

COVID-19 and the Cross-Section of Equity Returns: Impact and Transmission

Lorenzo Bretscher

London Business School and HEC Lausanne

Alex Hsu

Georgia Institute of Technology

Peter Simasek

Georgia Institute of Technology

Andrea Tamoni

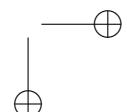
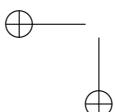
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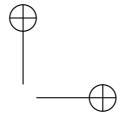
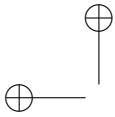
Using the first reported case of COVID-19 in a given US county as the event day, firms headquartered in an affected county experience on average 27 bps lower return in the 10-day post-event window. This negative effect nearly doubles in magnitude for firms in counties with a higher infection rate (-50 bps). We test a number of transmission channels. Firms belonging to labor intensive industries and residing in counties with large mobility decline have worse stock performance. Firms sensitive to COVID-19 induced uncertainty also exhibit more negative returns. Finally, more negative stock returns are associated with downward revisions of earnings forecast. (*JEL* E4, E6, G12)

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Amid the pandemic caused by the coronavirus in the first quarter of 2020, financial markets around the world were roiled in crisis. By late March, the U.S. equity market had declined roughly 40% in value as the working population sheltered in place and businesses shuttered. Despite the Federal Reserve’s commitment to implement quantitative easing measures, the market turmoil is challenging firm balance sheets,

We would like to thank the editor, Nikolai Roussanov, for his detailed comments. Send correspondence to Alex Hsu, Georgia Institute of Technology, Scheller College of Business, 800 West Peachtree St. NW, Atlanta, GA 30022; telephone: (404) 385-1123. E-mail: alex.hsu@scheller.gatech.edu.





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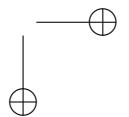
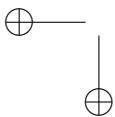
which in turn can have ripple effects. The sense of a deepening economic depression started to set in as grim GDP growth predictions for the second quarter are updated. In this paper, we document that the domestic spread of COVID-19 in the U.S. has a negative and significant impact on firm equity valuations. In particular, we show that the pandemic negatively affects firms through its impact on labor supply and the uncertainty it generates. Furthermore, the shock propagates through the equity market by putting downward pressure on analyst earnings forecasts.

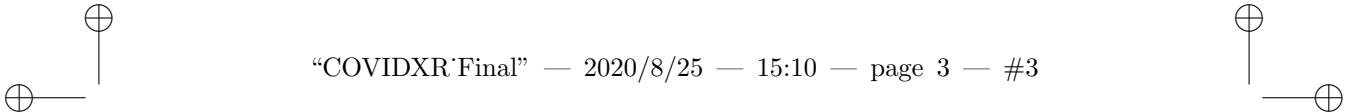
We attempt to address two questions: (1) how does the sudden collapse in economic activity caused by COVID-19 affect equity valuation in the cross-section of firms? And (2) what are the channels through which the COVID-19 induced economic downturn propagates and affects firm-level outcomes? The first question has important implications for investors' portfolio choices, banks' lending policies, and managers' investment decisions. The second question is key to understanding the effectiveness of policy interventions to stabilize the economy.

Using geographical dispersion of firm headquarter locations and the fact that the pandemic spread through the U.S. with variable timing, we perform a difference-in-difference estimation to understand the effect of the pandemic on equity returns. We find that, on average, daily returns of public firms are 27 bps lower in the 10-day window right after the first case of COVID-19 is recorded (event day) in the county where the firm is headquartered. When we consider counties with high infection rates (100 or more cases reached in less than 20 days), the negative effect of the COVID-19 shock nearly doubles to 50 bps. That is, returns are lower relative to days before the event day as well as to returns of firms residing in counties which have never experienced a COVID-19 case during our sample period.¹

The transmission of COVID-19 from a health care crisis to a corporate slump may be driven by several different economic mechanisms. To investigate the transmission mechanism, we focus on four potential, and not mutually exclusive, channels: labor supply, uncertainty, government spending and monetary policies, and cash flow expectations. In particular, the stay-at-home orders resulting from the spread of the virus may depress workers' ability to travel to work, while the largely unknown factors surrounding the disease generated considerable uncertainty about future economic activity. Some firms may be less impacted thanks to existing government contracts providing stable demand. Ultimately, given the widespread and rapid advance of COVID-19 we would anticipate frequent revisions of analysts' earnings expectations.

¹ The end of our sample is March 20, 2020, one week before the passage of the CARES Act.





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Various recent studies and many economists describe the impact of the pandemic on the economy predominantly as a demand shock. Indeed, due to social distancing measures and closure of public gatherings, consumer demand dropped significantly during March 2020.² The resulting momentous rise in unemployment further suggests that demand will be depressed for the foreseeable future. However, this does not rule out that the pandemic is also a supply shock. In fact, Guerrieri, Lorenzoni, Straub, and Werning (2020) suggest that negative supply shocks can turn into negative demand shocks. Using a multi-sector model in incomplete markets, they show that a negative supply shock can trigger changes in aggregate demand as firms exit and jobs disappear.

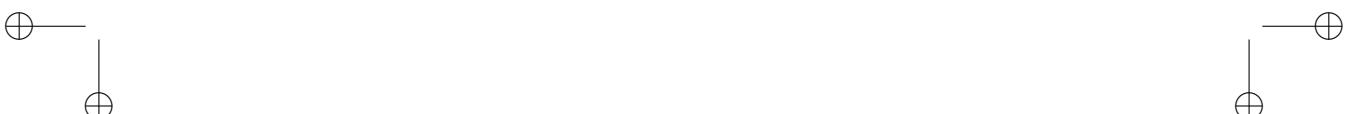
We believe that our natural experiment combining the geographical dispersion of firms with the staggered impact of COVID-19 provides a unique setting to examine the relative strength of various demand and supply channels through which the COVID-19 shock affects firm valuations. In our empirical setting, we rely on large public firms which sell their goods and services across the entire continental U.S., and in many instances, internationally. Hence, it is very unlikely that our county-level valuation effect due to the presence of confirmed virus cases is a pure demand-side phenomena.³ In fact, our baseline regression results suggest that the COVID-19 crisis negatively impacts the supply-side and labor productivity.

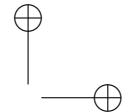
Specifically, to study the labor supply channel of the COVID-19 propagation, we estimate difference-in-difference regressions on a subsample of “labor intensive” firms. We classify as labor intensive firms within the mining, construction, and manufacturing sectors. The regression results show that the average daily return of a labor intensive firm residing in a high COVID-19 intensity county is 1% lower in the 10-day post-event window. This suggests that the negative effect of COVID-19 shocks on equity returns is considerably stronger for labor intensive firms. In other words, the COVID-19 pandemic negatively affects economic output through its impact on labor supply.

To further tie return dynamics to labor supply, we use the University of Maryland COVID-19 mobility data to document that the county-level percentage of people staying at home increased following the first reported case of coronavirus in the county. The decline in mobility due to the virus spread suggests that the pandemic negatively impacts labor

² E.g., Baker, Farrokhnia, Meyer, Pagel, and Yannelis (2020c) examine US consumers’ reaction to the pandemic and finds elevated grocery spending that continued through the month of March (when President Trump declared a national emergency) and sharp drops in restaurants, retail, air travel, and public transport as people began to stay at home.

³ We use the term “pure” demand to stress that we only rule out that the propagation takes place just via demand. Clearly, we do not exclude that demand *and* supply channels are both working to propagate the shock.

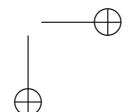
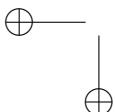


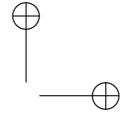
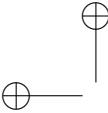


supply. Next, we sort counties according to changes in the percentage of people staying at home before and after the first reported case. We find that firms with headquarters located in those counties with large increases in percentage staying at home have more negative stock returns in the days following the first reported case compared to firms residing in counties with small changes in percentage staying at home. Taken together, results using mobility data provides evidence that the virus spread causes the population to stay at home more, which worsens the financial performance of local firms.

Using the date of the first reported case as opposed to another threshold allows us to separate out the effect stemming from the second moment (uncertainty) of the shock from its first moment (level). For example, it is possible that productivity level does not fall immediately after the first case is reported, but business activity can be negatively affected in expectation due to the uncertainty. To tease out the impact of COVID-19 induced uncertainty on equity returns, we employ data from Hassan, Hollander, van Lent, and Tahoun (2020). These authors use textual analysis of earnings call transcripts to obtain firm-level measures of COVID-19 risk exposure. The risk measure is related to the mentioning of words synonymous to “risk” or “uncertainty” in transcripts, and by construction it captures the management’s attitude towards COVID generated uncertainty. We find that firms concerned with the elevated uncertainty induced by COVID-19 exhibit particularly negative returns after the event day.

Moreover, we examine whether firm-level exposure to government spending and monetary policies can produce the heterogeneous return reaction we observe in the data. For government spending, Goldman (2019) shows that government contractor firms weathered the 2008 financial crisis relatively better compared with non-contractor firms. We apply the Goldman (2019) definition of government contractors to our sample of firms and check whether their stock outperformed the non-contractors after the first case of the coronavirus was reported in the county the firm is headquartered. In contrast to Goldman (2019), we do not find this to be the case, which highlights a fundamental difference between the pandemic and the financial crisis. Large government contractors are primarily in labor intensive manufacturing industries leaving them more susceptible to the negative labor supply shock induced by the pandemic. Focusing on a subsample of labor intensive firms, we find that government contractors’ stock returns are relatively more negative than non-contractors following the first reported case. Hence, despite having stable demand due to contractual relationships with the government, contractors stocks perform worse. This result suggests that government contractors might be particularly reliant on the presence of the labor force they employ. Furthermore, we do not





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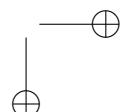
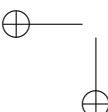
find evidence that heterogeneous sensitivity to monetary policy drives the cross-sectional return dynamics following the COVID-19 news.

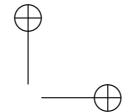
The last channel of transmission we investigate concerns how the spread of COVID-19 affects expected corporate earnings. To this end, we use analyst forecast data from the I/B/E/S database and document that the first reported coronavirus case results in downward revision of earnings estimates of firms located in the same county. Moreover, we find that firms with negative earnings revisions experience greater stock return declines relative to firms with no revisions or positive revisions in the 10-day window after the first case of COVID-19 is reported in a county. Taken together, we deduce that the spread of COVID-19 leads to financial market fragility partially by depressing the expected cash flows of affected firms.

Our work is related to a fast growing literature on the asset price response to the COVID-19 pandemic in the first quarter of 2020.⁴ Gormsen and Kojen (2020) look at the aggregate equity market and dividend futures during the outbreak to infer bounds on future GDP growth. Baker et al. (2020b) use text-based methods to study the U.S. stock market reaction to the COVID-19 pandemic. Cejnek, Rndl, and Zechner (2020) provide evidence that index-level and single-stock near-maturity dividend futures reflect expectations of dividend cuts. Pettenuzzo et al. (2020) analyze the signaling role of dividend announcements during the COVID-19 pandemic by looking at the stock market reaction of firms that changed their dividend policy. Alfaro, Chari, Greenland, and Schott (2020) show that aggregate equity market returns respond to daily unanticipated changes in predicted COVID-19 cases. Toda (2020) uses a SIR model to study the impact of the epidemic on the stock market.⁵ In cross-country settings, Ru, Yang, and Zou (2020) find that stock markets reacted more quickly and strongly in countries that suffered from 2003 SARS diseases, while Gerding, Martin, and Nagler (2020) show that stock price reactions were stronger in countries with higher debt-to-GDP ratios. In a cross-country and cross-asset-class setting, Croce, Farroni, and Wolfskeil (2020) study how epidemic news identified from Twitter are reflected in asset prices. They conclude that the market price of contagion risk is very high. Distinct from these studies, we do not focus on the aggregate U.S. equity market, but rather we rely on geographical heterogeneity of firm headquarters to

⁴ A large number of papers investigate the effect of pandemics on economic growth, rather than asset prices. See Barro, Ursua, and Weng (2020), Correia, Luck, and Verner (2020), Ludvigson, Ma, and Ng (2020). Several papers also model the interaction between economic activity, economic decisions, and epidemic dynamics (see, e.g., Alvarez et al., 2020; Eichenbaum et al., 2020; Jones et al., 2020; van Binsbergen and Opp, 2020).

⁵ More generally, various streams of papers extend the canonical epidemiology SIR model to explore the implications for the COVID-19 epidemic (see, e.g., Atkeson, 2020; Favero, 2020).





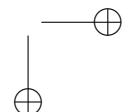
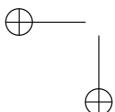
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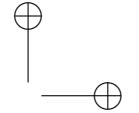
directly identify the consequences of the pandemic in the cross-section of U.S. equity returns.

