Staring Death in the Face: The Financial Impact of Corporate Exposure to Prior Disasters

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We examine how firms' exposure to prior disastrous events can influence their stock market footprint during the coronavirus crisis. While others have drawn comparisons between past pandemics and Covid-19, we argue that such comparisons are skewed due to the unprecedented reach and consequences of the latter. To better model the structural shock caused by Covid-19 in the USA, we look at the 9/11 terrorist attacks and specifically examine how firms based in New York City back then reacted to the associated financial turmoil. While 9/11 and Covid-19 are categorically different events, their short-term impacts on the stock market, and on New York exchanges in particular, are surprisingly similar. We find firms that financially 'survived' 9/11 also managed to do better – or suffer less – by about 7% in terms of stock returns during Covid-19, compared to control firms that were not exposed to 9/11. In a sense, we show that companies' prior exposure to 9/11 partly 'immunized' them against the consequences of a similarly destabilizing event, albeit two decades later. Interestingly, the trading volume of exposed firms increased due to market buying pressures. Our analysis is robust to various financial proxies, alternative definitions of control firms and varying estimation windows.

Introduction

It is difficult to imagine an event in the past few decades with similarly wide-reaching and catastrophic consequences for individuals, society and the economy as Covid-19. The aggregate economic damage caused by Covid-19 (henceforth, Covid) is already well documented by international organizations such as the IMF and the World Bank, as well as national statistics agencies around the world.[1] Indeed, a significant part of the economic turmoil caused by Covid is intermediated through loss of productivity and lower or negative earnings in the corporate sector. Research published in finance journals since the emergence of Covid similarly attests to its devastating impact on firms' corporate financial variables. Acharya and Steffen (2020) show that firms drew down bank credit lines and consistent with the risk of becoming a fallen angel, the lowest-quality BBB-rated firms behaved more similarly to non-investment-grade firms. Halling, Yu and Zechner (2020) discuss how Covid affected firms' access to public capital markets. Bond issues increased substantially for all bond types, while equity issues slowed tremendously. Ramelli and Wagner (2020) argue that firms more exposed to trade with China underperformed. Further, corporate debt and cash holdings emerged as important value drivers. Salisu and Vo (2020) show that stock returns were very sensitive to any health news related to Covid.

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[1]See the various factsheets available at the IMF Covid database (https://www.imf.org/en/Topics/imf-and-covid19) and the World Bank Covid database (https://www.worldbank.org/en/who-we-are/news/coronavirus-covid19).

Our study attempts to fill an important gap in this body of research. While certain sectors of the economy, such as travel, tourism and hospitality, suffered more heavily during Covid than others (Izzeldin *et al.*, 2021), it is not sufficiently clear what cross-sectional variations exist among firms in each industry sector. In other words, after controlling for known factors such as industry characteristics and financial position that often contribute to cross-sectional variations in corporate responses, it would be theoretically interesting, and practically of significant importance, to explore which particular firms showed more financial resilience during the Covid disruption. Hence, we use the Covid disruption as an empirical setting to examine corporate financial resilience, and the common factors that contribute to it.

Crucially, we provide evidence suggesting that firms' exposure to prior disasters in the corporate world makes them more resilient in the face of new but fundamentally similar disruptions. Specifically, we examine companies headquartered in New York City (henceforth, NYC) and trading in one of the city's three stock exchanges. Among such firms, we focus on those that were active both during the 11 September 2001 terrorist attacks (henceforth, 9/11) and the 2020 Covid period. Importantly, we show such firms displayed more financial resilience during the Covid turmoil compared to control groups. Our findings show that the stock price losses of these companies during Covid were about 7% lower compared to firms that were not exposed to 9/11. This figure is both statistically and economically significant, and represents billions of dollars of market value 'saved' compared to the control group.

In other words, the group of firms which were exposed to 9/11 are found to be, in some sense, *immunized* or more immune to the financial hit of Covid compared to their peers. We argue that this may be due to such firms having learnt how to cope with a sudden shock to their workforce, management (given their central location in NYC), office space, supply chains (see e.g. Harland, 1996; Verbeke, 2020), need for urgent crisis management, stakeholder communication and, of course, shocks to their share price and associated financial metrics. Thus, their resilience is a product of organizational learning and internalizing this learning in their organizational culture (e.g. Walsh and Ungson, 1991). It is also plausible that the investors of such firms may 'price in' the fact that they have

learnt their lesson and, therefore, regard them as more resilient against systemic shocks of a comparable nature.[2]

Organizational learning from disasters (Smith and Elliott, 2007) initially takes place at the level of senior managers who have to firefight the disaster at hand, and then trickles down the organization. Disasters, by definition, are 'serious disruptions of the functioning of a community or a society at any scale due to hazardous events interacting with conditions of exposure, vulnerability and capacity, leading to one or more of the following: human, material, economic and environmental losses and impacts' (UNGA, 2017). Prior literature also refers to 'surprises' (e.g. Bechky and Okhuysen, 2011; Lampel and Shapira, 2001), 'rare events' (e.g. Lampel, Shamsie and Shapira, 2009; Starbuck, 2009), 'catastrophes' (e.g. Majchrzak, Jarvenpaa and Hollingshead, 2007) or 'crises' (e.g. Rerup, 2009). While not the direct focus of our study, the question of which managerial skills and attributes may facilitate more effective decision-making and subsequent learning in disaster situations (Akinci and Sadler-Smith, 2019) is an interesting research focus in and of itself (Amabile and Pratt, 2016).

Particularly with unprecedented disasters that require low-probability yet high-consequence decisions, and where situations with no similarities to previous experiences arise, adaptiveness and agility can be demonstrated in the form of initial situational assessment followed by mental simulation and consultation (Curnin, Brooks and Owen, 2020). The learning process is driven by two key cognitive functions. Firstly, expert intuition, domain-specific learning and experience (Salas, Rosen and DiazGranados, 2010) and secondly, rational, analytical thinking – see, *inter alia*, the 4Is organizational learning framework (Intuiting, Interpreting, Integrating, Institutionalizing) of Crossan, Lane and White (1999).

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[2]While the timelines of 9/11 and Covid are not identical, we argue that the learning which took place following 9/11 coupled with the organizational memory has equipped survivor firms to fare better during Covid. The similarities between the two events are not just limited to the shocks exerted on their workforce, management, office space, supply chains, share price and associated financial metrics. Their legacy effects have also been comparable and long-lasting. In fact, 9/11 left a long shadow of fear and concern on the public in relation to new attacks, not dissimilar to current fears around new virus variants.

While Covid and 9/11 are categorically different disasters, for our purposes, the comparison between them is appropriate for several reasons. Both these events were exogenous, unforeseen and extremely destabilizing. As far as the USA is concerned, NYC was very severely hit and was in fact the epicentre of both these disasters. And the same goes for firms headquartered in NYC or trading in that city. Both events shocked investors and the stock markets, and both had devastating effects on supply chains, although far more short-lived in the case of 9/11. Air travel was similarly suspended during 9/11, albeit again for a much shorter period, and consequences for the tourism and hospitality sectors were similarly grave. As a recent *Financial Times* article puts it, 'the industry in late 2001 experienced many of the ills it is seeing now. Airlines bled cash. Their survival was threatened. Government stepped in with financial support, as they are doing today' (Skapinker, 2020).[3]

Further, we find that the difference between firms exposed to 9/11 and their peers is not limited to their stock price reaction. The immunized firms happen to outperform their peers in a clean difference-in-difference estimation of both stock returns and market-adjusted excess returns. In fact, controlling for overall risk, immunized firms earn 14% higher raw returns and 15% higher excess returns compared to the control group. When we control for Covid-specific risks, these figures go down only to 13%, which is still a considerable difference statistically and economically. In addition, the trading volume of the immunized firms increases due to buying pressures in the market, again compared to their peers. These results are consistent across various industry sectors, as explained in the main empirical section of the paper.

