

Essays on Corporate Resilience and Risk Pricing
During the COVID-19 Pandemic

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Abstract

The Covid-19 pandemic, initially a global health crisis, rapidly evolved into a full-scale economic shock, deeply impacting firms, financial markets, and policymaking. This thesis explores how firms responded to the pandemic across three dimensions: firm-level resilience, intertemporal market responses across multiple waves, and the pricing of firm-specific Covid and political risk. This study uses the US, UK, China, Brazil, India, France, Germany, and Italy as our sample countries as these countries were seriously affected by Covid in terms of death rate. This thesis uses relevant methods like OLS, fixed effects, quintile regressions. By combining cross-country and firm-level data, the thesis provides a comprehensive analysis of the heterogeneity in firm performance and risk pricing during the pandemic. Empirical chapter one investigates whether firm characteristics measured prior to the pandemic can explain variations in firm performance during the first wave of COVID-19. The analysis reveals that firm size, cash holdings, capital expenditure, executive compensation, risk, and ownership concentration significantly predict stock returns during the crisis. Empirical chapter two examines whether investors and firms learned from earlier waves of COVID-19 or whether firm performance was driven by persistent, underlying business models. This chapter tests two competing hypotheses—the *learning hypothesis* and the *business model hypothesis*. The findings lend greater support to the latter: performance in one wave is positively correlated with performance in subsequent waves, particularly for the second, third, and fourth waves. Empirical chapter three explores whether firm-level COVID risk and political risk were priced in financial markets during the pandemic. The study finds that both types of risk are significantly and positively related to stock returns, particularly in 2020 when the crisis was most acute. This suggests investors required a risk premium to hold stocks exposed to higher COVID and political uncertainty.

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Declaration

I declare that this thesis is a presentation of original work, and I am the sole author. This work has not previously been presented for a degree or other qualification at this University or elsewhere. All sources are acknowledged as references.

Dedication

To my parents, and my wife, for their support, sacrifice and care.

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Chapter 1

1.Introduction

1.1 Preamble

The outbreak of the novel coronavirus (COVID-19) in late 2019 and its escalation into a global pandemic in early 2020 brought about unprecedented disruptions to human lives, economies, and financial systems. With over 6 million confirmed deaths globally by 2023 (WHO, 2023), the human toll of COVID-19 has been profound. Beyond its public health implications, the pandemic triggered one of the most volatile periods in modern financial history, severely affecting global stock markets and firm performance. Understanding the wide-ranging impacts of COVID-19 on financial markets and corporations is vital for building more resilient systems in the face of future crises.

The COVID-19 pandemic represents an unprecedented health shock that fundamentally differs from previous crises in both its scale and its transmission mechanisms across economies and firms. Unlike financial or regionally contained health crises, COVID-19 simultaneously disrupted labour supply, consumer demand, global supply chains, and financial markets through government-mandated lockdowns, mobility restrictions, and prolonged uncertainty. The shock unfolded in distinct waves rather than as a single event, with each wave triggering renewed public health interventions and policy responses that altered firms' operating environments. Beginning with the first wave from January to May 2020, economies experienced abrupt shutdowns and market collapses, followed by subsequent waves that brought recurring disruptions, regulatory uncertainty, and uneven recovery across sectors and regions. This wave-based nature of the pandemic created persistent and evolving constraints on firms' production, financing, and risk management decisions, distinguishing COVID-19 from earlier health shocks and underscoring its role as a systemic, economy-wide institutional

shock rather than a transitory or localized event. As the covid-19 unfolded in different waves, hence this thesis provides a deeper examination of different waves for different countries.