In this respect, our work contributes to a large number of contemporaneous papers that investigate the firm- and industry-level price responses to COVID-19. Albuquerque, Koskinen, Yang, and Zhang (2020) focus on the performance of firms with high environmental and social ratings during the COVID-19 outbreak. Ramelli and Wagner (2020) focus on the importance of trade (e.g., China-oriented stocks) and financial policies for firm value. These authors document that firms with more leverage and minimal cash holdings suffered severely in the period from February 24 through March 20 – even if these firms did not have international activities. They interpret this finding as evidence that business uncertainty caused by COVID-19 is amplified through certain financial channels. Interestingly, Hassan, Hollander, van Lent, and Tahoun (2020) document that financing concerns are mentioned relatively rarely in earnings conference transcripts as COVID-19 spreads globally. On the contrary, these authors find evidence for decreasing demand, disruption of the supply chain and closure of production facilities, and increased uncertainty as major concerns for firms. Papanikolaou and Schmidt (2020) construct an industry-level measure of exposure to COVID-19 work disruptions, and investigate whether the cross-sectional differences are predictive of differential economic outcomes during the pandemic. Pagano, Wagner, and Zechner (2020) investigate the asset pricing implications of companies exposure to social distancing not only for the period of the COVID-19 outbreak, but also prior and after its occurrence. Despite sharing a similar interest on the cross-sectional response of stock prices to the pandemic, we differ from all these papers in two respects. First, our econometric analysis combines the geographical dispersion of firms with the staggered impact of COVID-19 and is akin to the classical difference-in-difference approach commonly used in corporate finance. Second, and related, a unique advantage of our natural experiment is that it allows us to examine the relative strength of various channels (specifically, the labor supply channel, the uncertainty channel, the government policy channel, and the cash flow news channel) through which the COVID-19 shock affects firm valuations.⁶

We also contribute to broader streams of literature in finance and economics. First, our analysis of the labor supply channel speaks to the literature studying how labor-induced operating leverage affects asset

⁶ Pastor and Vorsatz (2020) investigate the mutual fund performance during the COVID-19 crisis. These authors document that active funds underperform passive benchmarks, and that investors' flows favor sustainable funds, contrary to the notion that sustainability is a luxury good. The role of institutional and retail investors as a propagation channel of the pandemic is an interesting avenue for future research.





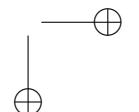
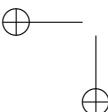
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prices. For example, Donangelo, Gourio, Kehrig, and Palacios (2019) show that high labor-share firms have operating profits that are more sensitive to shocks and have higher expected asset returns. Moreover, Donangelo (forthcoming) shows that operating leverage due to labor is important in explaining the value premium. Belo, Lin, Li, and Zhao (2017), Belo, Lin, and Bazdresch (2019), and Belo, Donangelo, Lin, and Ding (2020) study the implications of labor market frictions for asset prices, and Favilukis and Lin (2016a,b) study the consequences of rigid wages on asset prices and return predictability. Our analysis of the labor supply channel also contributes to the recent theoretical contributions. E.g., in the model by Eichenbaum, Rebelo, and Trabandt (2020), an epidemic has both aggregate demand and aggregate supply effects. Guerrieri, Lorenzoni, Straub, and Werning (2020) develop a theory of Keynesian supply shocks that trigger changes in aggregate demand larger than the shocks themselves. These authors argue that the economic shocks associated to the COVID-19 epidemic may have this feature.

Second, our analysis of uncertainty as a possible propagation channel through which the news of the virus’s spread onto asset prices speaks to a large literature on second moment shocks. Starting with Bloom (2009), an increasing body of research studies how uncertainty shocks influence economic activity and asset prices. Pastor and Veronesi (2013, 2012) examine the response of the equity risk premium to government-induced (political) uncertainty. Croce, Nguyen, and Schmid (2012) show that a reduction of model uncertainty can come at the cost of depressing growth for the long-run. Finally, Bianchi, Kung, and Tirsikh (2018) evaluate the effect of different sources of uncertainty (i.e. demand and supply uncertainty) on macroeconomic and financial outcomes via structural estimation.

Third, our analysis of the possible effects of fiscal and monetary policies during the pandemic complements the literature that has investigated the effectiveness of various policy measures during the Great Recession (e.g., Adelino et al., 2017; Chodorow-Reich et al., 2012; Goldman, 2019; Wilson, 2012).

Lastly, our investigation of the reaction of earning forecasts of analysts and their relation to returns during the pandemic contributes to a vast literature that analyzes the roles of cash flow expectations and discount rates for asset prices. Gormsen and Koijen (2020) and Landier and Thesmar (2020) are two contemporaneous studies that look at these two channels during the COVID-19 outbreak exploiting aggregate S&P500 dividend strips and IBES forecasts, respectively. Similar to Landier and Thesmar (2020), we also use IBES forecasts and focus on the cross-section of returns. We believe that our staggered difference-in-differences setup, and our analysis of returns reaction over a tight window around



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the event day, complements their analysis of cumulative returns response to the COVID-19 crisis.

1. Data and Variable Construction

We obtain public firm ticker symbols from Compustat at the end of 2019. Using these tickers, we download daily closing prices from Bloomberg from December 31, 2019 to March 20, 2020. We stop the sample on March 20th to minimize the effect of the CARES Act on stock prices. The CARES Act was passed on March 26, 2020 and, by design, impacts specific firms and industries in a heterogeneous manner. We then calculate daily returns for all firms in the sample using the end of day prices. We then drop firms that have at least one missing price or if the price dips below \$2 a share on any given trading day since the beginning of 2020.

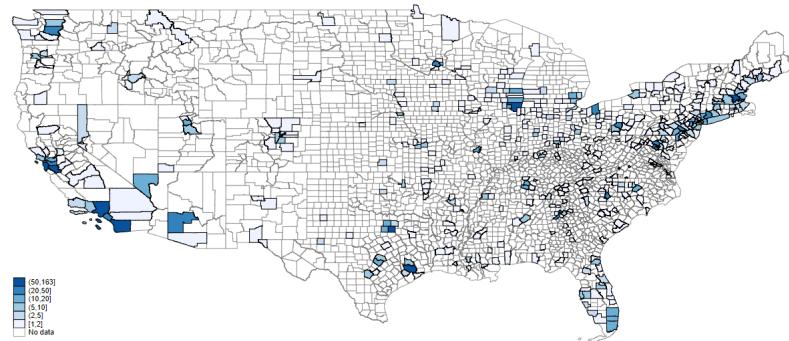
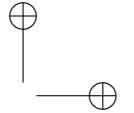
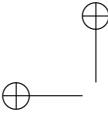


Figure 1
The map displays the number of firms in our dataset with the headquarters located in a particular county.

Firm headquarter locations are also obtained from Compustat. We convert zip codes to geographic identifiers (GEOID) using a crosswalk from the U.S. Census Bureau. GEOID's are unique to U.S. counties, which allows us to merge firm headquarter locations with the COVID-19 case data from The New York Times. Figure 1 reports the density of firms in our dataset headquartered in a particular county. The completed dataset matches trading day-firm observations (firm characteristics as of the end of 2019) and the calendar day on which the first reported COVID-19 case appears in the county where the firm is headquartered. Table 1 illustrates the geographical distribution of firms in our sample by state. Although California, New York, and Texas dominate the number



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of firm headquarters, accounting for roughly one third of the sample, it is evident that there is substantial heterogeneity in headquarter location across the U.S. In the appendix, as a robustness check, we repeat our baseline tests excluding the three populous states and document similar findings.

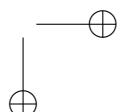
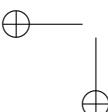
Table 1
Distribution of Firm Headquarter by State

Table 1 presents distribution of firms in our sample at the state level. ID is the geographic identifier of the state. Firm Count is the number of firms headquartered in a given state.

ID	State	Name	Firm Count	ID	State	Name	Firm Count
1	AL	Alabama	9	30	MT	Montana	2
2	AK	Alaska	1	31	NE	Nebraska	8
4	AZ	Arizona	37	32	NV	Nevada	20
5	AR	Arkansas	10	33	NH	New Hampshire	8
6	CA	California	373	34	NJ	New Jersey	71
8	CO	Colorado	45	35	NM	New Mexico	1
9	CT	Connecticut	44	36	NY	New York	158
10	DE	Delaware	10	37	NC	North Carolina	46
11	DC	D.C.	7	38	ND	North Dakota	2
12	FL	Florida	82	39	OH	Ohio	71
13	GA	Georgia	61	40	OK	Oklahoma	10
15	HI	Hawaii	8	41	OR	Oregon	11
16	ID	Idaho	5	42	PA	Pennsylvania	100
17	IL	Illinois	105	44	RI	Rhode Island	7
18	IN	Indiana	34	45	SC	South Carolina	12
19	IA	Iowa	14	46	SD	South Dakota	5
20	KS	Kansas	13	47	TN	Tennessee	34
21	KY	Kentucky	14	48	TX	Texas	173
22	LA	Louisiana	12	49	UT	Utah	21
23	ME	Maine	6	50	VT	Vermont	2
24	MD	Maryland	36	51	VA	Virginia	60
25	MA	Massachusetts	148	53	WA	Washington	44
26	MI	Michigan	37	54	WV	West Virginia	7
27	MN	Minnesota	40	55	WI	Wisconsin	36
28	MS	Mississippi	6	56	WY	Wyoming	0
29	MO	Missouri	29				

Using the day on which the first COVID-19 case is reported as the event day (COVID 0 dummy), we examine firm-level returns before and after the event day. We truncate our data at 10 calendar days post event day such that our post-event window is from day 1 to day 10 (Post COVID dummy). This choice aims to minimize the confounding effect due to other news arrivals. Figure 2 displays the evolution of COVID-19 cases by county. The figure reports time windows that contain the first reported case by county. The first window spans a longer time period as testing was initially sparse.

Table 2 presents summary statistics of firms in our study. Statistics (in millions of dollars) of total assets (Compustat variable: at), capital expenditure (capx), sales (sale), property, plants & equipment (ppent), and operating income (oibdp) for the baseline sample are shown in Panel A. There are a total of 99,729 trading day-firm observations in the



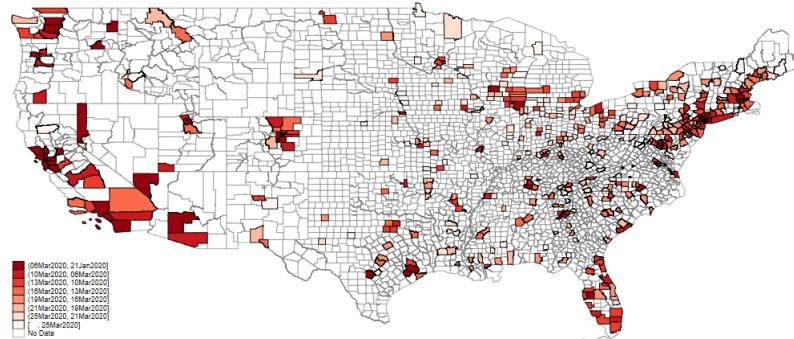


Figure 2

The map displays the evolution of the initial reported case of COVID-19 by county with the earliest reported cases represented by darker shades.

sample. These are large firms on average with mean total assets of \$14.78 billion and median of \$2.09 billion. They have substantial sales with mean of \$5.75 billion and median of \$973 million. These firms are also highly profitable with average operating income of more than \$1 billion. Taken together, Table 2 suggests the firms in our sample represent the largest companies in our economy. This matters for our identification strategy for the supply channel of the COVID-19 shocks. Because these companies are so large, it is unlikely their sales are highly concentrated in the same county where the firm is headquartered. Therefore, if there is any impact on their stock returns based on the initial reported case of COVID-19 in the county where the headquarters resides, it is more likely the effect is transmitted through the supply channel.

Table 2 Panels B, C, D, and E are firm summary statistics broken down by industry, defined by their Fama-French 17 (FF17) industry classification. For labor intensive firms (FF17 industry 1 to 13) firms in Panel B, the average total assets is \$9.91 billion and the average sales is \$7.35 billion. For retail (FF17 industry 15) firms in Panel C, the average total assets is \$10.09 billion and the average sales is \$15.79 billion. For financial (FF17 industry 16) firms in Panel D, the average total assets is \$38.49 billion and the average sales is \$5.01 billion. For services (FF17 industry 17) firms in Panel E, the average total assets is \$10.62 billion and the average sales is \$6.14 billion. The average operating income across all major industries is well over \$1 billion. We conclude that large firms with high sales volume are well distributed throughout various industries in our sample.

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Table 2
Summary Statistics of Firms in the Sample

Table 2 presents summary statistics of firms characteristics in the sample. Statistics (in millions of dollars) of total assets (Compustat variable: at), capital expenditure (capx), sales (sale), property, plants & equipment (ppent), and operating income (oibdp) are shown. Values recorded in 2019. Industries are broken down by Fama-French 17 (FF17) industry classification. Labor Intensive firms are those between FF17 industries 1 and 13. Retail firms are those in FF17 industry 15. Financial firms are those in FF17 industry 16. Services firms are those in FF17 industry 17.