This study makes several important contributions to the finance and management literatures. Firstly, our findings contribute to the literature on stock market reactions to the spread of diseases. For example, McTier, Tse and Wald (2013) explain how the US market reacts to influenza through time but do not highlight any patterns in the cross-sectional variation among firms. Our paper contributes to this body of work by highlighting a novel relationship between firms' prior disaster exposures and their market resilience during health pandemics.

Secondly, our findings contribute to the literature on stock market reactions to terrorist events – see, for example, Chesney, Reshetar and Karaman (2011), Karolyi (2006) and Nikkinen and Vähämaa (2010) – by showing that, at least in the case of 9/11, these shocks can make the surviving firms more resilient and their investors more forgiving or trusting once similar disasters strike again.

Thirdly, these results provide novel evidence that markets have long-term memory – see, for example, Lo (1991). This means that markets can 'price in' the success or failure of firms in extreme events, even after a couple of decades.

Fourthly, and equally importantly, we contribute to the management literature on organizational learning and memory by showing that prior exposure to unprecedented and traumatic events can have organizational learning and resilience benefits over the long term. The impact of organizational learning capabilities on a company's prospects for survival are widely documented in the management literature (see e.g. Argyris and Schön, 1996; Camps and Luna-Arocas, 2012).[4]

Our study contributes to this literature by highlighting the role of prior exposure to disasters in triggering organizational learning. While we cannot distinguish incremental from radical innovation in our firms, we nonetheless can best understand the key findings through the lens of companies 'learning' how to respond to systemic shocks of a disastrous nature, even if they are few and far between. The organization's response to these systemic shocks, when initially confronted with them, becomes integrated in organizational culture and work processes that constitute its 'organizational memory' (e.g. Walsh and Ungson, 1991).

The remainder of the paper is organized as follows. The second section discusses the relevant

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[3]Of course, these parallels have limitations. For example, it is documented that following air crash incidents, the overall air travel industry can benefit from customers shifting airlines (Bosch, Eckard and Singal, 1998). Such an outcome is unlikely to occur with Covid given the restrictions imposed on air travel globally.

[4]Examples from the financial services industry include Morgan and Turnell (2003), who show that the market information processing and analytical capabilities of organizations improve when they exhibit more favourable learning values. Chiva, Ghauri and Alegre (2014) explore the interface of organizational learning and innovation, by categorizing organizations into those characterized by adaptive learning and incremental innovation and those characterized by generative learning and radical innovation.

literature and motivates our theoretical hypotheses. The third section presents the data sample, data sources and definitions of variables. In the fourth section, we present the empirical approach and headline findings. The fifth section conducts a range of robustness tests which mainly confirm our core results, and the sixth section concludes.

Related literature and hypothesis development

Despite the recent emergence of Covid, there is already a substantial and fast-growing body of work on its financial aspects and implications. Altman (2020) shows that the non-financial corporate debt market in the USA reached a record percentage of gross domestic product. Further, investor appetite grew for higher promised yields on risky fixed-income assets. Baker *et al.* (2020a, 2020b) argue that Covid resulted in a year-on-year contraction in US real GDP of nearly 11% as of 2020 Q4. Guerrieri *et al.* (2020) illustrate that standard fiscal stimulus was less effective than usual, and monetary policy, unimpeded by the zero lower bound, had magnified effects by preventing firm exits. Chronopoulos, Lukas and Wilson (2020) find that discretionary spending declined throughout the pandemic. Favero, Ichino and Rustichini (2020) show that policies of epidemic containment were efficient with respect to the number of fatalities and GDP loss. Gormsen and Koijen (2020) discuss that dividends shrank throughout the pandemic, and fiscal stimulus boosted the stock market and long-term growth but did little to increase short-term growth expectations. And Mamaysky (2020) argues that markets frequently reacted to uninformative news in the early stages of the pandemic. As far as pandemics go, the health impact and economic footprint of Covid are unprecedented, at least as far back as the influenza pandemic of 1918. However, some prior studies have given warnings about these expected economic costs in foresight. For example, Bloom, Cadarette and Sevilla (2018) discuss the costs such pandemics incur to both public and private health organizations, as well as losses to workforce productivity and disruption caused by social distancing.

In a similar vein, Fan, Jamison and Summers (2018) estimate the expected annual losses from pandemics to be around 500 billion USD, which comes to about 0.6% of global income, which – with the benefit of Covid hindsight – appears to be a great underestimation. Similar studies emphasizing the need to anticipate and manage the economic consequences of pandemics include Lewis (2001), Tam, Khan and Legido-Quigley (2016) and several others – see Goodell (2020) for a summary. Of notable mention is the World Health Organization's Global Preparedness Monitoring Board (2019) report, which warns, only 3 months before the outbreak of Covid, that the world is at imminent threat of a global pandemic with little or no precaution being undertaken.

Another strand of the epidemics and pandemics literature (Page, Song and Wu, 2012) compares their financial hit to other forms of natural and man-made disasters. These can include various natural disasters (Toya and Skidmore, 2007), air crashes (Ho, Qiu and Tang, 2013) and acts of terrorism (Llussa and Tavares, 2011). In particular, research on the financial market impact of terrorist attacks can provide some form of parallel. While terrorist events are localized in their initial manifestation, they are by their nature designed to create a widespread shift in public mood (Goodell, 2020) and by implication, investor sentiment. This is an angle through which one can compare the market impact of a pandemic in its early days with that of a terrorist attack.

The associated spillover effects of terrorist attacks are, *inter alia*, discussed by Karolyi (2006), who concludes that, with some caveats, spillovers indeed occur as evidenced in tests examining volatility or beta risks with asset-pricing models. As regards 9/11, Choudhry (2005) examines whether the attacks created a shift in market betas. Similarly, Hon, Strauss and Yong (2004) find that the 9/11 attacks led to higher correlations in global markets, not unlike the Covid episode, with some geographic variations. Other studies with similar findings include Boin (2004), Chesney, Reshetar and Karaman (2011) and Nikkinen and Vähämaa (2010).

