-0.47
Panel A2: Large Firms						
Pre-COVID	8.39	1.56	10.34	3.19	8.57	2.01
Post-COVID	9.01	1.11	11.13	2.22	7.45	0.86
$\Delta(Post - Pre)$	0.62	-0.45	0.79	-0.97	-1.12	-1.15
	Shock 2: Higher Uncertainty (Asset Volatility)					
Panel B1: All Firms						
Pre-COVID	7.86	1.31	6.43	0.97	7.74	1.35
Post-COVID	8.73	1.03	7.3	0.96	7.79	1.17
$\Delta(Post - Pre)$	0.87	-0.28	0.87	-0.01	0.05	-0.18
Panel B2: Large Firms						
Pre-COVID	8.38	1.41	9.94	3.16	8.47	1.72
Post-COVID	8.96	1.11	10.94	2.28	7.58	0.89
$\Delta(Post - Pre)$	0.58	-0.30	1.00	-0.88	-0.89	-0.83

Notes: This table shows estimates of the distance to default metric using the asset volatilities and implied asset values from the structural model for pre and post-COVID onset samples subject to two stress tests. FR denotes "Financial Risk", BR denotes "Business Risk". The table shows number of standard deviations a company's asset value has to deviate from its mean before it defaults. In Panels A1 and A2, the estimated drift rate, μ , for each company is reduced by 20 percent. In Panels B1 and B2, the estimated volatility σ , for each company is raised by 20 percent. For estimating the asset volatilities, the assumed maturity is 1 year, the default barrier is assumed to be short-term debt plus half of long-term debt minus cash and cash equivalents. Risk-free rate is proxied by the 10-year constant maturity treasury rate. Large firms are defined as those with average total asset value greater than USD 1 billion.

We summarize our results in Table 10. Panel A1 presents results with a simulated 20 percent slowdown in growth. Looking at firms in the $25th$ percentile again reveals significant deterioration in credit risk following COVID. However, the levels are much lower relative to the estimates reported in Table 9, without a simulated growth slowdown. For example, post-COVID DTD for firms exposed to business risk in the $25th$ percentile is 1.06, or only one-standard deviation away from the default barrier. Panel A2 shows each of the simulated effects are amplified for larger firms. Specifically, we see a DTD decline of 0.97 for $25th$ percentile firms with rollover risk to 2.22 and a decline of 1.15 for $25th$ percentile firms with business risk to 0.86. These estimates suggest, there is a small subset of relatively large firms that are over-leveraged and their asset value is less than one-standard deviation away from the default barrier. Finally, Panel B1 and B2 repeat the same exercise for an alternate stress test: a 20 percent spike in cash flow return volatility which is our proxy for uncertainty. We document very similar patterns thus underscoring the risks of becoming over-leveraged.

7 Conclusion

In this paper, we provide the first large sample evidence on the impact of COVID-19 on optimal capital structure in US public firms. We suggest that the recessionary nature of the shock impact default probabilities and by extension, expected cost of distress. Traditional capital structure theory indicate a resultant change in optimal level of debt. Using data through 2020Q4, we exploit within-firm variation to estimate an empirical model of leverage. Our estimates show the shock from COVID decreased the level of leverage by 5.3 percent relative to the pre-shock mean of 19 percent, while debt maturity increased marginally. Several iterations and alternate measures of debt confirm our estimates. We show that the results were mostly driven by firms exposed to significant rollover risk pre-COVID, while those affected by social distancing maintained their leverage ratios and only shortened their debt maturity structure.

We find that a model of optimal capital structure characterized by a deterioration in expected growth rate of firm cash flows and surge in volatility of asset return is consistent with our benchmark de-leveraging results. Estimating drift and volatility directly from the data pre and post-COVID shows a significant reduction in the optimal levels of corporate leverage, a novel contribution to the literature. A key contribution of this paper is that we document firms most severely affected by social distancing chose to maintain their leverage levels and thus became over-leveraged. Using standard structural models of credit risk we confirm these firms experienced the largest deterioration in credit risk. Our simulation tests show the bottom quartile of these firms (sorted on default likelihood) are particularly vulnerable to future downturns. Distress Risk is also larger for the largest firms affected by social distancing. From a policy perspective, our results clearly raise serious implications for financial stability and systemic risk since large firms have the potential to generate a wave of defaults.