Panel A: All Firms								
	count	mean	p25	p50	p75	sd	max	min
Assets - Total	99729	14775.68	610.88	2092.20	7220.00	74787.30	1951158.00	3.56
Capital Expenditures	99323	362.05	5.45	29.56	142.00	1503.04	24361.00	0.00
Sales/Turnover (Net)	99729	5745.31	230.21	973.41	3539.85	19793.99	280522.00	0.00
PP&E	83131	5266.56	93.35	520.76	2306.30	22871.97	493335.00	0.00
Operating Income	99408	1080.52	29.49	166.54	631.50	3946.62	76477.00	-922.83

Panel B: Labor Intensive								
	count	mean	p25	p50	p75	sd	max	min
Assets - Total	32456	9907.82	784.08	2341.82	7102.36	29058.21	362597.00	8.54
Capital Expenditures	32374	446.16	19.50	69.75	251.37	1571.04	24361.00	0.00
Sales/Turnover (Net)	32456	7352.77	589.46	2041.96	5681.10	20049.06	260174.00	0.00
PP&E	31650	6312.31	284.08	928.97	3165.00	27403.39	493335.00	0.40
Operating Income	32401	1272.14	66.73	272.88	893.90	3862.00	76477.00	-922.83

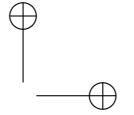
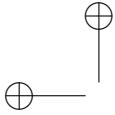
Panel C: Retail								
	count	mean	p25	p50	p75	sd	max	min
Assets - Total	3769	10091.59	867.89	2722.98	6660.10	28193.57	222449.00	22.66
Capital Expenditures	3714	417.76	31.67	138.29	328.36	721.78	3128.00	0.00
Sales/Turnover (Net)	3769	15793.69	946.90	3618.77	11486.00	39237.46	256776.00	0.00
PP&E	3645	6757.37	724.11	2312.82	5162.57	11714.67	52661.00	1.40
Operating Income	3769	1279.24	75.07	336.86	1352.70	2608.41	17073.00	-737.52

Panel D: Financial								
	count	mean	p25	p50	p75	sd	max	min
Assets - Total	18567	38486.07	2068.77	5656.96	18242.58	158637.87	1951158.00	7.50
Capital Expenditures	18407	147.88	2.52	8.52	38.84	759.12	8589.78	0.00
Sales/Turnover (Net)	18567	5013.08	174.53	506.43	1649.88	19619.29	242155.00	0.00
PP&E	6497	2013.07	71.51	266.44	1216.00	4798.63	34196.00	0.00
Operating Income	18517	1113.67	51.57	179.43	643.65	3822.03	44336.00	-66.50

Panel E: Services								
	count	mean	p25	p50	p75	sd	max	min
Assets - Total	23168	10615.33	532.02	1693.35	5828.02	40085.43	551669.00	3.56
Capital Expenditures	23113	421.47	7.89	38.69	138.79	2036.68	23548.00	0.00
Sales/Turnover (Net)	23168	6144.83	334.64	1160.64	3460.44	22494.64	280522.00	0.00
PP&E	22600	4704.43	97.56	441.92	1890.20	24840.76	357577.00	0.00
Operating Income	23061	1313.48	25.97	186.23	654.50	5368.56	59286.00	-916.08

2. Empirical Analysis

In this section, we examine the impact of the COVID-19 pandemic on firm-level equity returns. We devise a natural experiment by combining the geographical heterogeneity of firm headquarter location with the staggered spread of the virus to identify the causal relationship between COVID-19 and firm performance. The date on which the first case of COVID-19 is reported in a given county in the U.S. defines our event. The differential timing of the first reported case across counties allows us to pin down the treatment effect of COVID-19 on the cross-section of firms. Employing difference-in-difference estimations and spline regressions, we compare stock performance of firms before and



after the first reported case as well as between firms located in COVID-19 and non-COVID-19 (no reported COVID-19 case during our sample period) counties.

2.1 The Impact of COVID-19 on the Cross-Section of Returns

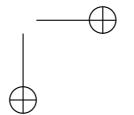
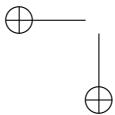
To establish our baseline result, we perform a diff-in-diff estimation of firm-level returns in the event window around the first confirmed case of COVID-19, or event day, in the county a given firm headquarter is located. Specifically, we regress the panel of daily log returns on the COVID 0 dummy and the Post COVID dummy as shown in Equation (1):

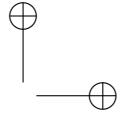
$$\log(\text{Return})_{ijct} = \alpha + \beta \text{COVID 0}_{ct} + \gamma \text{Post COVID}_{ct} + \psi_i + \rho_j + \delta_c + \phi_t + \varepsilon_{ijct}. \quad (1)$$

Coefficient loadings β and γ are meant to capture the difference in returns on the day of the event and in the 10 day post-event window, respectively, compared with returns prior to the event day. Returns of firms residing in a county which never reported a COVID-19 case in the sample period also serve as part of the control group. To control for unobserved heterogeneity along several dimensions, we include firm (ψ_i), industry (ρ_j), county (δ_c), and day (ϕ_t) fixed effects in the analysis. Standard errors are double clustered at the county and trading day levels. There are 99,729 trading day-firm observations in the full sample.

Results of the baseline diff-in-diff regression are presented in Column (1) of Table 3. Although the estimated coefficient on the COVID 0 dummy is insignificant, the estimated coefficient on the Post COVID dummy is negative and statistically significant at the 5% level. The point estimate of -0.00274 suggests that returns are on average 27 bps lower in the 10-day post-event window relative to returns in the control group. In Column (2), instead of using raw returns, we use total returns as the dependent variable. Total returns are obtained from Bloomberg, and adjust for near term cash dividends. The point estimate on the Post COVID dummy is -0.00256, very similar to the counterpart in Column (1). Using excess return over the effective Fed funds rate leaves the results unchanged. This also holds true for all results discussed below.

Given the baseline finding showing there is a localized impact of COVID-19 on firm-level returns, we postulate that this effect should be stronger in counties where the spread of the virus is more intense. We then construct a growth intensity measure for each affected county using the number of days for reported cases to go over 100 (see Figure 3). Employing only observations in high growth intensity counties (20 days or less), we repeat the diff-in-diff regression in Equation (1) and tabulate results in Columns (3) and (4) of Table 3. For raw returns,





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Table 3
Difference-in-Difference Regression Results of Firm-Level Returns on the COVID-19 Shock

Table 3 presents difference-in-difference regression results. The sample period is between January 1, 2020 and March 20, 2020. The regression equation is:

$$\log(Return)_{ijct} = \alpha + \beta \text{COVID}_0_{ct} + \gamma \text{Post COVID}_{ct} + \psi_i + \rho_j + \delta_c + \phi_t + \varepsilon_{ijct},$$

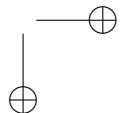
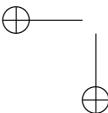
where i, j, c and t represent firm, industry, county, and day, respectively. Estimated coefficients β and γ are shown. Both raw returns and total returns (including dividends) are used as dependent variables. The COVID 0 dummy denotes the day on which the first case of COVID-19 is reported in the same county where the firm is headquartered in. The Post COVID dummy encompasses 10 days after the event day. The high (COVID-19) growth subsample includes only firms residing in counties where the growth between 1 and 100 reported cases took less than 20 days. Robust standard errors with double clustering at the county and day level are used in reporting the t -statistics in parentheses.

	Full sample		High Growth	
	(1) Raw Return	(2) Total Return	(3) Raw Return	(4) Total Return
COVID 0	-0.000841 (-0.49)	-0.000809 (-0.49)	-0.000699 (-0.28)	-0.000789 (-0.34)
Post COVID	-0.00274** (-2.08)	-0.00256* (-1.97)	-0.00499** (-2.14)	-0.00465** (-2.13)
Constant	-0.00744*** (-37.04)	-0.00609*** (-33.49)	-0.00821*** (-20.92)	-0.00675*** (-20.15)
Firm FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	99729	99729	58870	58870
R^2	0.432	0.410	0.420	0.398

the γ coefficient is still negative and significant at the 5% level; more importantly, the magnitude has increased to -0.00499, almost doubling relative to the estimate in Column (1). For total returns, the coefficient loading strengthened from -0.00256 in Column (2) to -0.00465 in Column (4). A graphical representation can be seen in Figure 4. The divergence between cumulative returns in high growth versus low growth intensity counties widens dramatically after the first reported case. These findings validate our hypothesis that in locations considered “hot zones” (likely more densely populated), returns are more negatively affected by the spread of coronavirus.

2.2 The Timing of the Impact of COVID-19

To further dissect the response of firm-level returns to the COVID-19 shocks, we utilize spline regressions around the day the first coronavirus case is reported in a county. In particular, we regress firm level returns on 15 dummies assigned to each day around the event. We assign individual dummies to each of the days in the post-event window, COVID (+1) to COVID (+10). In the pre-event window, we assign individual dummies to each of the five calendar days leading up to COVID 0 (COVID (-5)



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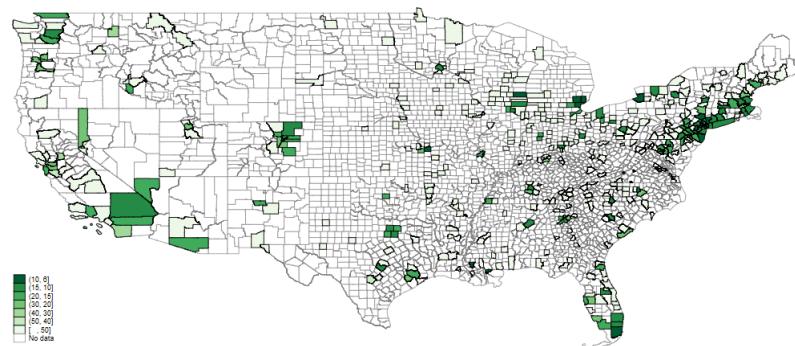


Figure 3

This map displays the growth intensity of COVID-19 cases by county. Growth intensity is defined as the number of days to reach 100 reported cases measured from the day the initial case was reported in a county.

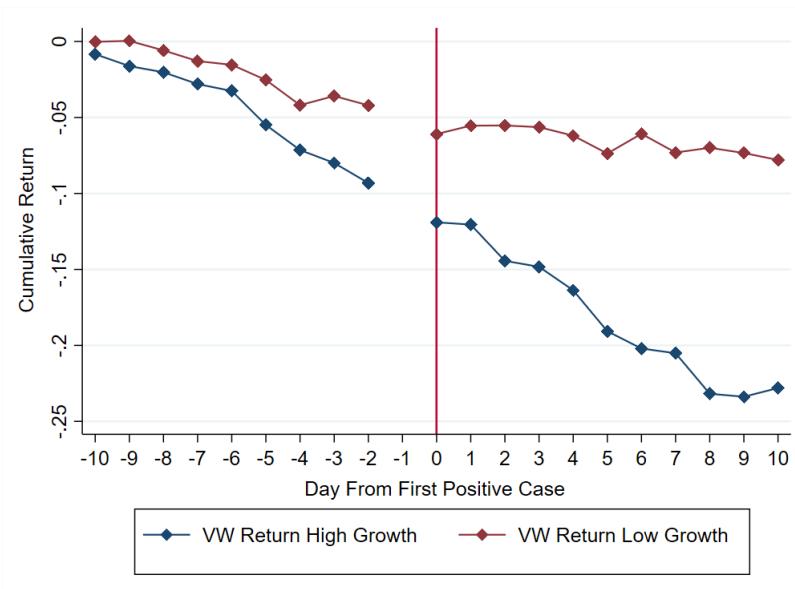
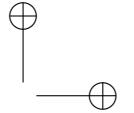


Figure 4

Value weighted cumulative returns for firms relative to the first day (0) of a reported positive test in the county where the firm is headquartered. The sample is split based on the median (18 days) of days from the first reported case to the one hundredth reported case.

to COVID (-1)), as well as one dummy to capture all the days prior to the pre-event window (COVID <(-5)). The regression specification is



shown in Equation (2),

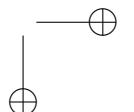
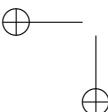
$$\begin{aligned} \log(Return)_{ijct} = & \sum_{k=3}^{<5} \Phi_k \text{COVID } (-k)_{ct} + \beta \text{COVID } 0_{ct} \\ & + \sum_{k=1}^{10} \Psi_k \text{COVID } (+k)_{st} + \psi_i + \rho_j + \delta_c + \phi_t + \varepsilon_{ijd} \end{aligned} \quad (2)$$

where the COVID (-k) dummies capture days leading up to the event day, the COVID 0 dummy represents the day of the first reported case, and the COVID (+k) dummies are assigned to individual days following the event. The COVID (-2) and COVID (-1) dummies are dropped so the returns on those days serve as the benchmark.⁷ As mentioned previously, all trading days from the beginning of the sample up to six days before the event day are designated by the COVID <(-5) dummy. We also truncate the data at 10 days post the event. Similar to Equation (1), firm, industry, county, and day fixed effects are included to control for unobserved heterogeneity.

Spline regression results are documented in Table 4. Column (1) represents the full sample using raw returns, Column (2) represents the full sample using total returns, Column (3) represents the high COVID growth intensity sample using raw returns, and Column (4) represents the high COVID growth intensity sample using total returns. Across the four columns, none of the coefficients on the dummies denoting days immediately before the event day, COVID (-5) to COVID (-3), are statistically significant. This suggests there is no pre-trend leading up to the event, thus satisfying the parallel trend assumption of diff-in-diff estimation. The second item of interest is that the COVID 0 dummy is not significant across the four columns of Table 4. There does not appear to be an immediate impact of reported virus cases to stock returns on the same day.

In the post event window, estimated coefficients on the COVID (+k) dummies are generally negative. In Table 4 Columns (1) and (2) for the full sample, there is no statistical significance on these coefficients until COVID +8. Although the coefficient loadings on the Post COVID dummy in Table 3 Columns (1) and (2) are negative and significant, it takes about a week for the stock valuation impact to be realized. However, when the sample is narrowed to high growth intensity counties, results shown in Column (3) and Column (4) of Table 4 demonstrate

⁷ Since the day on which the first COVID-19 case is reported in a county can fall on a Sunday, we drop both COVID (-2) and COVID (-1) dummies to allow for firms located in those counties to have at least one day of pre-COVID return to serve as the benchmark for post-COVID returns to be measured against. Our results go through if we only drop the COVID (-1) dummy.