Organizational resilience can be broken down into three components, namely, anticipation, coping and adaptation (Ducheck, 2020). We propose that while companies exposed to the 9/11 shock were not necessarily superior in anticipating the Covid shock, they were better at coping with its associated tremors – such as its effects on their supply chain, workforce and customers. It is also likely that such companies will adjust and adapt better once the Covid chapter is completely
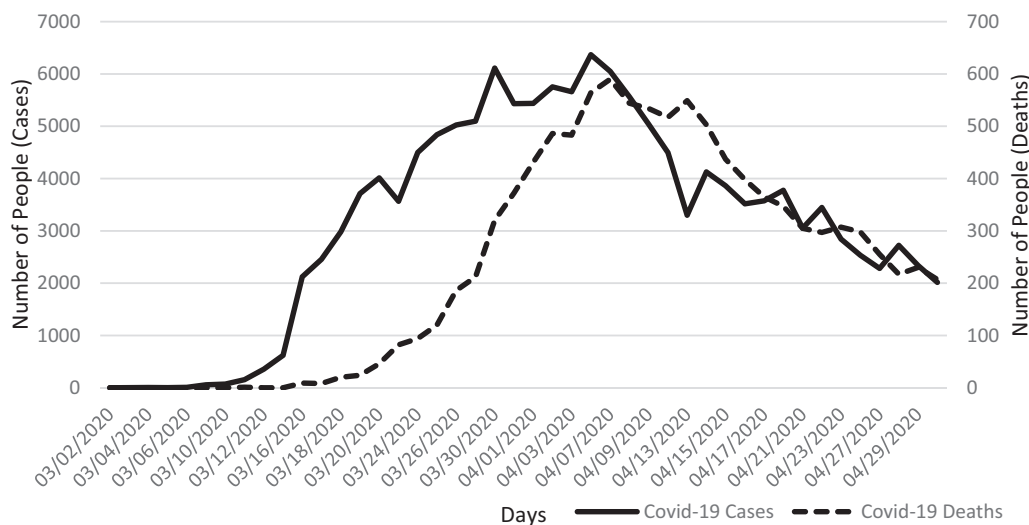
Figure 1. Official Covid-19 cases and deaths in New York City
This figure presents the daily new Covid-19 cases and deaths in New York City between 2 March 2020 and 30 April 2020. The very first official Covid-19 case was after 2 March. Data obtained from NYC government website.

closed, although we cannot formally test this as Covid is still an unfolding though near-ending turmoil.

Therefore, we hypothesize that prior exposure to disastrous events (terrorist attacks in particular) can result in firms having a 'softer landing' when a new unforeseen event of similar nature hits them. In other words, we expect financial markets to remember and 'price in' a company's prior successful experience with disastrous events that threaten their supply chains and workforce, among other things. Therefore, we form the following testable hypothesis:

H1: Firms with prior exposure to disastrous events experience smaller stock market losses during the Covid pandemic.

Also, as explained above, we expect such firms to be in more demand by the market. This, we would anticipate, is because investors value the advantageous position of these immunized firms relative to their peers. Hence:

H2: Firms with prior exposure to disastrous events have higher trading volumes due to larger buying pressures from the market.

Later, we test these hypotheses together with a range of alternative variations and a battery of robustness tests.

Sample selection and variables

Data sample

The period of our analysis runs from 9 December 2019 to 30 April 2020. The first official Covid cases in NYC date back to 2 March 2020, and the deaths start soon after.[5] Figure 1 shows that the daily new Covid cases in NYC have a slow progress until mid-March, when they jump from 620 to 2,122, and keep rising until 6 April to 6,367, the peak of the first wave in NYC. The daily new cases drop to 1,004 by 30 April. The daily new deaths have a similar distribution. They start on 11 March and peak at 590 on 7 April. The number of daily new deaths drops to 56 by 30 April. The time interval for this study includes 2 months as the treatment period and 3 months before 2 March 2020 as the control period.

To determine the *immune* firms in our sample, we consider companies with headquarters (HQ) in NYC that were traded in three major stock markets in NYC, that is the New York Stock Exchange (NYSE), NYSE American and NASDAQ stock market, between 10 September 2001 and 30 November 2001 – a 3-month period. We aim to focus on firms that have experienced the 9/11 terrorist attacks at first sight, with the highest exposure. Of the firms above, only 114 were still traded

[5]For more details, see https://www1.nyc.gov/site/doh/covid/covid-19-data.page

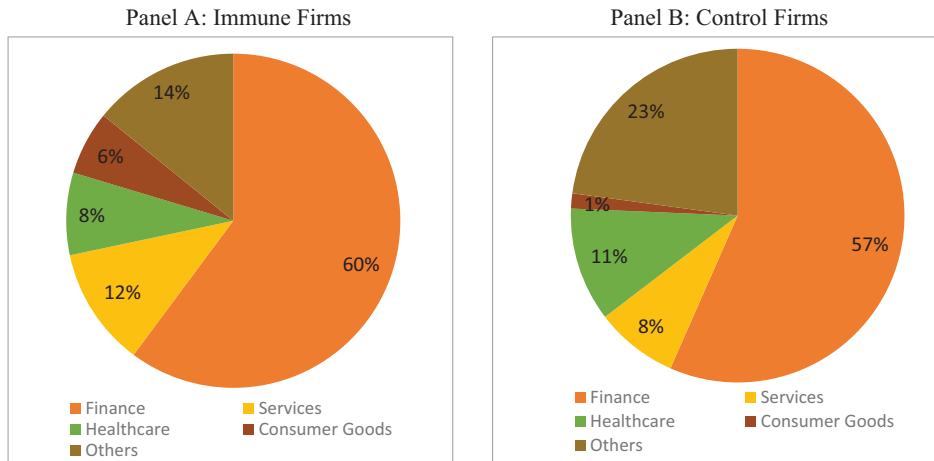Panel A: Immune Firms   Panel B: Control Firms

Figure 2. Industry distribution for immune and control firms
This figure shows the distribution of immune and control firms according to their industry classification. Industry aggregation is based on four-digit SIC codes. The 30 industry classification codes are used to construct the industries. They are obtained from Kenneth French's website. The period is between 9 December 2019 and 30 April 2020. Panel A: Distribution for 114 immune firms. Panel B: Distribution for 331 control firms.
[Colour figure can be viewed at wileyonlinelibrary.com]

during the Covid period, thus resulting in a set of 114 immune firms. For the control sample, we include firms with HQ in NYC that were traded on the NYSE, NYSE American or NASDAQ during the Covid period but not during the 9/11 period. These are the control firms that have not experienced the 9/11 shock before but are exposed to Covid. We have 331 control firms in the sample. Overall, the sample includes 445 firms and 43,124 firm-day observations.

Figure 2 presents the breakdown of immune and control firms by four-digit SIC industries. Both groups have a similar distribution of firms across industries. The majority of immune and control firms operate in the Finance sector (60% and 57%, respectively). Services and Healthcare are the next big industries for both immune and control groups. These three sectors correspond to about 80% of immune (76% of control) firms. Remaining minor industries include Consumer Goods, Communication, Utilities and Others.

Firm and market variables

Table 1A describes the variables used in this paper. We obtain daily data on firm stock prices, traded volume and dollar volume for publicly traded US firms from CRSP. Excess returns are defined as the daily returns in excess of the risk-free rate that is proxied by the 1-month T-bill rate. Market activity is measured using three different variables: the daily average traded volume of shares, dollar volume in US dollars and a signed version of traded volume calculated as the product of the realized daily returns and the daily average traded volume. While the former two represent a proxy for the aggregate fund flows that come into the marketplace, the latter one gives a sense of the direction of trading activity. The signed traded volume takes a positive (negative) value if there is buy (sell) pressure in the market (see e.g. Campbell, Grossman and Wang, 1993; Llorente *et al*., 2002; Tosun, 2021). As part of our robustness tests, we follow Mc-Tier, Tse and Wald (2013) and construct the daily change in natural logarithm of the traded volume and the dollar volume as dependent variables. To mitigate the influence of outliers, all variables are winsorized at the 1st and 99th percentiles.