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Appendix A

Data Appendix

Table A1: Variable Definition

Variable	Definition
Total Debt	Debt in Current Liabilities + Total Long-term Debt
Leverage Ratio	Total Debt Net of Cash /Total Assets
Long-term Debt Ratio	Total Long-term Debt Net of Cash /Total Assets
Debt Maturity	Total Long-term Debt/Total Debt
EBITDA Margin	Earnings Before Interest, Taxes, Depreciation and Amortization/Operating Revenue
Return on Assets	Earnings Before Interest and Taxes/Assets
Cash Ratio	Cash/Current Liabilities
Tangibility	Share of Tangible Assets
Market-to-Book	Market Value of Equity/(Book Value of Equity)
Exposure to Rollover Risk	(Long-Term Debt due in 1 year)/Total Debt $\geq$ *75th percentile* of all firms in 2019Q4: 20.1 percent
Highly Vulnerable to Social Distancing	Sales Growth (ROA change) $\leq$ *25th percentile* in 2020Q2 relative to 2019Q2.

Table A2: Summary Statistics: Full Sample

Variable	Obs	Mean	Std. Dev	50th Percentile	75th Percentile
Total Assets ($ Mn)	44744	9481	27720	1343	5534
EBITDA Margin	40157	-65	14391	15.46	33.06
Sales Growth (%)	38799	61.69	2556	-0.18	13.58
Tangibility	43995	0.83	0.22	0.95	0.99
Share of LT Debt due in 12 Months	32032	0.15	0.21	0.07	0.2
Cash Ratio	33326	1.24	3.48	0.4	1.09

8 Appendix B

Building Blocks of Leland and Toft (1996) Model

In this section we outline the Leland and Toft (1996) Model. We point readers to the original paper for a detailed discussion. The LT model builds on the trade-off theory of capital structure (i.e. corporate tax benefits versus bankruptcy costs and agency costs). Debt issues provide tax benefits that are balanced with higher probabilities of default. Equity holders aim to achieve the lowest bankruptcy trigger (equity value is maximized at the expense of the debt holders). This is the well-known asset substitution problem where around the optimal bankruptcy trigger, equity holders would want to take on riskier projects. Consider a firm that has productive assets whose unleveraged value A_t, follows standard geometric brownian motion:

$$\frac{dA_t}{A_t} = [\mu_a(A,t) - \delta]dt + \sigma_a dB_t^A \tag{19}$$

where $\mu_a(A,t)$ is the total expected rate of return on asset value; δ is the constant fraction of value paid out to security holders; dB is the increment of the standard brownian motion. The stochastic process of A is assumed to be unaffected with the choice of leverage (eg: coupons after tax benefits). Following Modigliani and Miller (1957), Merton (1975), Leland (1994) and Leland and Toft (1996), we assume that a riskless asset exists and pays a constant rate of interest r. Now consider any claim on the firm that continuously pays a non-negative coupon, $c(t)$, per instant of time when the firm is solvent, has maturity t periods from the present and principal $p(t)$. Let $\rho(t)$ represent the fraction of asset value A_B which debt of maturity t receives in the event of bankruptcy. Under risk-neutral valuation and letting $f(s;A,A_B)$ denote the density of the first passage time s to A_B from A when the drift rate is $r-\delta$, gives debt the following value:

$$\begin{aligned} d(A;A_B;t) = \int_0^t e^{-rs}c(t)[1-F(s;A;A_B)]ds + e^{-rt}\rho(t)[1-F(t;A;A_B)] \\ + \int_0^t e^{-rs}p(t)A_B[1-F(s;A;A_B)]ds \end{aligned} \tag{20}$$

Eq. (4) can be integrated by parts to obtain a closed-form solution, as outlined below.