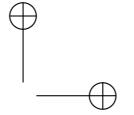
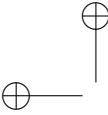


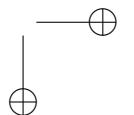
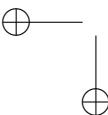
Table 4
Spline Regression Results of Firm-Level Returns on the COVID-19 Shock

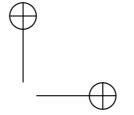
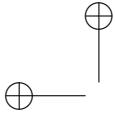
Table 4 presents spline regression results. The sample period is between January 1, 2020 and March 20, 2020. The regression specification is shown in Equation (2). Both raw returns and total returns (including dividends) are used as dependent variables. The COVID 0 dummy denotes the day on which the first case of COVID-19 is reported in the same county where the firm is headquartered in. The COVID <(-5) dummy encompasses all trading days prior to the 5-day window leading up to the event day. The high (COVID-19) growth subsample includes only firms residing in counties where the growth between 1 and 100 reported cases took less than 20 days. All regressions include firm, industry, county, and day fixed effects. Robust standard errors with double clustering at the county and day level are used in reporting the *t*-statistics in parentheses.

	Full sample		High Growth	
	(1) Raw Return	(2) Total Return	(3) Raw Return	(4) Total Return
COVID <(-5)	-0.000313 (-0.23)	-0.000580 (-0.41)	-0.00188 (-0.95)	-0.00194 (-0.87)
COVID (-5)	-0.000730 (-0.44)	-0.00113 (-0.66)	-0.000551 (-0.26)	-0.000626 (-0.27)
COVID (-4)	-0.00174 (-0.92)	-0.00181 (-0.91)	-0.00197 (-0.58)	-0.00148 (-0.44)
COVID (-3)	0.00117 (0.80)	0.000712 (0.47)	0.00142 (0.67)	0.00123 (0.54)
COVID 0	-0.00109 (-0.55)	-0.00131 (-0.63)	-0.00146 (-0.58)	-0.00160 (-0.60)
COVID +1	0.000209 (0.06)	-0.000163 (-0.05)	-0.00175 (-0.35)	-0.00171 (-0.34)
COVID +2	-0.00375 (-1.56)	-0.00392 (-1.61)	-0.00642** (-2.16)	-0.00653** (-2.16)
COVID +3	-0.00394 (-1.34)	-0.00377 (-1.36)	-0.00558 (-1.36)	-0.00508 (-1.32)
COVID +4	-0.00562 (-1.17)	-0.00410 (-1.00)	-0.0110* (-1.73)	-0.00845 (-1.61)
COVID +5	-0.00233 (-1.00)	-0.00293 (-1.16)	-0.00555 (-1.64)	-0.00592 (-1.64)
COVID +6	-0.00322 (-1.16)	-0.00343 (-1.27)	-0.00383 (-1.19)	-0.00404 (-1.28)
COVID +7	0.000306 (0.07)	-0.000548 (-0.13)	-0.0000308 (-0.01)	-0.000953 (-0.22)
COVID +8	-0.00754* (-1.85)	-0.00802** (-2.05)	-0.0100* (-1.74)	-0.0103* (-1.94)
COVID +9	-0.00415 (-1.16)	-0.00450 (-1.25)	-0.00811* (-1.77)	-0.00836* (-1.93)
COVID +10	-0.0000193 (-0.01)	0.000146 (0.04)	-0.00184 (-0.37)	-0.000830 (-0.16)
Constant	-0.00715*** (-5.57)	-0.00554*** (-4.01)	-0.00664*** (-3.80)	-0.00511** (-2.53)
Observations	99729	99729	58870	58870
R ²	0.433	0.411	0.421	0.398

that the impact of the COVID shock is concentrated on day 2 and after from the initial reported case. The estimated coefficient of -0.00642 and -0.00653, in Column (3) and Column (4) respectively, are significant at the 5%. This implies the average return is roughly 65 bps lower 2 days after the event day relative to the 2 days immediately prior to the event day.

We conclude from the spline exercise that the first reported case of COVID-19 in the county where a firm is headquartered has a significant negative effect on its stock return, but there is a delay between the





COVID-19 and the Cross-Section of Equity Returns: Impact and Transmission

reporting date and the stock reaction date. This delay is minimized in counties which have high rates of virus spread.

3. How Does COVID-19 Affect the Cross-Section of Returns?

The COVID-19 pandemic is all encompassing. For the financial markets, other than generating unprecedented uncertainty (or risk), it also changes investors' expectations about the future level of earnings and dividends. In this section, we examine a number of potential channels through which the pandemic potentially impacts firms. In what follows, we focus on four aspects of the COVID-19 crisis: the labor supply channel, the uncertainty channel, the government spending and monetary policies channel, and the cash flow expectations channel.

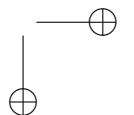
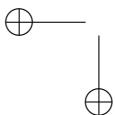
3.1 The Labor Supply Channel

We start by investigating whether our evidence of localized negative firm returns is consistent with the pandemic having a negative effect on local labor productivity. If this is indeed the case, we would expect firms relying more on labor input in the production function to be asymmetrically affected. To test this hypothesis, we focus on "labor intensive" firms and repeat the diff-in-diff analysis. Labor intensive firms are defined to encompass Fama-French 17 industry codes between 1 and 13, which excludes firms in utilities, retail, financial, and services industries. Results are shown in Table 5.

For both raw returns and total returns, coefficient loadings on the Post COVID dummy in the labor intensive sub-sample are negative and statistically significant at the 10% level in Columns (1) and (2). In terms of magnitude, -0.00451 and -0.00386 respectively, these estimates are larger than the full sample estimates in Tables 3, Columns (1) and (2). Furthermore, when we focus on labor intensive firms headquartered in high COVID growth intensity counties, the γ coefficients are significant at the 5% level. This can be seen from Columns (3) and (4) in Table 5. When compared with Columns (1) and (2) in Table 3, the point estimates suggest that labor intensive firms located in high COVID growth intensity counties experience a much larger drop in equity value.

To further examine how labor supply is affected by the outbreak of the pandemic, we use data from the University of Maryland COVID-19 Impact Analysis Platform.⁸ Specifically, we obtain the county-level variable "% staying home" to investigate how the first reported case of coronavirus in a given county affects the population's ability to go to work. Similar to our analysis of firm-level returns, we perform a difference-in-difference estimation and a spline regression at the county

⁸ <https://data.covid.umd.edu/>



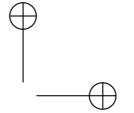
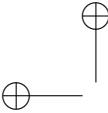


Table 5
Difference-in-Difference Regression Results of Firm-Level Returns on the COVID-19 Shock - Labor Intensive Firms

Table 5 presents difference-in-difference regression results. The sample period is between January 1, 2020 and March 20, 2020. The regression equation is:

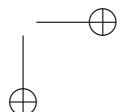
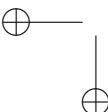
$$\log(Return)_{ijct} = \alpha + \beta \text{COVID 0}_{ct} + \gamma \text{Post COVID}_{ct} + \psi_i + \rho_j + \delta_c + \phi_t + \varepsilon_{ijct},$$

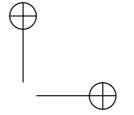
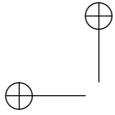
where i, j, c and t represent firm, industry, county, and day, respectively. Estimated coefficients β and γ are shown. Both raw returns and total returns (including dividends) are used as dependent variables. The COVID 0 dummy denotes the day on which the first case of COVID-19 is reported in the same county where the firm is headquartered in. The Post COVID dummy encompasses 10 days after the event day. The labor intensive subsample includes only firms in the Fama-French 17 industries 1 to 13 (excluding utilities, retail, financial, and services). Robust standard errors with double clustering at the county and day level are used in reporting the t -statistics in parentheses.

	Labor Intensive		High Growth & Labor Intensive	
	(1) Raw Return	(2) Total Return	(3) Raw Return	(4) Total Return
COVID 0	-0.0000996 (-0.04)	0.000150 (0.06)	-0.00606 (-1.32)	-0.00541 (-1.29)
Post COVID	-0.00451* (-1.68)	-0.00386* (-1.71)	-0.0126** (-2.23)	-0.0108** (-2.38)
Constant	-0.00834*** (-18.63)	-0.00705*** (-19.55)	-0.00852*** (-9.07)	-0.00723*** (-9.80)
Firm FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	32456	32456	19917	19917
R ²	0.443	0.436	0.455	0.451

level employing “% staying home” as the dependent variable. The results are shown in Table 6. The sample period is from January 1, 2020 to March 20, 2020. In Column (1), the difference-in-difference estimates on the COVID 0 dummy and the Post COVID dummy are both positive and significant at the 1% level. For example, after the first case of COVID-19 is reported in a given county, the percent staying home goes up by 1.609% in the 10-day post-window relative to all days prior to the news. From the spline regression results displayed in Column (2) of Table 6, we see that there is no parallel trend violation as all dummies before COVID 0 are insignificant, and all indicator dummies from COVID 0 up to COVID +10 are positive and highly statistically significant, which validates the difference-in-difference finding in Column (1). Thus, we conclude that the first reported case of coronavirus in a county has a noticeably negative effect on labor supply in the same county as the population stay at home more.

Next, we link the results documented in Table 6 to firm-level returns. To this end we conjecture that firms located in counties with a large increase in the percentage staying home should have worse stock performance in comparison to firms residing in counties with small changes in percent staying home. That is, if labor supply is indeed





COVID-19 and the Cross-Section of Equity Returns: Impact and Transmission

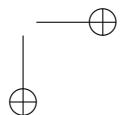
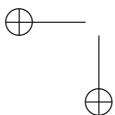
Table 6
Percent Staying Home After First Reported COVID-19 Case

Table 6 regresses percentage of people staying home by county on date dummy variables around the event day. Data for the percentage of each county staying home is sourced from Maryland Transportation Institute. The sample period is between January 1, 2020 and March 20, 2020. The COVID 0 dummy denotes the day on which the first case of COVID-19 is reported in the county. The Post COVID dummy encompasses 10 days after the event day. The COVID <(-5) dummy encompasses all trading days prior to the 5-day window leading up to the event day. Robust standard errors with double clustering at the county and day level are used in reporting the *t*-statistics in parentheses.

	(1) % staying home	(2) % staying home
COVID <(-5)		-0.0928 (-0.65)
COVID (-5)		-0.207 (-1.40)
COVID (-4)		-0.114 (-0.90)
COVID (-3)		-0.112 (-1.10)
COVID 0	0.387*** (3.02)	0.341*** (5.22)
COVID +1		0.588*** (4.02)
COVID +2		0.928*** (4.24)
COVID +3		1.124*** (3.44)
COVID +4		1.454*** (4.00)
COVID +5		1.651*** (4.10)
COVID +6		1.817*** (5.05)
COVID +7		2.094*** (5.63)
COVID +8		2.382*** (5.45)
COVID +9		2.831*** (6.58)
COVID +10		2.677*** (3.79)
Post COVID	1.609*** (4.62)	
Constant	18.58*** (754.40)	18.67*** (163.43)
County FE	Yes	Yes
Day FE	Yes	Yes
Observations	21996	21996
R ²	0.802	0.804

a factor in the transmission of the COVID-19 news to the financial market, firms located in areas where labor is most negatively impacted by the pandemic should be penalized more by investors. To test this hypothesis, we sort counties into bins according to the change in percent staying home in a window around the first reported case of coronavirus.⁹ Then, we assign a staying home dummy to all firms headquartered in

⁹ We perform the sort using the median as well as terciles with consistent results. For simplicity, we only report results using the median below.



counties with large increases in percent staying home. In the return regression, we interact this staying home dummy with the COVID 0 dummy and the Post COVID dummy, as defined previously. The full regression specification is:

$$\begin{aligned} \log(\text{Return})_{ijct} = & \alpha + \beta \text{COVID 0}_{ct} + \gamma \text{Post COVID}_{ct} + \tilde{\beta} \text{COVID 0}_{ct} \times \mathbb{I}_c^{SH} \\ & + \tilde{\gamma} \text{Post COVID}_{ct} \times \mathbb{I}_c^{SH} + \rho_j + \phi_t + \varepsilon_{ijct}, \end{aligned}$$

where \mathbb{I}^{SH} is the staying home dummy. $\tilde{\beta}$ and $\tilde{\gamma}$ are estimated coefficients for firms located in counties experiencing large staying at home increases following the COVID-19 news. Results can be found in Table 7.

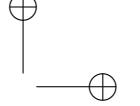
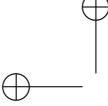
Table 7 Columns (1) and (2) report regression results when the county-level change in percent staying home is measured from 5 days prior to the first reported case to 10 days after, Δ % Stay Home (-5,+10), whereas Columns (3) and (4) report results when the change is measured from 10 days before the first reported case to 10 days after, Δ % Stay Home (-10,+10). In all scenarios, we find that the Post COVID dummy by itself is no longer statistically significant. On the other hand, all coefficient loadings on the interaction between the Post COVID dummy and the staying home dummy are negative and statistically significant at the 5% level. Firms headquartered in counties experiencing large rises in percent staying home earn 50 basis points lower returns relative to those firms residing outside of these counties in days following the first reported case of coronavirus.

Overall, the findings documented in this section verify our conjecture that the labor supply channel plays an important role in the transmission of the COVID-19 shock to firm performance.

3.2 COVID-19 Induced Uncertainty and Returns

With no known cure or vaccine as of May 2020, the economic outlook around the world is highly variable. Citizens are left wondering when state-by-state shelter-in-place orders will be lifted, when social distancing measures will be relaxed, and when eating and drinking establishments will be allowed to open up again. Medical experts have also warned about the risk of a second wave of contagion as the lockdown measures are gradually relaxed (see, e.g., Xu and Li, 2020). At the same time, due to the lack of historical precedence of comparable events, economists and market participants are perplexed by the magnitude and length with which output, demand, employment, earnings, etc., are expected to decline.¹⁰ In a recent paper, Baker, Bloom, Davis, and

¹⁰ The largely unanticipated nature of the current pandemic is confirmed by the widely read Global Risk Report: the World Economic Forum did not report a global pandemic among the most likely risks. The first five most likely risks were related to the environment, with



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Table 7
Interaction Results of Firm-Level Returns on COVID-19 Shock and Percent Staying Home

Table 7 presents interaction regression results. The sample period is between January 1, 2020 and March 20, 2020. We interact COVID0 and Post COVID dummies with indicators for whether a county has experienced above median change in the percentage of the population staying home. We use windows of both 5 and 10 days prior to the event day to a period of 10 days after the event day.