We use aggregate risk factors, such as market risk, size, value, investment opportunities and profitability (see e.g. Fama and French, 2015) in our models. In unreported tests, we also control for momentum following Carhart (1997) and obtain virtually similar and robust results. We obtain factor-mimicking portfolios that proxy for these risk factors on a daily basis from the Kenneth R. French online library.[6] The daily change in these

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[6]https://mba.tuck.dartmouth.edu/pages/faculty/Ken. French/data_library.html

Table 1A. Definition of variables

Variable	Description
Immune	The dummy variable for firms with HQ in NYC and traded on NYSE, NYSE American and NASDAQ during both 9/11 and the Covid period; 0 for firms with HQ in NYC and traded only during the Covid period not 9/11.
Post	The daily dummy variable equal to 1 between 2 March and 30 April 2020, and 0 between 9 December 2019 and 28 February 2020.
Return	The daily stock return as a percentage.
Excess Return	The daily stock return in excess of the risk-free rate that is proxied by the 1-month T-bill rate.
Traded Volume	The amount of shares traded daily, in millions.
Dollar Volume	The amount of shares traded multiplied by the daily closing price, in million USD.
Signed Volume	The amount of shares traded multiplied by the daily stock return, in tens of thousands.
Delta Ln(Traded Volume)	The daily change in natural logarithm of the traded volume.
Delta Ln(Dollar Volume)	The daily change in natural logarithm of the dollar volume.
Market Value	The daily closing price multiplied by common shares outstanding, in billion USD.
Mktrf	The daily market return in excess of the risk-free rate that is proxied by the 1-month T-bill rate (Fama and French, 2015).
SMB	Small minus big (SMB) is the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios (Fama and French, 2015).
HML	High minus low (HML) is the average return on the two value portfolios minus the average return on the two growth portfolios (Fama and French, 2015).
RMW	Robust minus weak (RMW) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios (Fama and French, 2015).
CMA	Conservative minus aggressive (CMA) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios (Fama and French, 2015).
Overall Risk	Following Hassan *et al.* (2019), this risk measure relies on word counts that condition on proximity to the use of synonyms for 'risk' or 'uncertainty'. This measure counts the frequency of mentions of synonyms for risk or uncertainty, divided by the length of the transcript.
Covid-19 Risk	Following Hassan *et al.* (2020), this risk measure relies on word counts that condition on proximity to the use of synonyms for 'risk' or 'uncertainty'. This measure counts the frequency of mentions of synonyms for risk or uncertainty, particularly related to Covid-19, divided by the length of the transcript.

control variables is used in 'change regressions' as robustness tests. We also control for the aggregate market behaviour in return regressions by the total market value expressed in billions of USD. As part of the robustness tests, we follow Hassan *et al.* (2019, 2020) and further control different firm-level risks.[7] These risk measures rely on word counts that condition on proximity to the use of synonyms for 'risk' or 'uncertainty'. Overall Risk (Covid-19 Risk) is the frequency of mentions of synonyms for risk or uncertainty (related to Covid), divided by transcript length.

Table 1B provides the summary statistics for key variables of immune and control firms, in Panels A and B, respectively. Immune firms are larger in general ($11.9 billion) compared to control firms ($1.4 billion). The right-skewed distribution of Market Value suggests that there are few big firms in both samples of immune and control firms. While the average Return seems to be around −0.1% for both types of firms, highly right-skewed distributions of Traded and Dollar Volume imply that the stocks of certain firms are traded excessively more than others. The positive mean values for Signed Volume indicate that there is a buy pressure in the market.

Finally, Table 1C reports the correlations between the key variables.

Empirical approach and main findings

Empirical approach

We first examine whether markets react differently to immune firms than other control firms during the Covid period. Abnormal returns (AR) are measured using three different estimation windows: 3-month, 6-month and 9-month, which end 60 days before the Covid period, that is 2 March 2020. We estimate abnormal returns using two different event windows: 1-month and 2-month, starting on 2 March 2020. Expected returns are

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[7]We obtain the data from https://www.firmlevelrisk.com

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Table 1B. Descriptive statistics of key variables

Panel A: Immune firms

	Mean	Standard deviation	P25	Median	P75
Market value (billion USD)	11.871	24.664	0.153	0.714	8.721
Return (%)	−0.137	6.210	−3.071	0.000	2.812
Traded volume (millions)	2.867	5.532	0.077	0.621	2.441
Dollar volume (million USD)	117.121	239.300	0.576	4.630	99.865
Signed volume (10 thousands)	0.065	25.711	−1.473	0.000	1.198

Panel B: Control firms

	Mean	Standard deviation	P25	Median	P75
Market value (billions)	1.362	6.300	0.058	0.198	0.730
Return (%)	−0.099	6.222	−2.271	0.000	2.298
Traded volume (millions)	0.917	2.503	0.015	0.131	0.643
Dollar volume (millions)	17.393	66.415	0.150	1.142	7.443
Signed volume (10 thousands)	0.137	16.521	−0.289	0.000	0.260

This table presents mean, standard deviation, 25th percentile (P25), median and 75th percentile (P75) values of immune and control firms in the sample. While Panel A provides the statistics for 114 immune firms, Panel B gives the values for 331 control firms. The period is between 9 December 2019 and 30 April 2020. Market Value is daily closing price multiplied by common shares outstanding, in billion USD. Return is the daily stock return as a percentage. Traded Volume is the amount of shares traded daily for a stock in millions. Dollar Volume is the amount of shares traded multiplied by the daily closing price, in million USD. Signed Volume is the amount of shares traded multiplied by the daily stock return in tens of thousands.

Table 1C. Correlation table

	Return	Excess Return	Traded Volume	Dollar Volume	Signed Volume	Market Value	Mktrf	SMB	HML	RMW	CMA
Return	1										
Excess Return	1.000	1									
Traded Volume	0.006	0.006	1								
Dollar Volume	0.009	0.010	0.650	1							
Signed Volume	0.594	0.595	−0.009	−0.009	1						
Market Value	0.012	0.012	0.455	0.827	−0.009	1					
Mktrf	0.543	0.541	−0.021	−0.011	0.299	0.005	1				
SMB	0.210	0.211	−0.014	−0.013	0.105	0.001	0.055	1			
HML	0.398	0.396	−0.026	−0.014	0.219	0.007	0.553	0.290	1		
RMW	0.006	0.004	−0.009	−0.003	0.012	0.003	0.157	−0.327	0.151	1	
CMA	−0.094	−0.096	0.000	0.004	−0.047	0.001	−0.020	−0.492	0.134	0.408	1

This table presents the correlation between Return, Excess Return, Traded Volume, Dollar Volume, Signed Volume, Market Value, Mktrf, SMB, HML, RMW and CMA. Variable definitions are given in Table 1A.

estimated using the recent five-factor specification outlined in Fama and French (2015). As discussed by Blitz *et al.* (2018), we use the three-factor model and Carhart four-factor model in separate analyses to address the concerns around risk–return and momentum issues, as well as robustness concerns regarding the two additional factors in the five-factor model. We estimate AR and obtain very similar results. As is common in event study analysis, the identifying assumption is that the Covid pandemic is not correlated with an immune firm's expected return after controlling for the tradable risk factors. Lastly, we construct the cumulative abnormal returns (CARs) for firms in the Covid

period. To benchmark our results, we repeat this exercise for control firms as well.