The expression for debt in Eq. (4) can be integrated by part to obtain:

$$d(A;A_B;t) = \frac{c(t)}{r} + e^{-rt}[p(t) - \frac{c(t)}{r})][1-F(t)] + [\rho(t)A_B - \frac{c(t)}{r}]G(t) \tag{21}$$

where

$$G(t) = (\frac{A}{A_B})^{(-a+z)}N[q_1(t)] + (\frac{A}{A_B})^{(-a-z)}N[q_2(t)] \tag{22}$$

$$F(t) = N[h_1(t)] + (\frac{A}{A_B})^{(-2a)}N[h_2(t)] \tag{23}$$

$q_1(t) = \frac{-b-z\sigma^2 t}{\sigma t}$; $q_2(t) = \frac{-b+z\sigma^2 t}{\sigma t}$;
$h_1(t) = \frac{(-b-a\sigma^2 t)}{\sigma t}$; $h_2(t) = \frac{(-b+a\sigma^2 t)}{\sigma t}$

$a = (r - \delta - (\sigma^2/2))/\sigma^2$; $z = ((a\sigma^2)^2 + 2r\sigma^2)^{1/2}/\sigma^2$

As in Leland and Toft (1996), the value-process for company continues until maturity of debt unless A falls to a default-triggering value A_B. Assuming that the firm continuously issues a constant principal amount of new debt with maturity T and simultaneously retires the same amount of debt, then the debt structure becomes independent of t, and the value of all outstanding bonds $D(A; A_B, T)$ can be determined by integrating the debt flow, $d(A; A_B, t)$, over a period of T:

$$D(A; A_B; t) = \int_t^T d(A; A_B; t) = \frac{C}{r} + (P - \frac{C}{r})(\frac{1-e^{-rT}}{rT} - I(T)) + ((1-\alpha)A_B - \frac{C}{r})J(T) \tag{24}$$

where

$$I(T) = \frac{G(T) - F(T)e^{-rT}}{rT}$$

J(T) = [-(A/A$_B$)$^{a+z}N(q_1(T))q_1(T) + \frac{A}{A_B})^{-a-z}N(q_2(T))q_2(T)]/b\sigma\sqrt{T}$
(25)

The fraction of firm value lost in bankruptcy is α. We hypothesize $\alpha = \alpha(r)$ where r represents the borrower's bargaining power. Intuitively we predict that firm's with higher bargaining power can reduce bankruptcy costs. Considering the difficulty in estimating this bargaining power parameter, we estimate our baseline model holding α constant. This is typically ignored in the literature and we aim to explore the heterogeneity it introduced in future drafts. Firm value is captured as the function of the unlevered value of assets, tax benefits and bankruptcy costs.

$$\begin{gathered} v(A) = A + TB(A) - BC(A) = \\ A + \frac{\tau C}{r}[1 - (\frac{A}{A_B})^{-x}] - \alpha A_B(\frac{A}{A_B})^{-x} + \frac{C}{r}[1 - (\frac{A}{A_B})^{-x}] \end{gathered} \tag{26}$$

where x = $a + z$. The Equity Value $E(A)$ is the difference between firm value $v(A)$ and debt value $d(A)$:

$$E(A; A_B; T) = v(A; A_B) - D(A; A_B; T) \tag{27}$$

The default A_B is chosen endogenously ex post to maximize the value of equity at $A = A_B$, given the limited liability of equity and the debt structure. To determine the equilibrium bankruptcy-triggering asset value A_B endogenously, we invoke the smooth-pasting condition. A_B solves the equation

$$h(P, A_B) = \frac{\partial E(A, A_B)}{\partial V}\bigg|_{A=A_B} = 0 \tag{28}$$

Using the expressions for debt, total firm value and equity, we can derive the default-triggering asset level. The result is similar to Leland and Toft (1996) apart from the parameter capturing reduced incentive-misalignment, ϵ :

$$A_B = \frac{\frac{C}{r}(\frac{M}{rT-G}) - \frac{MP}{rT} - \frac{(\epsilon+\tau)Cx}{r}}{1 + ax - (1-a)G} \tag{29}$$