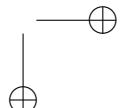
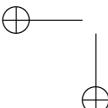
$$\begin{aligned} \log(\text{Return})_{ijct} = & \alpha + \beta \text{COVID 0}_{ct} + \gamma \text{Post COVID}_{ct} + \tilde{\beta} \text{COVID 0}_{ct} \times \mathbb{I}_c^{SH} \\ & + \tilde{\gamma} \text{Post COVID}_{ct} \times \mathbb{I}_c^{SH} + \delta_c + \phi_t + \varepsilon_{ijct}, \end{aligned}$$

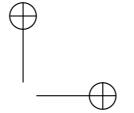
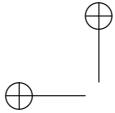
where i, j, c and t represent firm, industry, county, and day, respectively. Estimated coefficients β , γ , $\tilde{\beta}$, and $\tilde{\gamma}$ are shown. Both raw returns and total returns (including dividends) are used as dependent variables. The COVID 0 dummy denotes the day on which the first case of COVID-19 is reported in the same county where the firm is headquartered in. The Post COVID dummy encompasses 10 days after the event day. \mathbb{I}_c^{SH} is a dummy variable which turns to 1 if a county is designated above median change in percent staying home. Robust standard errors with double clustering at the county and day level are used in reporting the t -statistics in parentheses.

	$\Delta \% \text{ Stay Home } (-5, +10)$		$\Delta \% \text{ Stay Home } (-10, +10)$	
	(1)	(2)	(3)	(4)
	Raw Return	Total Return	Raw Return	Total Return
COVID 0	-0.002 (-0.71)	-0.001 (-0.61)	-0.002 (-0.95)	-0.002 (-0.95)
Post COVID	-0.001 (-0.68)	-0.001 (-0.62)	-0.001 (-1.20)	-0.001 (-1.10)
$\text{COVID 0} \times \mathbb{I}^{SH}$	0.001 (0.30)	0.001 (0.23)		
$\text{Post COVID} \times \mathbb{I}^{SH}$	-0.005** (-2.03)	-0.005** (-2.10)		
$\text{COVID 0} \times \mathbb{I}^{SH}$			0.002 (0.47)	0.002 (0.54)
$\text{Post COVID} \times \mathbb{I}^{SH}$			-0.005** (-2.27)	-0.005** (-2.23)
Constant	-0.007*** (-48.50)	-0.006*** (-37.75)	-0.007*** (-46.02)	-0.006*** (-36.15)
Industry FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	97969	97969	97969	97969
R^2	0.436	0.414	0.436	0.414

Terry (2020a) use three different forward-looking uncertainty measures to document the enormous rise in economic uncertainty as of March of 2020. Further, their economic model attributes 60% of the forecasted output contraction by Q4 of 2020 (mean of 11%) to COVID-19-induced uncertainty. Figure 5 plots the quarter-on-quarter GDP forecast

climate change listed as the main threat to the planet in 2020 (c.f. WEF Global Risks Perception Survey 2019–2020). However, we cannot rule out that alert investors may have taken into account pandemic concerns in their portfolio choices in advance of the current COVID event. See, e.g., Pagano et al. (2020) for an analysis of firm returns before the disaster.





dispersion from professional forecasters between 1968 and 2020.¹¹ The spike at the end of this series corresponds to a dramatic increase in uncertainty unlike anything we have experienced in the post-war period.

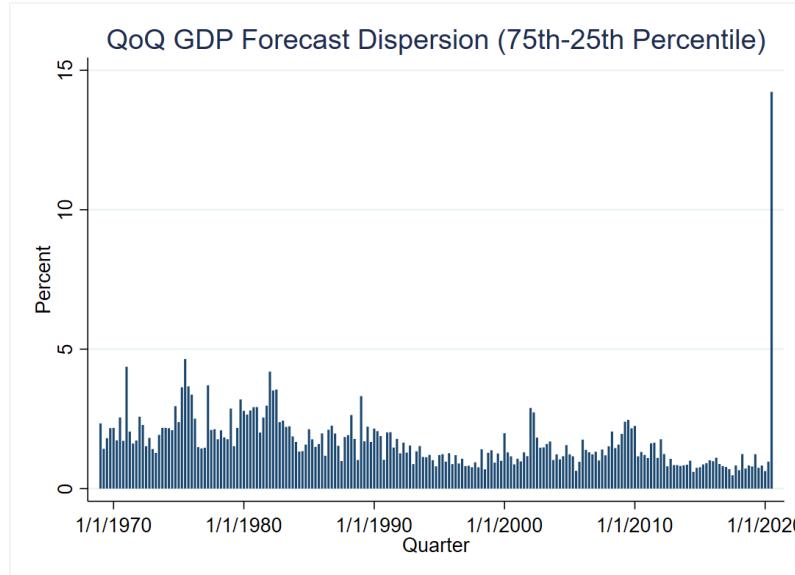


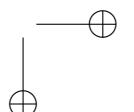
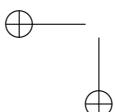
Figure 5
GDP forecast dispersion from professional forecasters between 1968 and 2020.

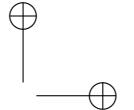
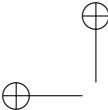
We attempt to tease out the impact of COVID-19 on equity returns due to the uncertainty it produces. To that end, we employ data from the work of Hassan, Hollander, van Lent, and Tahoun (2020) (HHvLT herein). These authors use textual analysis of earning call transcripts to obtain firm-level measures of COVID-19 exposure as well as sentiment and risk associated with that exposure. The sentiment measure is related to the conditional mean of the shock, whereas the risk measure is related to the variance of the shock. By construction, the risk measure captures the management’s attitude towards COVID-19 generated uncertainty.¹²

We merge our return dataset with the HHvLT dataset from 2020Q2. The two variables of interest are COVID Net Sentiment and COVID Risk. Net sentiment can be positive or negative depending on the firm’s

¹¹ According to Bloomberg data as of April 16, 2020. Historical data from Philadelphia Fed.

¹² The text-classification approach used to construct the risk and sentiment measures has been validated in recent work by Hassan et al. (2019) in the context of measuring a firms exposure to, e.g., political risk.





outlook due to the COVID shock. Risk can be 0 or a positive value if the firm expresses an uncertain outlook following the shock. After merging, we construct a COVID Risk dummy \mathbb{I}^{Risk} to denote any firm in our sample that has a non-zero Risk measure in the first quarter of 2020. We then eliminate all firms with a positive Net Sentiment value since these firms are expecting to benefit from the pandemic.

To see if COVID-19 induced uncertainty is associated with the decline in equity following the first reported case of coronavirus in the same county where the firm is headquartered, we extend the diff-in-diff regression from Section 2.1 to include interaction terms with \mathbb{I}^{Risk} . In particular, the regression specification is:

$$\begin{aligned} \log(Return)_{ijct} = & \alpha + \beta \text{COVID 0}_{ct} + \gamma \text{Post COVID}_{ct} + \beta' \text{COVID 0}_{ct} \times \mathbb{I}_i^{Risk} \\ & + \gamma' \text{Post COVID}_{ct} \times \mathbb{I}_i^{Risk} + \psi_i + \rho_j + \delta_c + \phi_t + \varepsilon_{ijct}, \end{aligned}$$

where β' and γ' are coefficient loadings on the interaction between the COVID 0 dummy and the Post COVID dummy, respectively, with the COVID Risk dummy. Similar to the baseline diff-in-diff regressions, firm, industry, county, and day fixed effects are used as controls. Results are presented in Tables 8.

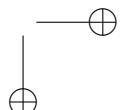
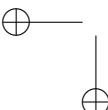
In Table 8, we show results for the full sample and the high COVID-19 growth intensity sample. Notice the γ' coefficients in the fourth row are negative and statistically significant across the columns for both raw and total returns. This means that firms affected by COVID-19 induced uncertainty (COVID Risk > 0) experience even lower returns after the event day (COVID 0) relative to those firms not affected by this uncertainty (COVID Risk = 0). Overall, we find confirmation in these interaction regressions that COVID-19 induced uncertainty drives firm-level equity returns after the shock is realized.

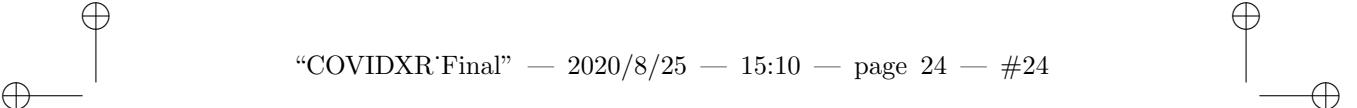
3.3 Sensitivity to Government Spending and Monetary Policies

In this section, we investigate whether the stability of recurrent government purchases makes firms more resilient to the economic shock induced by the pandemic. Indeed, in the context of the 2008-09 financial crisis, Goldman (2019) shows that government contractors – defined as firms deriving more than 10% of sales from the federal government – experienced smaller declines in sales, profitability and market values than otherwise similar firms.

To assess the (direct) effect of government purchases at the firm level, we compare the stock performance of government contractors (GC) and other firms (non-GC) during the pandemic.¹³ The regression

¹³ Government purchases *directly* affect the performance of government contractors that derive a large portion of their revenues from those purchases; in turn, government





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Table 8
Interaction Regression Results of Firm-Level Returns on the COVID-19 Shock and Risk (Uncertainty)

Table 8 presents interaction regression results. The sample period is between January 1, 2020 and March 20, 2020. We merge our sample with the Hassan, Hollander, van Lent, and Tahoun (2020) dataset from 2020Q1. Their data using textual analysis contains firm-level exposure to COVID-19. In particular, we use variables Net Sentiment and Risk to measure the first (level) and second (uncertainty) moment, respectively, of the COVID-19 shock to each firm. All firms with a positive Net Sentiment with respect to the COVID-19 shock are dropped. The regression equation is:

$$\begin{aligned} \log(Return)_{ijct} = & \alpha + \beta \text{COVID 0}_{ct} + \gamma \text{Post COVID}_{ct} + \beta' \text{COVID 0}_{ct} \times \mathbb{I}_i^{Risk} \\ & + \gamma' \text{Post COVID}_{ct} \times \mathbb{I}_i^{Risk} + \psi_i + \rho_j + \delta_c + \phi_t + \varepsilon_{ijct}, \end{aligned}$$

where i, j, c and t represent firm, industry, county, and day, respectively. Estimated coefficients β , γ , β' , and γ' are shown. Both raw returns and total returns (including dividends) are used as dependent variables. The COVID 0 dummy denotes the day on which the first case of COVID-19 is reported in the same county where the firm is headquartered in. The Post COVID dummy encompasses 10 days after the event day. \mathbb{I}_i^{Risk} is a dummy variable which turns to 1 if a firm has a COVID-19 Risk value greater than 0 in 2020Q1. The high (COVID-19) growth subsample includes only firms residing in counties where the growth between 1 and 100 reported cases took less than 20 days. Robust standard errors with double clustering at the county and day level are used in reporting the t -statistics in parentheses.

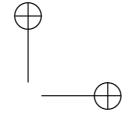
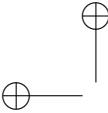
	Full sample		High Growth	
	(1) Raw Return	(2) Total Return	(3) Raw Return	(4) Total Return
COVID 0	-0.000363 (-0.23)	-0.000275 (-0.18)	-0.00164 (-0.68)	-0.00176 (-0.78)
Post COVID	-0.00185* (-1.72)	-0.00159 (-1.57)	-0.00407* (-1.79)	-0.00372* (-1.74)
COVID 0 $\times \mathbb{I}_i^{Risk}$	0.000474 (0.10)	0.000413 (0.09)	0.00516 (0.68)	0.00529 (0.71)
Post COVID $\times \mathbb{I}_i^{Risk}$	-0.00251** (-2.61)	-0.00261*** (-2.83)	-0.00322* (-1.82)	-0.00347** (-2.27)
Constant	-0.00736*** (-39.73)	-0.00610*** (-37.76)	-0.00821*** (-21.15)	-0.00681*** (-20.46)
Firm FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	82299	82299	50048	50048
R ²	0.452	0.436	0.445	0.427

specification is:

$$\begin{aligned} \log(Return)_{ijct} = & \alpha + \beta \text{COVID 0}_{ct} + \gamma \text{Post COVID}_{ct} + \tilde{\beta} \text{COVID 0}_{ct} \times \mathbb{I}_i^{GC} \\ & + \tilde{\gamma} \text{Post COVID}_{ct} \times \mathbb{I}_i^{GC} + \psi_i + \rho_j + \delta_c + \phi_t + \varepsilon_{ijct}, \end{aligned}$$

contractors performance may also spill over onto other firms, e.g., along the supply chains. We study only the direct effect.





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where \mathbb{I}_i^{GC} is a dummy variable that flags government contractor firm i .¹⁴ The parameters of interest are $\tilde{\beta}$ and $\tilde{\gamma}$ – the difference-in-differences estimate of the effect of being a government contractor during the pandemic.

Table 9 presents the regression results. Columns (1) and (2) summarize findings in the full sample. We observe that none of the coefficient loadings on the interaction terms is statistically significant. This implies that following the first reported case of coronavirus in a county, government contractors' financial performance is not better compared to non-contractor firms. This result suggests that the current economic contraction and the one observed in the financial crisis are fundamentally different phenomena. Indeed, while the stability of government purchases provided government contractors with a hedge during the 2008-09 financial crisis (Goldman, 2019), this effect is largely absent in the current pandemic.