To better understand the causal effect of *immunization* on firms during the Covid pandemic regarding returns and trading activity, we run a difference-in-difference (DID) analysis by estimating a set of panel regressions of the form

$$\text{Market reaction}_{i,t} = \alpha + \beta \, \text{Immune}_i \times \text{Post}_t$$
$$+ \gamma \, \text{Controls}_{i,t} + \delta_i + \mu_t + \varepsilon_{i,t} \quad (1)$$

where Market reaction$_{i,t}$ represents return, excess return, traded volume, dollar volume, signed volume for firm i on day t; Immune$_i$ is a dummy

Table 2. Cumulative abnormal returns of immune and control firms during Covid

Event window:	1 month			2 months		
Estimation window	Immune firms I	Control firms II	Difference III	Immune firms IV	Control firms V	Difference VI
3 months	−0.017	−0.085***	0.068***	0.123***	0.071***	0.052*
	(0.020)	(0.012)		(0.025)	(0.013)	
6 months	−0.009	−0.074***	0.066***	0.135***	0.090***	0.045*
	(0.018)	(0.012)		(0.021)	(0.013)	
9 months	0.003	−0.068***	0.071***	0.156***	0.106***	0.050**
	(0.018)	(0.012)		(0.020)	(0.012)	

This table presents the cumulative abnormal returns for immune and control firms during the Covid pandemic. Daily abnormal returns represent the return realized by an investor in excess of sources of systematic risk. The table reports the results using the Fama–French Five-Factor model for different estimation periods (3 months, 6 months and 9 months), 2 months before the first official Covid-19 case in NYC. The results are given for two different event windows (1 month and 2 months) after the first official Covid case recorded in NYC. The differences between CAR values of immune and control firms are also reported, along with the statistical significance. Robust standard errors are reported in parentheses.
*p < 0.10.
**p < 0.05.
***p < 0.01.

variable for immunized firms as described before; $Post_t$ is a dummy that is equal to 1 for the 2-month period starting on 2 March 2020, and 0 for the 3-month period before 2 March 2020; $Controls_{i,t}$ is a set of control variables, that is Mktrf, SMB, HML, RMW and CMA; δ_i and μ_t are firm and time fixed effects, respectively. Immune and Post dummies enter into the model as the interaction term only because individually they are subsumed by the firm and time fixed effects, respectively. Market Value is added as a control for all return regressions. In robustness tests, Overall Risk and Covid-19 Risk are included as additional controls. In further analyses, the $Post_t$ dummy is adjusted to cover only the first month of the Covid period, to measure the most immediate reaction of the markets to immune firms. In other analyses, Delta Ln(Traded Volume) and Delta Ln(Dollar Volume) are used as dependent variables representing the daily changes. The associated control variables are also transformed into daily changes for those regressions. For all analyses in this paper, standard errors are clustered at the firm level.

Meyer (1995) discusses the main advantages of the DID approach as its simplicity and potential to evade the endogeneity problems that arise when making comparisons between heterogeneous entities. Another key point of DID is that it accounts for change due to factors other than the treatment or intervention being studied. Also, since it focuses on change rather than the absolute levels, the groups being compared can start at different lev-els. Further, the DID method allows the treatment effect to be estimated, and when used in conjunction with a natural experiment, for example Covid, the shock provides the randomization which is essential for DID. Due to these reasons and advantages, we decided to use the DID approach in this study.

Considering the rapid increase in cases and deaths in Figure 1, Covid appears to be an unanticipated, random shock and its impact is immediate and sharp. Hence, endogeneity of this shock should not be an issue for our DID approach. Further, our analysis on daily data includes a 2-month post-Covid period in NYC. Due to these reasons, we believe the DID model is adequate concerning any periodicity. However, the assumption is that the errors in the DID model are correlated and residuals are not independent. Hence, simple residual resampling to replicate the correlation in the data fails under a simple bootstrapping method. To validate our results, we conduct block bootstrapping as suggested by Bertrand, Duflo and Mullainathan (2004). In particular we implement the overlapping (moving) block bootstrapping method, and our data are split into blocks of 50 observations,[8] that is block length b, as by

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[8]As discussed by Radovanov and Marcikic (2014), block length may influence the entire block bootstrapping exercise, while there are no definite rules on how to determine the block length. Hence, we also repeat the analysis with shorter and longer block lengths, for example 25, 75 and 100.

Table 3. Difference-in-difference analysis on returns

	Return (%) I	Excess return (%) II
Immune × Post	0.140**	0.146**
	(0.067)	(0.068)
Market Value	0.036***	0.035***
	(0.008)	(0.0086)
Mktrf	0.581***	0.572***
	(0.042)	(0.043)
SMB	0.308***	0.394***
	(0.098)	(0.100)
HML	0.224***	0.174***
	(0.060)	(0.062)
RMW	−0.027	0.365*
	(0.204)	(0.206)
CMA	−1.906***	−2.158***
	(0.334)	(0.338)
Constant	−0.685***	−1.409***
	(0.187)	(0.189)
Firm fixed effects	YES	YES
Day dummies	YES	YES
Observation	43,110	43,110
Adj. R^2	0.360	0.367

This table presents estimates for Immune × Post along with Mktrf, SMB, HML, RMW and CMA as control variables. Return and Excess Return are the dependent variables. Immune is the dummy variable for firms with HQ in NYC and traded on the NYSE, NYSE American and NASDAQ during both 9/11 and the Covid period, and 0 for firms with HQ in NYC and traded only during the Covid period but not 9/11. Post is the daily dummy variable that is equal to 1 between 2 March and 30 April 2020, and 0 between 9 December 2019 and 28 February 2020. Return is the daily stock return as a percentage. Excess Return is the daily stock return in excess of the risk-free rate that is proxied by the 1-month T-bill rate. Variable definitions are given in Table 1A. Time and firm fixed effects are included. Standard errors are clustered by firms and given in parentheses.
*$p < 0.10$.
**$p < 0.05$.
***$p < 0.01$.

Table 4. Difference-in-difference analysis on trading activity

	Traded Volume I	Dollar Volume II	Signed Volume III
Immune × Post	0.543***	18.890***	0.607***
	(0.189)	(5.264)	(0.233)
Mktrf	−0.147***	−2.172***	0.997***
	(0.018)	(0.416)	(0.127)
SMB	0.209***	4.085***	0.600**
	(0.033)	(0.829)	(0.266)
HML	−0.085***	−3.466***	0.251
	(0.019)	(0.641)	(0.171)
RMW	0.744***	9.584***	−0.115
	(0.112)	(2.392)	(0.541)
CMA	−0.872***	−9.860***	−0.569
	(0.117)	(2.233)	(0.899)
Constant	0.490***	27.250***	0.347
	(0.083)	(2.454)	(0.455)
Firm fixed effects	YES	YES	YES
Day dummies	YES	YES	YES
Observation	43,124	43,124	43,108
Adj. R^2	0.081	0.058	0.115

This table presents estimates for Immune × Post along with SMB, HML, RMW and CMA as control variables. Traded Volume, Dollar Volume and Signed Volume are the dependent variables. Immune is the dummy variable for firms with HQ in NYC and traded on the NYSE, NYSE American and NASDAQ during both 9/11 and the Covid period, and 0 for firms with HQ in NYC and traded only during the Covid period but not 9/11. Post is the daily dummy variable that is equal to 1 between 2 March and 30 April 2020, and 0 between 9 December 2019 and 28 February 2020. Traded Volume is the amount of shares traded daily, in millions. Dollar Volume is the amount of shares traded multiplied by the daily closing price, in million USD. Signed Volume is the amount of shares traded multiplied by the daily stock return, in tens of thousands. Variable definitions are given in Table 1A. Time and firm fixed effects are included. Standard errors are clustered by firms and given in parentheses.
*$p < 0.10$.
**$p < 0.05$.
***$p < 0.01$.

definition we form n − b + 1 blocks, where n is the length of the time series in our sample. Observations 1 to 50 will be block #1, observations 2 to 51 will be block #2, and so on. Hence, the block bootstrapping approach can replicate the correlations by resampling inside blocks of data. In unreported analyses, we obtain robust results consistent with our original findings.