where

$$M = 2ae^{-rT}N(a\sigma\sqrt{T}) - 2zN(z\sigma\sqrt{T}) - \frac{2}{\sigma\sqrt{T}}n(z\sigma\sqrt{T}) + \frac{2e^{-rT}}{\sigma\sqrt{T}}n(a\sigma\sqrt{T}) + (z-a)$$

$$G = -(2z + \frac{2}{z\sigma^2 T})N(z\sigma\sqrt{T}) - \frac{2}{\sigma\sqrt{T}} - \frac{2}{\sigma\sqrt{T}}n(z\sigma^2 T) + (z-a) + \frac{1}{z\sigma\sqrt{T}}$$

and n(·), N(·) denote the standard normal density function and cumulative standard normal density function respectively. We can now define the optimization problem for the firm. The public company solves the following problem at T_0:

$$\max_{P, A_B} v(A, A_B, P, m)\big|_{A=A_0} \tag{30}$$

subject to optimal bankruptcy condition and return process of the fundamental value of the underlying asset.

9 Appendix C

Comparing Baseline Regressions with Past Recessions

To understand the significance of the reduction in debt and increase in maturity presented in our baseline results in Section 3, we repeat the benchmark regressions with a longer time-series to document capital structure response during past recessions. We augment our baseline dataset with similar firm-level data around the time of the Global Financial Crisis (GFC) and the Dotcom crash. The data is cleaned and filtered as described in section 3. Specifically, we estimate a similar pre-post regression for the GFC and the Dotcom crash in 2001.

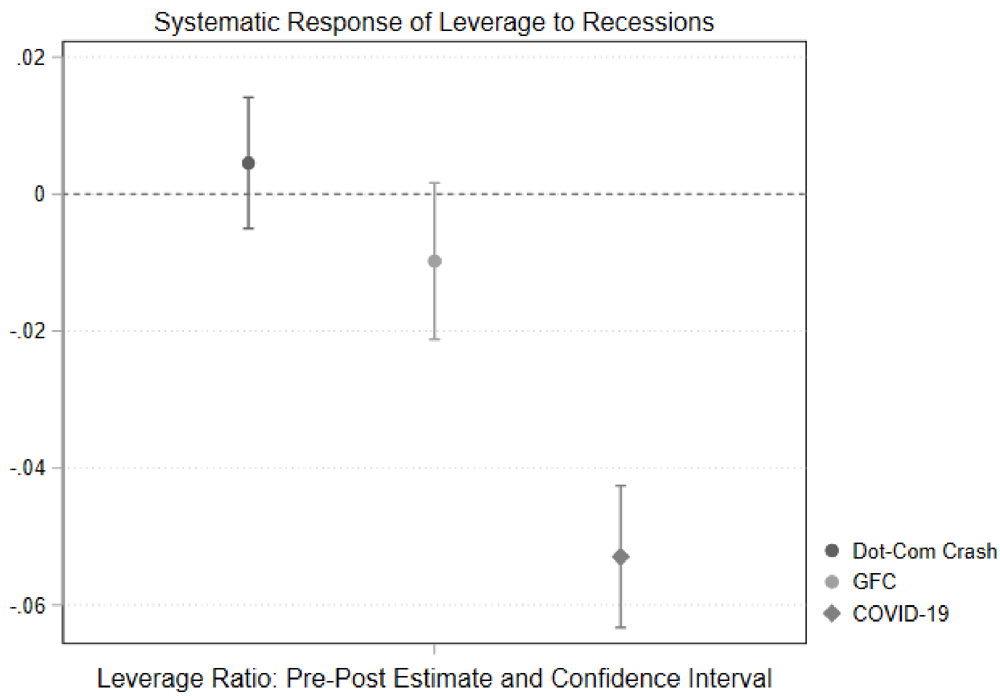

Figure A1: *This chart plots coefficient estimates of $Post$ outlined in Eq. (1) for three recessions: the dot-come crash, GFC and COVID-19. The outcome is leverage ratio. We follow the NBER's timeline of recession onset to construct our pre-post dummy variable. For both GFC and the dot-com crash recession, we retain 6 quarters for the pre-recession phase. For GFC we examine 8 post-recession quarters (2008 and 2009) consistent with past studies such as Demirguc-Asli Kunt (2015). For the dotcom crash, we look at 6 quarters post-recession.*

We observe that both the amount and maturity of debt declined during GFC. However, the reduction is significantly lower post-GFC compared to post-COVID. The point estimate is reported at -0.015 or a 1.5 percent decline. We also observe that the change in leverage during the dotcom crash was statistically insignificant.