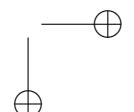
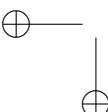
Most large government contractors belong to the manufacturing industry (defined as belonging to Fama-French industry code 1 to 13). Hence, it is possible, that they are particularly susceptible to negative labor supply shocks. As a result, despite the fact that GC's benefit from the stability of having government contracts during economic downturns, the COVID-19 pandemic adversely affects these firms' productivity through the labor supply channel, as discussed in Section 3.1. To test this hypothesis, we focus on the subsample of labor intensive firms and re-estimate the regressions including the GC dummy. Results are presented in Columns (3) and (4) of Table 9.

Within the labor intensive subsample, estimated coefficients on the COVID 0 $\times \mathbb{I}^{GC}$ and the Post COVID $\times \mathbb{I}^{GC}$ terms are all negative and statistically significant. In particular, the interaction between the post-COVID dummy and the GC dummy exhibits high statistical significance at the 1% level in Columns (3) and (4). GC's have lower equity returns than non-GC's in labor intensive industries in the aftermath of the first reported COVID case. Hence, this evidence suggests that the strain on labor supply due to the pandemic appears to outweigh the benefits of stable demand for the GC firms.¹⁵

Next, we investigate whether heterogeneous exposure to monetary policy can generate the return reaction to COVID-19 news. To the

¹⁴ We kindly thank Jim Goldman for providing us with the GC identifier. Specifically GC equals one if a firm reports the federal government as a significant client at any fiscal year-end between 2004q4 and 2007q2.

¹⁵ This evidence is suggestive as there are several potential channels at work. For example, investors may expect massive fiscal stimulus that, in turn, would require diverting funds from, e.g., the defense sector; this would reduce the value of government suppliers. It may also simply be the case that government contractors are headquartered in counties where the intensity of the pandemic is stronger. Disentangling the various channels is an interesting avenue for future research.



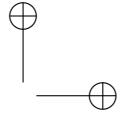
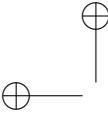


Table 9
Interaction Regression Results of Firm-Level Returns on the COVID-19 Shock and Government Contractors

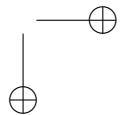
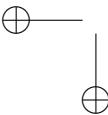
Table 9 presents interaction regression results. The sample period is between January 1, 2020 and March 20, 2020. We merge our sample with the Goldman (2019) dataset, where the author identify government contractors from Compustat. These are firms deriving more than 10% of sales from the federal government. The regression equation is:

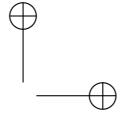
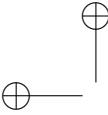
$$\begin{aligned} \log(Return)_{ijct} = & \alpha + \beta \text{COVID 0}_{ct} + \gamma \text{Post COVID}_{ct} + \tilde{\beta} \text{COVID 0}_{ct} \times \mathbb{I}_i^{GC} \\ & + \tilde{\gamma} \text{Post COVID}_{ct} \times \mathbb{I}_i^{GC} + \psi_i + \rho_j + \delta_c + \phi_t + \varepsilon_{ijct}, \end{aligned}$$

where i, j, c and t represent firm, industry, county, and day, respectively. Estimated coefficients β , γ , $\tilde{\beta}$, and $\tilde{\gamma}$ are shown. Both raw returns and total returns (including dividends) are used as dependent variables. The COVID 0 dummy denotes the day on which the first case of COVID-19 is reported in the same county where the firm is headquartered in. The Post COVID dummy encompasses 10 days after the event day. \mathbb{I}_i^{GC} is a dummy variable which turns to 1 if a firm is designated a government contractor. The labor intensive subsample includes only firms in the Fama-French 17 industries 1 to 13 (excluding utilities, retail, financial, and services). Robust standard errors with double clustering at the county and day level are used in reporting the t -statistics in parentheses.

	Full Sample		Labor Intensive	
	(1) Raw Return	(2) Total Return	(3) Raw Return	(4) Total Return
COVID 0	-0.000124 (-0.07)	0.0000350 (0.02)	0.0000116 (0.00)	0.000436 (0.16)
Post COVID	-0.00213* (-1.87)	-0.00186* (-1.74)	-0.00476 (-1.55)	-0.00397 (-1.53)
COVID 0 $\times \mathbb{I}^{GC}$	-0.00330 (-0.58)	-0.00477 (-0.82)	-0.0128* (-1.78)	-0.0138* (-1.94)
Post COVID $\times \mathbb{I}^{GC}$	0.000277 (0.09)	-0.0000736 (-0.03)	-0.00223*** (-2.70)	-0.00180*** (-3.11)
Constant	-0.00737*** (-39.50)	-0.00610*** (-37.48)	-0.00805*** (-16.76)	-0.00681*** (-17.53)
Firm FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	82299	82299	28664	28664
R ²	0.452	0.436	0.451	0.444

extent that the pandemic causes the Federal Reserve to implement accommodative monetary policy for the foreseeable future, it is possible that some firms benefit from this (expected) monetary policy easing more than others. For a simple measure of monetary policy exposure at the firm level, we use the financial constraint index developed by Whited and Wu (2006). Chava and Hsu (2019) show that financially constrained firms are especially sensitive to monetary policy shocks around FOMC announcements. Firms for which it is more difficult to obtain external financing, as proxied by a high value of the Whited and Wu (2006) index, respond strongly to monetary policy surprises.





In Appendix Table B.1, we find this not to be the case. The interaction term between the Post COVID dummy and the financial constraint dummy is insignificant in the full sample as well as in the labor intensive subsample. Our analysis suggests that the pandemic effects are not confined to financially constrained firms, as these firms do not display differential returns following the first reported COVID-19 case relative to unconstrained firms. We thus conjecture that monetary policy is unlikely to be a primary driver of stock market reaction to the coronavirus spread. This is in line with the findings by Ramelli and Wagner (2020). These authors show that the liquidity facilities announced by the Fed – the “Primary Market Corporate Credit Facility” and the “Secondary Market Corporate Credit Facility” – had only a temporarily effect, which was largely reversed within a 10 days window.

3.4 EPS Forecasts and the Cross-section of Returns

In this section we evaluate the effect of the COVID-19 crisis on earnings revisions, and link these revisions back to the cross-sectional variation in firm returns documented in Section 2.1.

We use firm-level earnings per share (EPS) forecasts for various forecast horizons (1-year, 2-years, and 3-years, corresponding to fiscal years 2020, 2021, and 2022) from the I/B/E/S database. To construct a firm-level EPS forecast at a daily frequency, we follow Landier and Thesmar (2020) and construct the daily forecast as the average of the analysts individual forecasts for a given firm. We then calculate daily forecast revisions that either equal the average across the three forecast horizons (combined revisions) or horizon-specific revisions. That is, the combined revision is defined as

$$Rev_{ijct}^{Combined} = \frac{1}{3} \sum_{h=2020}^{2022} logF_t EPS_{ih} - logF_{t-1} EPS_{ih}$$

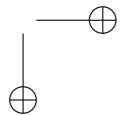
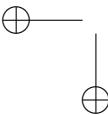
and the horizon-specific revisions as

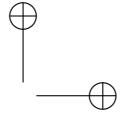
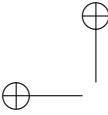
$$Rev_{ijct}^h = logF_t EPS_{ih} - logF_{t-1} EPS_{ih}$$

where $h \in \{2020, 2021, 2022\}$ and $F_t EPS_{ih}$ is the earnings per share forecast at time t for a firm i and forecast horizon h .¹⁶ In an attempt to capture the evolution of firm-level EPS forecasts we then construct the cumulative revisions for a window from ten days before to ten days after the first COVID-19 case is reported in a given county. Cumulative revisions are defined as follows

$$CumRev_{ijct}^X = \sum_{D=10}^t Rev_{ijct}^X$$

¹⁶ We are implicitly assuming that there is no revision in earnings beyond 2022. This assumption is indeed supported in the data. See discussion in Landier and Thesmar (2020).





where $X \in \{Combined, 2020, 2021, 2022\}$, D corresponds to the day on which the first COVID-19 case is reported and $t \in [D-10, D+10]$.

We start by performing an analysis similar to that reported in Table 3. Specifically, we regress the panel of cumulative earnings revisions on the COVID 0 dummy and the Post COVID dummy. Table 10 presents the results for revisions averaged across the forecast horizons (Column 1), as well as for revisions occurring at the individual 1-year (Column 2), 2-year (Column 3), and 3-year (Column 4) horizons. Focusing on column (1), we observe that the estimated coefficient γ on the Post COVID dummy is negative and statistically significant at the 5% level. The point estimate of -0.0105 suggests that there is on average a negative 1.05% change in analyst revisions in the 10-day post-event window relative to firms in the control group. The remaining columns shows that the coefficient stays flat across forecast horizons at about -0.01 (although it misses statistical significance at the shortest 1-year horizon).

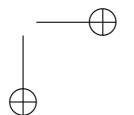
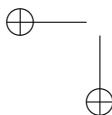
Table 10
Earnings Per Share Forecast Revisions

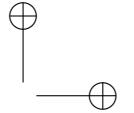
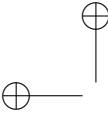
Table 10 presents difference-in-difference regression results. The sample period is between January 1, 2020 and March 20, 2020. The regression equation is:

$$CumRev_{ijct}^X = \alpha + \beta COVID 0_{ct} + \gamma Post COVID_{ct} + \psi_i + \rho_j + \delta_c + \phi_t + \varepsilon_{ijct},$$

where i, j, c and t represent firm, industry, county, and day, respectively. Estimated coefficients β and γ are shown. Cumulative EPS revisions are measured over the time window starting 10 days before and ending 10 days after the first COVID-19 case is reported in a county. Moreover, the revisions are either averaged across the 1-, 2-, and 3-year forecast horizons ($X = Combined$) or horizon-specific (i.e., $X = 2020$, $X = 2021$, and $X = 2022$, respectively). The COVID 0 dummy denotes the day on which the first case of COVID-19 is reported in the same county where the firm is headquartered in. The Post COVID dummy encompasses 10 days after the event day. Robust standard errors with double clustering at the county and day level are used in reporting the t -statistics in parentheses.

	(1) Combined EPS Revisions	(2) 1-Year EPS Revisions	(3) 2-Year EPS Revisions	(4) 3-Year EPS Revisions
COVID 0	-0.00713 (-1.52)	-0.00796 (-1.00)	-0.00165 (-0.47)	-0.00911*** (-2.68)
Post COVID	-0.0105** (-2.58)	-0.0121 (-1.48)	-0.00744** (-2.33)	-0.0122*** (-3.34)
Constant	0.00616*** (3.65)	0.00565* (1.68)	0.00448*** (3.47)	0.00835*** (5.52)
Firm FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	30485	30775	30798	30541
R^2	0.392	0.401	0.330	0.315





Tables 3 and 10 together provide evidence that both returns and cumulative EPS revisions are significantly lower in the 10-day post-event window relative to before. Motivated by these findings, we investigate to what extent EPS forecast revision can account for decreases in returns.¹⁷

To this end, we interact the Post COVID dummy with three indicators $\mathbb{I}_i^{Neg.Rev.}$, $\mathbb{I}_i^{NoRev.}$, and $\mathbb{I}_i^{Pos.Rev.}$. The dummy $\mathbb{I}_i^{NoRev.}$ singles out firms whose earnings are not revised, whereas $\mathbb{I}_i^{Neg.Rev.}$ ($\mathbb{I}_i^{Pos.Rev.}$) equals one if a firm i experiences a negative (positive) EPS forecast revision on a given day. The full specification is given by:

$$\begin{aligned} \log(Return)_{ijct} = & \alpha + \beta \text{COVID}_{0ct} + \gamma_1 \text{Post COVID}_{ct} \times \mathbb{I}_i^{Neg.Rev.} \\ & + \gamma_2 \text{Post COVID}_{ct} \times \mathbb{I}_i^{NoRev.} \\ & + \gamma_3 \text{Post COVID}_{ct} \times \mathbb{I}_i^{Pos.Rev.} \\ & + \psi_i + \rho_j + \delta_c + \phi_t + \varepsilon_{ijct}. \end{aligned} \quad (3)$$

Table 11 reports the results. Interestingly, only those firms whose earnings forecasts have been revised downward experience returns that are lower (relative to returns in the control group) in the 10-day post-event window. Despite it being possible for firms with no earnings revisions to experience lower returns (relative to the control group) due to an increase in discount rates, we find no evidence supporting this channel in our event window. Relative to the baseline estimate of -27 bps reported in Table 3, the effect in Table 11 is substantially larger in absolute terms. That is, returns are on average 88 bps lower in the 10-day post-event window relative to returns in the control group. The remaining columns highlight that the relationship between firm returns and revisions in earnings forecasts is similarly strong for short- and medium-term expectations (i.e., for 2020 and 2021 earnings), but weakens substantially, both statistically and economically, at the 3-year forecast horizon.¹⁸

In all, our evidence suggests that, over a tight window around the event day, downward revisions in earnings expectations constitute an important driver of the firm returns response.

4. Conclusion

In this paper, we document how the cross-section of equity returns is differentially affected by the COVID-19 pandemic in the U.S.

¹⁷ Our analysis is motivated by the classical Campbell and Shiller (1988) decomposition (and its manipulations), where unexpected stock returns are related to changes in expectations of future dividend growth and future stock returns: $r_{t+1} - E_t r_{t+1} = (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j} - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{t+j+1}$.