Main findings

In Table 2, we report the CARs for immune firms and control firms during our event periods. We start by discussing the results for CAR analyses

regarding how 1-month and 2-month event periods support our hypothesis that firms which survived the financial distress associated with 9/11 (Sudarsanam and Lai, 2001) fared better during the Covid period. The results are robust to the choice of different estimation windows. We stress the statistically significant differences in results between immune and control firms. When we use a 1-month event window, we observe that CARs are not significantly different from zero and immune firms do not react to the Covid news. However, control firms have a negative reaction to the Covid news. The differences between the CARs of immune firms and those of control firms are

Table 5. Placebo test and t test for returns and trading activity

Panel A: Placebo test on returns and trading activity for immune and peer (control) firms

	Return (%) I	Excess Return (%) II	Traded Volume III	Dollar Volume IV	Signed Volume V
Immune × Post	0.036	0.035	0.028	0.503	0.071
	(0.043)	(0.043)	(0.032)	(1.347)	(0.079)
Market Value	0.105***	0.105***			
	(0.018)	(0.017)			
Mktrf	0.782***	0.724***	−0.052***	−2.630***	0.735***
	(0.037)	(0.037)	(0.012)	(0.667)	(0.081)
SMB	0.251***	0.251***	0.035*	−0.117	0.150*
	(0.062)	(0.062)	(0.018)	(0.528)	(0.081)
HML	0.100	0.094	−0.020	−0.087	0.197**
	(0.066)	(0.066)	(0.017)	(0.515)	(0.100)
RMW	−0.131	−0.122	0.035	4.754***	−0.434**
	(0.158)	(0.157)	(0.055)	(1.678)	(0.220)
CMA	0.089	0.057	0.010	−0.093	0.285*
	(0.102)	(0.102)	(0.022)	(1.051)	(0.157)
Constant	−0.588***	−1.457***	0.746***	30.680***	0.030
	(0.096)	(0.096)	(0.018)	(0.781)	(0.059)
Firm fixed effects	YES	YES	YES	YES	YES
Day dummies	YES	YES	YES	YES	YES
Observation	44,210	44,210	44,234	44,234	44,210
Adj. R^2	0.088	0.088	0.026	0.023	0.039

Panel B: T Test on returns for immune and peer (non-survivor) firms

	Period	Immune firms	Peer firms	Difference	p
Full period	1984–2000	0.086	0.116	*−0.030*	0.652
	2002–2018	0.187	0.178	*0.009*	0.926
5-Year period	1996–2000	0.108	0.109	*−0.001*	0.991
	2002–2006	0.231	0.211	*0.020*	0.905

Panel A of this table presents estimates for Immune × Post along with Market Value, SMB, HML, RMW and CMA as control variables. Return, Excess Return, Traded Volume, Dollar Volume and Signed Volume are the dependent variables. For this analysis, the main model is the same, but the timeline is shifted 6 months backwards. Post is the daily dummy variable that is equal to 1 between 3 September 2019 and 31 October 2019, and 0 between 3 June and 30 August 2019. Immune is the dummy variable for firms with HQ in NYC and traded on the NYSE, NYSE American and NASDAQ during both 9/11 and the Covid period, and 0 for the peer (control) firms with HQ in NYC and traded only during the Covid period but not 9/11. Variable definitions are given in Table 1A. Time and firm fixed effects are included. Standard errors are clustered by firms and given in parentheses.
*p < 0.10.
**p < 0.05.
***p < 0.01.
Panel B of this table gives t-test results on annual returns for immune firms and their peers (non-survivors). For this panel, peers (non-survivors) are firms with HQ in NYC trading during 9/11 but not Covid. Immune firms are defined the same as before.

economically significant and vary between 6.8%, 6.6% and 7.1% when we use estimation windows of 3, 6 and 9 months, respectively. When we consider CARs during the extended 2-month event window, we observe again that the differences between the CARs of immune and control firms are economically significant and vary between 5.2%, 4.5% and 5%, respectively.

Table 3 presents results from our DID estimations for firms exposed to 9/11 and those that were

not. The first column reports results for stock returns and the second column reports results for excess returns. The findings are robust to the choice of return definitions. The DID term is Immune × Post, where Immune takes the value 1 if the firm is exposed to 9/11 and survived, and 0 otherwise. Post is a dummy variable equal to 1 during Covid, and 0 otherwise. Control variables are significant with expected signs. We observe that the firms exposed to 9/11 and survived have gained immunity

Table 6. Additional risk factors

Panel A: Controlling for overall risk

	Return (%) I	Excess Return (%) II	Traded Volume III	Dollar Volume IV	Signed Volume V
Immune × Post	0.143**	0.150**	0.552***	18.910***	0.611***
	(0.066)	(0.067)	(0.185)	(5.265)	(0.232)
Overall Risk	−0.001	−0.001	−0.006**	−0.016	−0.003
	(0.001)	(0.001)	(0.003)	(0.049)	(0.003)
Other controls	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES
Day dummies	YES	YES	YES	YES	YES
Observation	43,110	43,110	43,124	43,124	43,108
Adj. R^2	0.360	0.367	0.089	0.058	0.115

Panel B: Controlling for Covid-19 risk

Immune × Post	0.126*	0.133**	0.541***	18.740***	0.606***
	(0.067)	(0.068)	(0.189)	(5.250)	(0.234)
Covid-19 Risk	−2.508***	−2.547***	−0.462	−26.240***	−0.156
	(0.908)	(0.909)	(0.293)	(9.088)	(1.614)
Other controls	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES
Day dummies	YES	YES	YES	YES	YES
Observation	43,110	43,110	43,124	43,124	43,108
Adj. R^2	0.360	0.367	0.081	0.058	0.115

This table presents estimates for Immune × Post along with Overall Risk (Panel A) and Covid-19 Risk (Panel B) as additional control variables. Original control variables are also included in the model. Return, Excess Return, Traded Volume, Dollar Volume and Signed Volume are the dependent variables. Following Hassan *et al*. (2019, 2020), Overall Risk (Covid-19 Risk) relies on word counts that condition on proximity to the use of synonyms for 'risk' or 'uncertainty'. This measure counts the frequency of mentions of synonyms for risk or uncertainty divided by transcript length. Variable definitions are given in Table 1A. Time and firm fixed effects are included. Standard errors are clustered by firms and given in parentheses.
*p < 0.10.
**p < 0.05.
***p < 0.01.

and learnt from such a disastrous experience, as they earn 14% (14.6%) more than their peers in stock returns (excess returns) during the Covid crisis. These findings support H1.

Table 4 presents results from our DID estimations on trading volume, dollar volume and signed volume for firms that faced 9/11 and those that did not during the Covid crisis. The results are robust to the choice of trading volume definitions. For all measures of trading activity, we observe the firms that were exposed to 9/11 and survived have learnt how to manage such crises as their trading activity was significantly higher than that of their peers during Covid, with coefficient estimates of 0.5 for Traded Volume, 18.9 for Dollar Volume and 0.6 for Signed Volume. The positive coefficient for Signed Volume indicates that the higher trading activity is due to buy pressure by investors requesting more shares of immune firms. These results support H2.