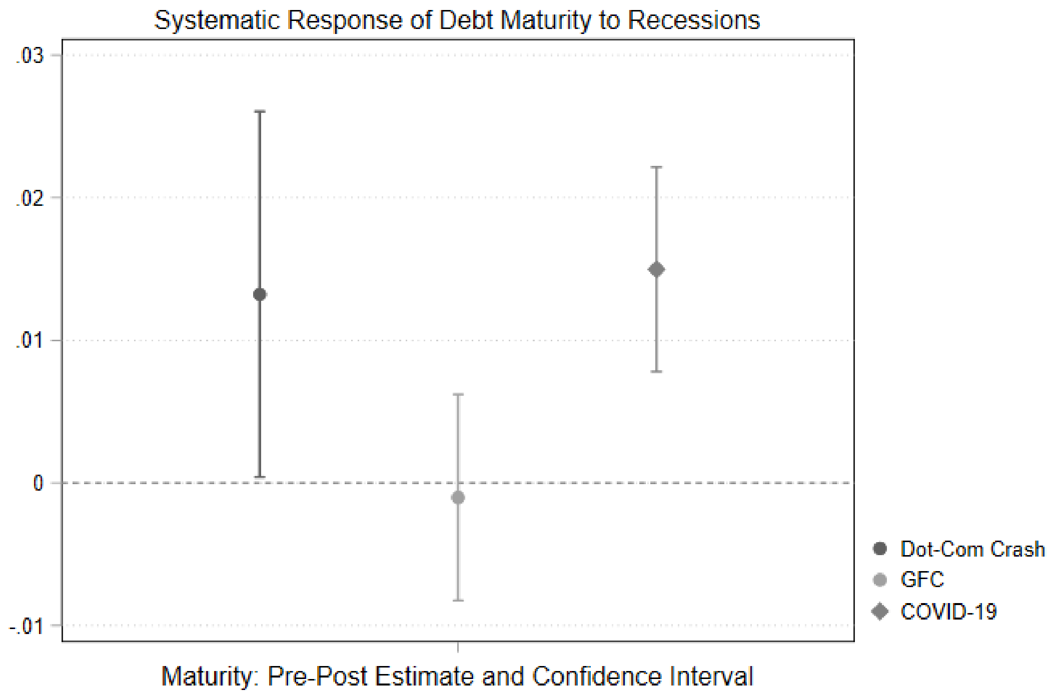

Figure A2: *This chart plots coefficient estimates of $Post$ outlined in Eq. (1) for three recessions: the dot-come crash, GFC and COVID-19. The outcome is debt maturity. We follow the NBER's timeline of recession onset to construct our pre-post dummy variable. For both GFC and the dot-com crash recession, we retain 6 quarters for the pre-recession phase. For GFC we examine 8 post-recession quarters (2008 and 2009) consistent with past studies such as Demirguc-Asli Kunt (2015). For the dotcom crash, we look at 6 quarters post-recession.*

We next repeat the analysis on maturity structure. Post-COVID, we document a moderate increase in the share of long-term debt in total debt, although previous studies document a decline in maturity post-GFC. Figure 5 reports out estimates for debt maturity. We find debt maturity remained relatively unchanged for our sample of publicly listed firms post-GFC consistent with Demirguc-Kunt (2015). However, we note that maturity increased following the dot-come crash. Overall we do not observe any clear patterns and find very different firm responses since the onset of the COVID-19 pandemic compared to other major recessions.