¹⁸ Appendix Table C.1 confirm that our conclusions continue to hold when we replace raw returns with cum-dividend returns.

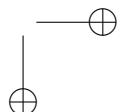
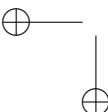


Table 11
Firm-Level Returns and Earnings Per Share Forecast Revisions

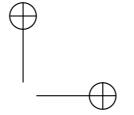
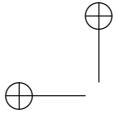
Table 11 presents interaction regression results. The sample period is between January 1, 2020 and March 20, 2020. We interact COVID0 and Post COVID dummies with indicators for whether a firm has experienced a negative, positive, or no earning forecast revisions. We use windows of both 5 and 10 days prior to the event day to a period of 10 days after the event day.

$$\begin{aligned} \log(Return)_{ijct} = & \alpha + \beta \text{COVID 0}_{ct} + \gamma_1 \text{Post COVID}_{ct} \times \mathbb{I}_i^{\text{Neg.Rev.}} \\ & + \gamma_2 \text{Post COVID}_{ct} \times \mathbb{I}_i^{\text{NoRev.}} + \gamma_3 \text{Post COVID}_{ct} \times \mathbb{I}_i^{\text{Pos.Rev.}} \\ & + \psi_i + \rho_j + \delta_c + \phi_t + \varepsilon_{ijct}, \end{aligned}$$

where i, j, c and t represent firm, industry, county, and day, respectively. Estimated coefficients β , γ_1 , γ_2 , and γ_3 are shown. Raw returns are used as dependent variable. The COVID 0 dummy denotes the day on which the first case of COVID-19 is reported in the same county where the firm is headquartered in. The Post COVID dummy encompasses 10 days after the event day. $\mathbb{I}_i^{\text{Neg.Rev.}}$ ($\mathbb{I}_i^{\text{NoRev.}}$ and $\mathbb{I}_i^{\text{Pos.Rev.}}$) is a dummy variable which equals 1 if a firm experiences a negative (no and positive, respectively) EPS forecast revision on a given day. Moreover, these revisions can be calculated across forecast horizon or horizon-specific. That is, Columns (1) to (4) present results for daily EPS forecast revisions averaged across the 1-, 2-, and 3-year forecast horizons (Column 1), 1-year (Column 2), 2-year (Column 3), and 3-year (Column 4) horizon. Robust standard errors with double clustering at the county and day level are used in reporting the t -statistics in parentheses.

	Dependent Variable: Raw Returns			
	(1) Combined	(2) 1-Year	(3) 2-Year	(4) 3-Year
COVID 0	0.0023 (0.98)	0.00018 (0.11)	-0.0000 (-0.01)	0.0001 (0.05)
Post COVID × Neg. Revision	-0.0088** (-2.30)	-0.0100*** (-2.86)	-0.0121** (-2.03)	-0.0055 (-0.77)
Post COVID × No Revision	-0.0006 (-0.44)	-0.0016 (-1.29)	-0.0015 (-1.29)	-0.0026 (-1.41)
Post COVID × Pos. Revision	0.0008 (0.21)	-0.0003 (-0.06)	0.0002 (0.05)	-0.0009 (-0.37)
Constant	-0.0098*** (-16.63)	-0.0087*** (-22.10)	-0.0086*** (-27.43)	-0.0085*** (-29.60)
Firm FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	79070	79070	80713	80713
R ²	0.527	0.519	0.514	0.513

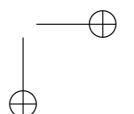
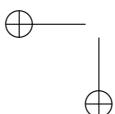
Specifically, we exploit the staggered geographical dissemination of the virus at the county level and take advantage of the headquarter location of U.S. publicly traded firms. Through our natural experiment, we find that firms headquartered in an affected county experience on average 27 bps lower daily returns in the 10-day post-event window relative to returns before the event and compared with firms headquartered in non-COVID counties. Further, we show that this negative relationship is stronger for firms in counties where the virus spread is more intense (-50 bps).

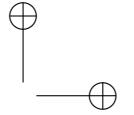
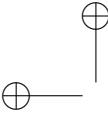


COVID-19 and the Cross-Section of Equity Returns: Impact and Transmission

We also shed new light on the economic channels through which the outbreak of COVID-19 affects firm-level returns. We focus on four non-mutually exclusive transmission channels: labor supply, uncertainty, government spending and monetary policies, and cashflow expectations. Concerning labor supply, firms in labor intensive industries exhibit more negative returns (-45 bps) relative to the full sample after the first reported case. We further show that the county-level percentage of people staying at home increases in the aftermath of the COVID-19 news. Related, firms residing in counties experiencing large rise in percent staying home have worse return performance than those located outside. Regarding uncertainty, firms with idiosyncratic exposure to COVID-induced risk are proven to have more negative returns. On government policy, heterogeneous sensitivity to government spending and monetary policies turn out to be ineffective in explaining the cross-section of return dynamics due to the virus spread. However, in the labor intensive subsample, government contractors actually experience larger return declines than non-contractors. This is suggestive evidence that the negative impact on labor productivity from the pandemic outweighs the benefit of stable demand provided by government contracts. Lastly, the first reported case of COVID-19, on average, puts downward pressure on analyst earnings forecasts of firms headquartered in the same county. As a result, firms with negative earnings revisions display more negative returns in the post-first-case news window.

This study is an early examination into the wide-ranging impact of the COVID-19 pandemic on the U.S. economy. By looking at the cross-section of equity returns, our empirical design allows us to better understand the propagation mechanism behind the crisis, which hopefully will inform the policy makers’ discussion about stabilizing the economy.





A. Robustness

We perform a number of robustness tests. First, we examine firm-level returns in a tight window around the event day. That is, we employ a 21-day event window (10 days before and 10 days after) and drop all return observations before the event window. Furthermore, we also delete returns belonging to untreated firms headquartered in non-COVID counties. We use the following spline regression specification:

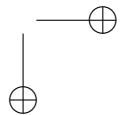
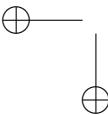
$$\begin{aligned} \log(\text{Return})_{ijct} = & \sum_{k=3}^{10} \Phi_k \text{COVID } (-k)_{ct} + \beta \text{COVID 0}_{ct} + \sum_{k=1}^{10} \Psi_k \text{COVID } (+k)_{st} \\ & + \psi_i + \rho_j + \delta_c + \phi_t + \varepsilon_{ijct}, \end{aligned} \quad (\text{A1})$$

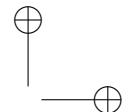
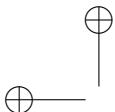
where the COVID (-2) and COVID (-1) dummies are not used so those returns serve as the benchmark.

Table A.1 reports the finding. The baseline sample results are shown in Column (1) and Column (2) for raw returns and total returns, respectively. The number of observations have dropped from 99,729 to 30,185 when compared to Columns (1) and (2) in Table 4. However, similar to before, the coefficient loading on the COVID +8 dummy remains significant at the 10% level. The magnitude is slightly smaller at -0.00593 and -0.00644 in the tight event window. In Column (3) and Column (4) of Table A.1, we repeat the exercise for labor intensive firms located in high COVID growth intensity counties and present the results. Again, estimated coefficients on the COVID (+2) to COVID (+4) dummies are negative and statistically significant. It is important to point out that there are no parallel trend violations in all columns of Table A.1. Overall, our main findings remain in the narrow window around the COVID 0 event day.

Next, we examine the subset of non-financial firms in the sample. It is common practice in the finance literature to leave banks and insurance companies out of the analysis due to their large asset size and balance sheet structure. We drop firms belonging to FF17 industry code 16. Spline regression results are shown in Table A.2. Regression specification follows Equation (2). Comparing Table A.2 with Table 4, two items are worth noting. First, none of the estimated coefficients are statistically significant in the pre-event period. Second, coefficient loadings on the COVID 0 dummy are also insignificant. Unlike Table 4, however, loadings on the COVID (+2) dummy are statistically significant across the four columns in Table A.2. In Column (1) and Column (2), the baseline sample, average non-financial firm return is 59.2 bps lower using raw returns and 60.4 bps lower using total returns than the benchmark return calculated from the two days immediately before the event day. The magnitude of these coefficients increase in Column (3) and Column (4). For non-financial firms residing in high COVID-19 growth intensity counties, the average raw return 2 days after the event day is 91.1 bps lower than the benchmark return in Column (3), and the average total return is 91.7 bps lower in Column (4). We do not report results for the subsample of labor intensive firms in this robustness check since they are by definition non-financial firms. Findings documented in Table A.2 suggests that our results actually strengthen in the subsample of non-financial firms.

To ease the concern that our results are driven by a few firms located in large counties or population centers, we drop firms headquartered in the states of California (CA), New York (NY), and Texas (TX) in the next robustness test. Spline regression specified in Equation (2) is then applied to the reduced sample. We report the results in Tables A.3. In the baseline sample, shown in Columns (1) and (2) of Table A.3, regression results are stronger when we exclude firms in CA, NY, and TX. Estimated





COVID-19 and the Cross-Section of Equity Returns: Impact and Transmission

coefficients of raw returns and total returns on COVID (+2) and COVID (+3) are all statistically significant, at the 1% and 5% level, respectively. In Columns (3) and (4) of Table A.3, for firms located in high COVID growth intensity counties, results are similar. Generally speaking, findings from this robustness test verify that our baseline results are not driven by a few firms located in large counties and population centers.

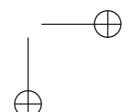
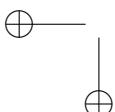
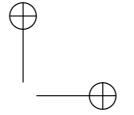
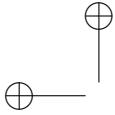


Table A.1
Spline Regression Results of Firm-Level Returns on the COVID-19 Shock - Tight Window

Table A.1 presents spline regression results in a 21-day event window. The regression specification is shown in Equation (A1). Firms headquartered in non-COVID counties are excluded. All regressions include firm, industry, county, and day fixed effects. Robust standard errors with double clustering at the county and day level are used in reporting the *t*-statistics in parentheses.

	Full Sample		High Growth & Labor Intensive	
	(1) Raw Return	(2) Total Return	(3) Raw Return	(4) Total Return
COVID (-10)	-0.000111 (-0.05)	-0.000338 (-0.17)	0.0296 (0.81)	0.0301 (0.93)
COVID (-9)	-0.00218 (-1.06)	-0.00250 (-1.25)	0.0248 (0.81)	0.0252 (0.93)
COVID (-8)	-0.00153 (-0.85)	-0.00174 (-0.98)	0.0209 (0.76)	0.0217 (0.89)
COVID (-7)	-0.000547 (-0.29)	-0.000853 (-0.45)	0.0143 (0.60)	0.0152 (0.73)
COVID (-6)	0.000821 (0.28)	0.000595 (0.20)	0.0205 (0.99)	0.0210 (1.17)
COVID (-5)	-0.00180 (-0.87)	-0.00201 (-0.97)	0.0103 (0.68)	0.0110 (0.82)
COVID (-4)	-0.00235 (-1.05)	-0.00230 (-1.08)	0.00352 (0.37)	0.00644 (0.74)
COVID (-3)	0.000820 (0.54)	0.000437 (0.28)	0.00543 (0.70)	0.00527 (0.76)
COVID 0	-0.000677 (-0.29)	-0.000916 (-0.39)	-0.0128 (-1.41)	-0.0117 (-1.38)
COVID +1	0.00107 (0.32)	0.000736 (0.22)	-0.0149 (-1.18)	-0.0136 (-1.16)
COVID +2	-0.00377 (-1.53)	-0.00386 (-1.51)	-0.0292* (-1.91)	-0.0277* (-2.06)
COVID +3	-0.00322 (-1.01)	-0.00304 (-1.00)	-0.0324 (-1.32)	-0.0296 (-1.41)
COVID +4	-0.00499 (-1.00)	-0.00344 (-0.81)	-0.0529* (-1.73)	-0.0454* (-1.86)
COVID +5	-0.000581 (-0.22)	-0.00125 (-0.45)	0.0308 (-1.13)	-0.0300 (-1.23)
COVID +6	-0.00159 (-0.47)	-0.00194 (-0.61)	-0.0405 (-1.24)	-0.0392 (-1.35)
COVID +7	0.00259 (0.55)	0.00156 (0.34)	-0.0385 (-1.05)	-0.0383 (-1.17)
COVID +8	-0.00593* (-1.69)	-0.00644* (-1.83)	-0.0446 (-1.05)	-0.0437 (-1.16)
COVID +9	-0.00359 (-0.97)	-0.00386 (-1.00)	-0.0561 (-1.18)	-0.0547 (-1.29)
COVID +10	0.00149 (0.31)	0.00164 (0.33)	-0.0537 (-1.01)	-0.0517 (-1.08)
Constant	-0.0196*** (-13.18)	-0.0162*** (-10.45)	-0.0170** (-2.56)	-0.0139** (-2.46)
Observations	30185	30185	5465	5465
R ²	0.499	0.489	0.487	0.497



COVID-19 and the Cross-Section of Equity Returns: Impact and Transmission

Table A.2
Spline Regression Results of Firm-Level Returns on the COVID-19 Shock - Non-Financials

Table A.2 presents spline regression results for non-financial firms (excluding Fama-French 17 industry 16). The sample period is between January 1, 2020 and March 20, 2020. The regression specification is shown in Equation (2). Both raw returns and total returns (including dividends) are used as dependent variables. The COVID 0 dummy denotes the day on which the first case of COVID-19 is reported in the same county where the firm is headquartered in. The COVID <(-5) dummy encompasses all trading days prior to the 5-day window leading up to the event day. The high (COVID-19) growth subsample includes only firms residing in counties where the growth between 1 and 100 reported cases took less than 20 days. All regressions include firm, industry, county, and day fixed effects. Robust standard errors with double clustering at the county and day level are used in reporting the *t*-statistics in parentheses.