Robustness tests

Tests on resilience and peer firms

To analyse the resilience of immune firms, we conduct a placebo test where we keep our main model the same but shift the timeline 6 months (also 9 and 12 months in untabulated analyses) backwards. If our main results are driven by the resilience or survivorship of immune firms, then those firms should still perform better than their peers, that is control firms, in 'normal times' when they cannot benefit from their prior 9/11 experience. Statistically insignificant results in Panel A of Table 5 indicate that resilience (or survivorship) of immune firms

Table 7. First month of Covid pandemic

	Return (%) I	Excess Return (%) II	Traded Volume III	Dollar Volume IV	Signed Volume V
Immune × Post	0.336***	0.343***	0.724***	31.140***	0.011
	(0.126)	(0.128)	(0.200)	(7.628)	(0.318)
Market Value	0.063***	0.062***			
	(0.014)	(0.014)			
Mktrf	0.628***	0.656***	0.092***	0.864**	0.796***
	(0.047)	(0.048)	(0.017)	(0.431)	(0.112)
SMB	0.361**	0.434***	0.221***	0.750	0.290
	(0.143)	(0.144)	(0.045)	(1.240)	(0.342)
HML	0.823***	0.759***	−0.409***	−3.748**	1.518***
	(0.162)	(0.163)	(0.067)	(1.647)	(0.374)
RMW	−1.275***	−1.278***	0.340***	7.812***	−1.239***
	(0.164)	(0.166)	(0.050)	(1.410)	(0.379)
CMA	−0.560	−0.360	0.999***	10.060**	−1.031
	(0.403)	(0.407)	(0.174)	(4.463)	(0.933)
Constant	−0.728***	−1.376***	1.020***	34.101***	−0.042
	(0.123)	(0.124)	(0.034)	(1.249)	(0.238)
Firm fixed effects	YES	YES	YES	YES	YES
Day dummies	YES	YES	YES	YES	YES
Observation	33,885	33,885	33,897	33,897	33,885
Adj. R^2	0.382	0.381	0.103	0.073	0.124

This table presents estimates for Immune × Post along with Market Value, SMB, HML, RMW and CMA as control variables. Return, Excess Return, Traded Volume, Dollar Volume and Signed Volume are the dependent variables. For this analysis, Post includes only the first month of the Covid period. Particularly, Post is the daily dummy variable that is equal to 1 between 2 March and 31 March 2020, and 0 between 9 December 2019 and 28 February 2020. Immune is the dummy variable for firms with HQ in NYC and traded on the NYSE, NYSE American and NASDAQ during both 9/11 and Covid, and 0 for firms with HQ in NYC and traded only during Covid but not 9/11. Variable definitions are given in Table 1A. Time and firm fixed effects are included. Standard errors are clustered by firms and given in parentheses.
*$p < 0.10$.
**$p < 0.05$.
***$p < 0.01$.

is not the reason leading our main results. Further, we compare the immune firms to their peers during 9/11 which did not survive until Covid, that is non-survivors. Considering a full period and 5-year period before and after 9/11, we conduct t tests on annual stock returns. The statistically insignificant results in Panel B of Table 5 show that immune firms do not perform differently from their peers, either pre- or post-9/11.

Additional risk factors

In this section we introduce additional risk factors. Panel A of Table 6 reports results for Overall Risk and Panel B for Covid-19 Risk, which we measure following the methodology as described in Hassan *et al.* (2019, 2020). We use word counts that condition on proximity using synonyms for 'risk' or 'uncertainty' overall or related to Covid scaled by the length of the transcript. Controlling for overall risk, firms exposed to the 9/11 shock earn 14.3% more in returns and 15% more in excess returns and have significantly higher trading activity regardless of the measure we use. Similarly, when we control for Covid-19 Risk in particular, immune firms earn 12.6% and 13.2% higher returns and excess returns than control firms and have higher trading activity during Covid.

Focused time period

In this section we focus on the very first outbreak period for Covid, that is the first month, to capture the very initial reaction of the markets towards immune firms (see Table 7). Our results indicate that during the initial outburst of Covid, firms that survived 9/11 earn economically significant and higher returns compared to their peers. Particularly, firms that survived 9/11 earn 33.6% (34.3%) more in (excess) returns than their peers during

Table 8. Difference-in-difference analysis with different measures for trading

	Delta Ln (Traded Volume) I	Delta Ln (Dollar Volume) II
Immune × Post	0.010*	0.012**
	(0.005)	(0.006)
Delta Mktrf	−0.005	−0.005
	(0.006)	(0.007)
Delta SMB	−0.001	0.004
	(0.013)	(0.014)
Delta HML	−0.017*	−0.012
	(0.009)	(0.010)
Delta RMW	−0.081**	−0.109***
	(0.038)	(0.040)
Delta CMA	0.054	0.089**
	(0.042)	(0.045)
Constant	0.014	0.017
	(0.061)	(0.066)
Firm fixed effects	YES	YES
Day dummies	YES	YES
Observation	42,679	42,679
Adj. R^2	0.026	0.022

This table presents estimates for Immune × Post along with Delta Mktrf, Delta SMB, Delta HML, Delta RMW and Delta CMA as control variables. Delta Ln(Traded Volume) and Delta Ln(Dollar Volume) are the new dependent variables. Following McTier, Tse and Wald (2013), Delta Ln(Traded Volume) and Delta Ln(Dollar Volume) are calculated as the daily change in natural logarithm of the traded volume and dollar volume, respectively. Immune is the dummy variable for firms with HQ in NYC and traded on the NYSE, NYSE American and NASDAQ during both 9/11 and the Covid period, and 0 for firms with HQ in NYC and traded only during the Covid period but not 9/11. Post is the daily dummy variable that is equal to 1 between 2 March and 30 April 2020, and 0 between 9 December 2019 and 28 February 2020. Variable definitions are given in Table 1A. Time and firm fixed effects are included. Standard errors are clustered by firms and given in parentheses.
*p < 0.10.
**p < 0.05.
***p < 0.01.

Covid. Similarly, their trading activity is significantly higher during this initial wave of Covid.

Different measures for trading activity

In this section we repeat the DID analysis using two different measures of trading activity (see Table 8). We follow the methodology in McTier, Tse and Wald (2013) and define Delta Ln(Traded Volume) and Delta Ln(Dollar Volume) as the daily change in natural logarithm of the traded volume and dollar volume, respectively. This measure is fit for our purpose as it introduces a daily change setup in the time frame of analysis, where information changes on a daily basis and there is ample uncertainly. Yet we observe that our main results are robust to the short-term definitions of trading volumes. Coefficient estimates are significant and in the range of 1% and 1.2%, respectively, for Delta Ln(Traded Volume) and Delta Ln(Dollar Volume).

Analysis excluding the finance sector

The finance sector corresponds to about 60% of our sample for immune firms, therefore it could be argued that our results are driven by them. In this section we exclude firms in the finance sector and repeat the analysis for firms in other service and manufacturing industries (see Table 9). Our results indicate that in fact those firms have higher levels of immunization. Firms that survived 9/11 have returns (excess returns) that are 36.4% (36.6%) higher than their peers. Similarly, all trading measures indicate trading activity is higher for such survivors of 9/11.

Analysis of shutdown industries

One of the main features of the Covid pandemic is the disproportionate treatment of immune firms in shutdown versus running industry classification. Following state regulation, the shutdown industries include Recreation, Entertainment, Textile, Mining, Construction, Restaurants and Hotels, and Others; while the running industries are Finance, Healthcare, Consumer Goods, Communication and Utilities. We estimate DID regressions separately for each group (see Table 10). We observe that immune firms in shutdown industries perform much better than their peers during the Covid crisis. They earn returns (excess returns) of 33.9% (33.1%) higher than their non-immune peers during the Covid crisis, and all trading activity measures indicate higher trading volumes. Immune firms in industries that continued to operate during the Covid crisis earn 10.6% (11.6%) more than their peers in stock returns (excess returns), yet marginally statistically significant despite trading activity measures indicating higher trading activity compared to their peers.