	Full sample		High Growth	
	(1) Raw Return	(2) Total Return	(3) Raw Return	(4) Total Return
COVID <(-5)	-0.00112 (-0.75)	-0.00138 (-0.85)	-0.00211 (-0.89)	-0.00220 (-0.83)
COVID (-5)	-0.00214 (-1.19)	-0.00263 (-1.40)	-0.00166 (-0.66)	-0.00188 (-0.69)
COVID (-4)	-0.00299 (-1.28)	-0.00299 (-1.22)	-0.00272 (-0.68)	-0.00209 (-0.54)
COVID (-3)	0.00111 (0.71)	0.000646 (0.39)	0.00195 (0.85)	0.00174 (0.69)
COVID 0	-0.000396 (-0.18)	-0.000671 (-0.28)	-0.00110 (-0.36)	-0.00130 (-0.39)
COVID +1	-0.000125 (-0.03)	-0.000509 (-0.12)	-0.00211 (-0.38)	-0.00204 (-0.35)
COVID +2	-0.00592** (-2.07)	-0.00604** (-2.04)	-0.00911*** (-2.70)	-0.00917** (-2.61)
COVID +3	-0.00469 (-1.34)	-0.00436 (-1.31)	-0.00731 (-1.32)	-0.00641 (-1.25)
COVID +4	-0.00627 (-1.11)	-0.00444 (-0.92)	-0.0120 (-1.62)	-0.00911 (-1.46)
COVID +5	-0.000978 (-0.44)	-0.00162 (-0.69)	-0.00366 (-1.01)	-0.00410 (-1.08)
COVID +6	-0.00245 (-0.82)	-0.00293 (-1.06)	-0.00439 (-1.21)	-0.00476 (-1.39)
COVID +7	0.000412 (0.10)	-0.000607 (-0.14)	0.000546 (0.11)	-0.000599 (-0.12)
COVID +8	-0.00736** (-2.02)	-0.00813** (-2.27)	-0.0101** (-2.12)	-0.0109** (-2.37)
COVID +9	-0.00491 (-1.16)	-0.00536 (-1.26)	-0.00932 (-1.66)	-0.00965* (-1.75)
COVID +10	-0.00112 (-0.36)	-0.000884 (-0.27)	-0.00429 (-0.96)	-0.00287 (-0.60)
Constant	-0.00629*** (-4.42)	-0.00467*** (-2.96)	-0.00630*** (-3.01)	-0.00472* (-1.95)
Observations	81162	81162	49586	49586
R ²	0.401	0.378	0.398	0.375

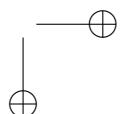
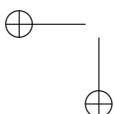
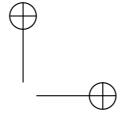
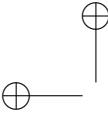


Table A.3
Spline Regression Results of Firm-Level Returns on the COVID-19 Shock - No CA, NY, and TX Counties

Table A.3 presents spline regression results for firms headquartered outside of the states of California, New York, and Texas. The sample period is between January 1, 2020 and March 20, 2020. The regression specification is shown in Equation (2). Both raw returns and total returns (including dividends) are used as dependent variables. The COVID 0 dummy denotes the day on which the first case of COVID-19 is reported in the same county where the firm is headquartered in. The COVID <(-5) dummy encompasses all trading days prior to the 5-day window leading up to the event day. The high (COVID-19) growth subsample includes only firms residing in counties where the growth between 1 and 100 reported cases took less than 20 days. All regressions include firm, industry, county, and day fixed effects. Robust standard errors with double clustering at the county and day level are used in reporting the *t*-statistics in parentheses.

	Full sample		High Growth	
	(1) Raw Return	(2) Total Return	(3) Raw Return	(4) Total Return
COVID <(-5)	-0.00112 (-0.69)	-0.00158 (-0.92)	-0.00304 (-1.10)	-0.00326 (-1.08)
COVID (-5)	-0.000950 (-0.50)	-0.00155 (-0.78)	-0.00141 (-0.48)	-0.00167 (-0.53)
COVID (-4)	-0.00167 (-0.56)	-0.00171 (-0.59)	-0.00347 (-0.66)	-0.00291 (-0.58)
COVID (-3)	-0.000639 (-0.43)	-0.00128 (-0.80)	-0.00165 (-0.64)	-0.00198 (-0.68)
COVID 0	-0.00295 (-1.31)	-0.00319 (-1.31)	-0.00353 (-1.21)	-0.00383 (-1.24)
COVID +1	0.000337 (0.09)	-0.000484 (-0.12)	-0.000927 (-0.21)	-0.00143 (-0.29)
COVID +2	-0.00744*** (-2.74)	-0.00756*** (-2.77)	-0.00957** (-2.40)	-0.00990** (-2.45)
COVID +3	-0.00863** (-2.11)	-0.00801** (-2.14)	-0.0114** (-2.40)	-0.0105** (-2.44)
COVID +4	-0.00526* (-1.71)	-0.00489 (-1.58)	-0.00699 (-1.40)	-0.00667 (-1.37)
COVID +5	-0.00357 (-1.03)	-0.00437 (-1.16)	-0.00838* (-1.77)	-0.00900* (-1.73)
COVID +6	-0.00456 (-1.46)	-0.00500 (-1.60)	-0.00594* (-1.86)	-0.00647* (-1.92)
COVID +7	-0.00180 (-0.42)	-0.00251 (-0.60)	-0.00293 (-0.65)	-0.00359 (-0.80)
COVID +8	-0.0121** (-2.08)	-0.0129** (-2.18)	-0.0135* (-1.71)	-0.0140* (-1.80)
COVID +9	-0.00815 (-1.34)	-0.00854 (-1.41)	-0.0130* (-1.76)	-0.0134* (-1.89)
COVID +10	-0.00397 (-0.75)	-0.00458 (-0.84)	-0.00750 (-1.04)	-0.00750 (-1.03)
Constant	-0.00701*** (-4.62)	-0.00512*** (-3.14)	-0.00535** (-2.14)	-0.00358 (-1.29)
Observations	70108	70108	40958	40958
R ²	0.449	0.427	0.427	0.402

B. Financial Constraint as Proxy for Monetary Policy Sensitivity



COVID-19 and the Cross-Section of Equity Returns: Impact and Transmission

Table B.1
Interaction Regression Results of Firm-Level Returns on the COVID-19 Shock and Financial Constraint

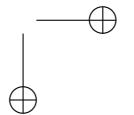
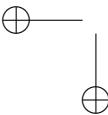
Table B.1 presents interaction regression results. The sample period is between January 1, 2020 and March 20, 2020. Financial constraint is measured by the Whited and Wu (2006) index. We split the sample by the medium of the WW index. The regression equation is:

$$\begin{aligned} \log(Return)_{ijct} = & \alpha + \beta \text{COVID 0}_{ct} + \gamma \text{Post COVID}_{ct} + \tilde{\beta} \text{COVID 0}_{ct} \times \mathbb{I}_i^{FC} \\ & + \tilde{\gamma} \text{Post COVID}_{ct} \times \mathbb{I}_i^{FC} + \psi_i + \rho_j + \delta_c + \phi_t + \varepsilon_{ijct}, \end{aligned}$$

where i, j, c and t represent firm, industry, county, and day, respectively. Estimated coefficients β , γ , $\tilde{\beta}$, and $\tilde{\gamma}$ are shown. Both raw returns and total returns (including dividends) are used as dependent variables. The COVID 0 dummy denotes the day on which the first case of COVID-19 is reported in the same county where the firm is headquartered in. The Post COVID dummy encompasses 10 days after the event day. \mathbb{I}_i^{FC} is a dummy variable which turns to 1 if a firm falls in the top half according to the WW index. The labor intensive subsample includes only firms in the Fama-French 17 industries 1 to 13 (excluding utilities, retail, financial, and services). Robust standard errors with double clustering at the county and day level are used in reporting the t -statistics in parentheses.

	Full Sample		Labor Intensive	
	(1) Raw Return	(2) Total Return	(3) Raw Return	(4) Total Return
COVID 0	-0.000712 (-0.33)	-0.000540 (-0.25)	-0.00145 (-0.35)	-0.00112 (-0.28)
Post COVID	-0.00279** (-2.17)	-0.00246** (-2.02)	-0.00513 (-1.17)	-0.00394 (-1.06)
COVID 0 $\times \mathbb{I}_i^{FC}$	0.00197 (0.46)	0.00162 (0.37)	-0.000418 (-0.06)	-0.0000266 (-0.00)
Post COVID $\times \mathbb{I}_i^{FC}$	0.00232 (1.00)	0.00236 (1.08)	0.00194 (0.42)	0.00136 (0.32)
Constant	-0.00740*** (-37.27)	-0.00614*** (-35.77)	-0.00819*** (-16.15)	-0.00697*** (-17.17)
Firm FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	76061	76061	26309	26309
R ²	0.451	0.435	0.449	0.443

C. Total Returns and EPS Forecast Revisions



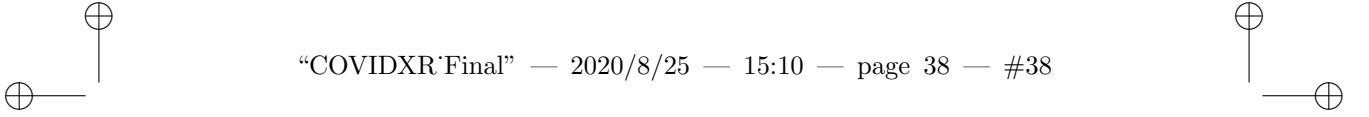


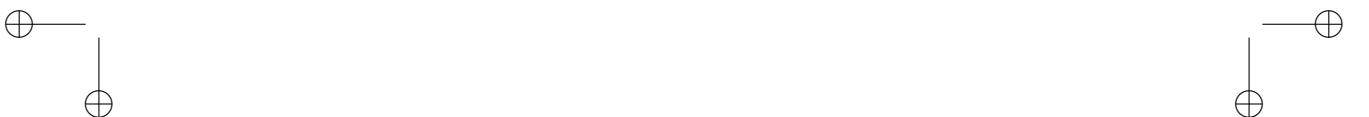
Table C.1
Firm-Level Returns and Earnings Per Share Forecast Revisions

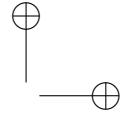
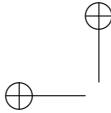
Table C.1 presents interaction regression results. The sample period is between January 1, 2020 and March 20, 2020. We interact COVID0 and Post COVID dummies with indicators for whether a firm has experienced a negative, positive, or no earning forecast revisions. We use windows of both 5 and 10 days prior to the event day to a period of 10 days after the event day.

$$\begin{aligned} \log(Return)_{ijct} = & \alpha + \beta \text{COVID 0}_{ct} + \gamma_1 \text{Post COVID}_{ct} \times \mathbb{I}_i^{\text{Neg. Rev.}} \\ & + \gamma_2 \text{Post COVID}_{ct} \times \mathbb{I}_i^{\text{No Rev.}} + \gamma_3 \text{Post COVID}_{ct} \times \mathbb{I}_i^{\text{Pos. Rev.}} \\ & + \psi_i + \rho_j + \delta_c + \phi_t + \varepsilon_{ijct}, \end{aligned}$$

where i, j, c and t represent firm, industry, county, and day, respectively. Estimated coefficients β , γ_1 , γ_2 , and γ_3 are shown. Total returns including dividends are used as dependent variable. The COVID 0 dummy denotes the day on which the first case of COVID-19 is reported in the same county where the firm is headquartered in. The Post COVID dummy encompasses 10 days after the event day. $\mathbb{I}_i^{\text{Neg. Rev.}}$ ($\mathbb{I}_i^{\text{No Rev.}}$ and $\mathbb{I}_i^{\text{Pos. Rev.}}$) is a dummy variable which equals 1 if a firm experiences a negative (zero, and positive, respectively) EPS forecast revision on a given day. Moreover, these revisions can be calculated across forecast horizon or horizon-specific. That is, Columns (1) to (4) present results for daily EPS forecast revisions averaged across the 1-, 2-, and 3-year forecast horizons (Column 1), 1-year (Column 2), 2-year (Column 3), and 3-year (Column 4) horizon. Robust standard errors with double clustering at the county and day level are used in reporting the t -statistics in parentheses.

	Dependent Variable: Total Returns			
	Combined	1-Year	2-Year	3-Year
COVID 0	0.00241 (0.97)	0.000348 (0.20)	0.000146 (0.08)	0.000241 (0.14)
Post COVID \times Neg. Revision	-0.0075** (-2.27)	-0.0093** (-2.75)	-0.0102* (-1.96)	-0.0027 (-0.45)
Post COVID \times No Revision	-0.0006 (-0.48)	-0.0014 (-1.21)	-0.0013 (-1.23)	-0.0025 (-1.37)
Post COVID \times Pos. Revision	0.0014 (0.45)	0.0008 (0.16)	0.0005 (0.15)	-0.0003 (-0.14)
Constant	-0.00824*** (-17.31)	-0.00737*** (-21.52)	-0.00722*** (-26.03)	-0.00721*** (-29.44)
Firm FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	79070	79070	80713	80713
R ²	0.519	0.512	0.506	0.506

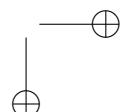
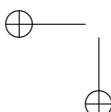


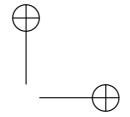
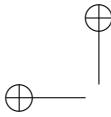


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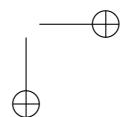
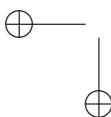
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