Table 9. Analyses excluding finance sector

	Return (%) I	Excess Return (%) II	Traded Volume III	Dollar Volume IV	Signed Volume V
Immune × Post	0.364***	0.366***	0.379*	25.830***	0.901*
	(0.121)	(0.122)	(0.192)	(8.853)	(0.478)
Market Value	0.127***	0.126***			
	(0.030)	(0.031)			
Mktrf	0.595***	0.589***	−0.130***	−1.823***	1.231***
	(0.078)	(0.079)	(0.029)	(0.647)	(0.225)
SMB	0.425**	0.509***	0.153***	3.162**	0.237
	(0.176)	(0.179)	(0.052)	(1.287)	(0.461)
HML	0.191*	0.141	−0.054*	−2.852***	0.444
	(0.104)	(0.106)	(0.029)	(0.944)	(0.300)
RMW	−0.164	0.218	0.520***	4.483	−1.780*
	(0.399)	(0.404)	(0.161)	(3.254)	(1.049)
CMA	−0.750	−0.988	−0.713***	−6.723*	1.732
	(0.600)	(0.609)	(0.183)	(3.414)	(1.462)
Constant	−1.083**	−1.796***	0.786***	36.250***	1.376
	(0.433)	(0.437)	(0.133)	(3.808)	(1.024)
Firm fixed effects	YES	YES	YES	YES	YES
Day dummies	YES	YES	YES	YES	YES
Observation	18,604	18,604	18,617	18,617	18,602
Adj. R^2	0.235	0.243	0.053	0.060	0.089

This table presents estimates for Immune × Post along with Market Value, SMB, HML, RMW and CMA as control variables. Return, Excess Return, Traded Volume, Dollar Volume and Signed Volume are the dependent variables. The analyses are conducted excluding the major industry in the sample (i.e. Finance) to test the robustness of the original findings in Tables 3 and 4. Immune is the dummy variable for firms with HQ in NYC and traded on the NYSE, NYSE American and NASDAQ during both 9/11 and the Covid period, and 0 for firms with HQ in NYC and traded only during the Covid period but not 9/11. Post is the daily dummy variable that is equal to 1 between 2 March and 30 April 2020, and 0 between 9 December 2019 and 28 February 2020. Variable definitions are given in Table 1A. Time and firm fixed effects are included. Standard errors are clustered by firms and given in parentheses.
*$p < 0.10$.
**$p < 0.05$.
***$p < 0.01$.

Conclusions

Economic turmoil during Covid is unparalleled in recent history. Just as scientists are challenged by the very many unanswered questions posed by coronavirus, economists are similarly puzzled by its associated economic consequences and how financial markets have reacted to this unprecedented disruption. In this paper, we show that to better understand how financial markets capture and price corporate risks associated with the pandemic, it may be best to take a step back and look at events that posed a similar degree of shock to the financial system. One such event with similar levels of shock imposed on financial markets is the terrorist attacks of September 2001, which mainly targeted NYC.

Having examined firms that were headquartered in NYC and traded on one of its three stock exchanges during 2001, we zero in on those firms that managed to financially survive 9/11 and were trading just before Covid hit them. We find that such firms displayed more financial resilience compared to their peer group during the Covid turmoil. Specifically, their stock price losses during the Covid episode were lower by about 7% compared to firms that were not exposed to the 9/11 shock, a figure both statistically and economically significant, and representing billions of dollars of market value 'saved' compared to the control group.

As explained in the empirical section of the paper, we ran various other tests to show that this finding is robust to alternative financial proxies, different definitions of estimation windows and control firms. Interestingly, we show that such immunized firms that have learnt from similar struggles in the past also experienced higher trading volumes due to buying pressures from the market. In other words, there is strong evidence that financial

Table 10. Analysis of shutdown and running industries during the Covid period

Panel A: Shutdown industries during the Covid pandemic

	Return (%) I	Excess Return (%) II	Traded Volume III	Dollar Volume IV	Signed Volume V
Immune × Post	0.339**	0.331**	0.321*	23.201*	0.279
	(0.168)	(0.169)	(0.187)	(14.050)	(0.224)
Controls	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES
Day dummies	YES	YES	YES	YES	YES
Observation	10,516	10,516	10,523	10,523	10,514
Adj. R^2	0.239	0.248	0.052	0.049	0.095

Panel B: Running industries during the Covid pandemic

	Return (%) I	Excess Return (%) II	Traded Volume III	Dollar Volume IV	Signed Volume V
Immune × Post	0.106	0.116*	0.577***	17.690***	0.685***
	(0.075)	(0.070)	(0.220)	(5.586)	(0.261)
Controls	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES
Day dummies	YES	YES	YES	YES	YES
Observation	32,594	32,594	32,601	32,601	32,594
Adj. R^2	0.408	0.413	0.092	0.064	0.125

This table presents estimates for Immune × Post along with control variables. Return, Excess Return, Traded Volume, Dollar Volume and Signed Volume are the dependent variables. Analyses are conducted for shutdown and running industries during the Covid-19 pandemic, separately. Shutdown industries include Recreation, Entertainment, Textile, Mining, Construction, Restaurants and Hotels, and Others; while running industries are Finance, Healthcare, Consumer Goods, Communication and Utilities. Immune is the dummy variable for firms with HQ in NYC and traded on the NYSE, NYSE American and NASDAQ during both 9/11 and the Covid period, and 0 for firms with HQ in NYC and traded only during the Covid period but not 9/11. Post is the daily dummy variable that is equal to 1 between 2 March and 30 April 2020, and 0 between 9 December 2019 and 28 February 2020. Variable definitions are given in Table 1A. Time and firm fixed effects are included. Standard errors are clustered by firms and given in parentheses.
*$p < 0.10$.
**$p < 0.05$.
***$p < 0.01$.

markets 'price in' and thus value corporate exposure to prior disasters, and by implication, the additional organizational resilience gained through such experiences. We argue that this organizational resilience is created through organizations 'learning' how to respond to systemic shocks of a disastrous nature, even if they are few and far between. The way organizations respond to these systemic shocks becomes part and parcel of their organizational culture and work processes that constitute their 'organisational memory' (Walsh and Ungson, 1991). Learning may also happen through fostering attitudes and processes that address error management within the organization following challenging times, particularly through a 'no blame' organizational learning approach (e.g. Provera, Montefusco and Canato, 2010).

In essence humans, and by extension organizations, categorize their knowledge around frames/schema. These frames typically enable organizations to interpret events through organizational learning and memory processes. However, at times, they can also lead to a distorted construction of the accepted version of 'reality' (Goffman, 1974). This is particularly the case for traumatic and unusual events, where the sense-making process is more easily disturbed and thus opportunities for genuine learning arise (e.g. Smith and Elliott, 2007; Weick, 1995). In our context, this learning occurred (and proved useful later during Covid) in organizations that were exposed to the unprecedented and traumatic experience of 9/11.

Thus, our findings make contributions to (1) the literature on market reactions to pandemics and other public health events; (2) the body of work on market reactions to terrorist events and the associated spillover; (3) the literature on the long-term memory of stock markets; and (4) the literature on organizational learning facilitated by exposure to disastrous events. Furthermore, these results are of considerable importance to the corporate sector and to policymakers from a practical point of view,

given that the likelihood of similar epidemics and pandemics occurring in the future is seen as non-trivial.

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