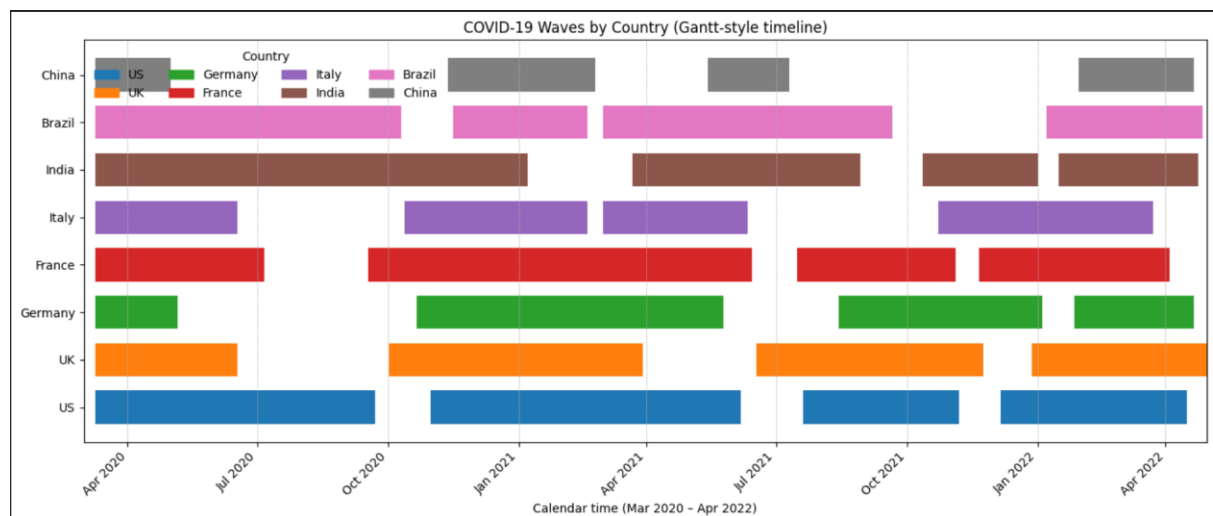


Figure 1. Timeline of Covid waves in different countries according to confirmed deaths
Source: Drawn by myself based on Our World in Data.

The beginning is when covid cases started to rise for at least three weeks (and then reaches at a peak) and the end is when covid cases declined until the deaths flatten out. I do not rely on confirmed cases as initially at the beginning of pandemic the testing of covid was not widespread.

COVID-19 was primarily a health crisis, but its economic consequences were quickly felt around the globe. Lockdowns, travel restrictions, and quarantines led to widespread business closures and unemployment. The International Monetary Fund (IMF) estimated that the global economy contracted by 3.1% in 2020, marking the worst peacetime recession since the Great Depression (IMF, 2021). This sharp downturn had cascading effects on firms' revenues, supply chains, and investor sentiment. The human cost of the pandemic had direct and indirect impacts on the economy. Mortality and morbidity affected labour supply, productivity, and consumer behaviour. Moreover, fear and uncertainty about the virus curtailed demand in sectors such as hospitality, tourism, and retail (Baker et al., 2020). These changes in consumer patterns were compounded by supply-side shocks, including factory shutdowns and shipping delays.

One of the most immediate financial consequences of the pandemic was the dramatic increase in stock market volatility. In March 2020, global stock indices experienced some of their sharpest declines in decades. The S&P 500 fell by more than 30% from its peak in February to its trough in March, triggering multiple circuit breakers to halt trading (Salisu & Vo, 2020). Similarly, the FTSE 100 and the Nikkei 225 experienced record losses, reflecting global investor panic.

Researchers have noted that COVID-19 induced "unprecedented levels of market uncertainty" (Zhang, Hu, and Ji, 2020). The Chicago Board Options Exchange Volatility Index (VIX), often referred to as the "fear index," spiked to levels not seen since the 2008 financial crisis. The health crisis, being exogenous and not rooted in economic or financial factors, rendered traditional risk assessment models inadequate. The financial panic was not simply a reflection of reduced earnings expectations but also the result of behavioural responses to uncertainty and the speed at which news disseminated through social and financial media (Haroon & Rizvi, 2020). News about infection rates, deaths, and government responses led to real-time adjustments in market valuations.

COVID-19 did not affect all firms and sectors equally. Companies in travel, hospitality, and retail were among the hardest hit, while others such as technology firms and online retailers thrived. This heterogeneity highlights the importance of disaggregating the impact of COVID-19 when analysing its effects on stock markets. Barro, Ursúa, and Weng (2020) found that pandemic-induced downturns can lead to long-lasting economic scars, especially in industries reliant on physical interaction. Meanwhile, firms with strong digital infrastructure, low leverage, or access to liquidity were more resilient (Ding et al., 2021). For example, Amazon and Zoom saw their stock prices surge during the pandemic due to increased demand for e-commerce and remote communication tools. Moreover, the pandemic exposed the vulnerabilities of small and medium enterprises (SMEs), which often lacked the buffers

necessary to weather prolonged periods of reduced activity. Unlike large corporations, many SMEs struggled to access emergency funding or adapt quickly to changing business environments (Juergensen, Guimón, & Narula, 2020).

The wide-ranging effects of COVID-19 on stock markets and firms necessitate a multidimensional approach to study its implications. First, the pandemic was not a single event but a series of waves, each with distinct economic and policy responses. Researchers such as Ramelli and Wagner (2020) argue that firm-level exposure to COVID-19 varied over time and by region, highlighting the need for temporal and geographic granularity in analysis. Second, the pandemic introduced new types of risk into the corporate environment: health risk, regulatory risk, and geopolitical risk, which were previously considered peripheral. For instance, firms had to adapt to sudden changes in government policy, such as lockdowns and stimulus programs, which had direct consequences on operational and financial performance (Fahlenbrach et al., 2021).

Third, the role of non-financial factors, such as corporate social responsibility (CSR), political connections, and supply chain resilience, gained prominence during COVID-19. Companies that demonstrated agility, transparency, and stakeholder commitment were perceived more favourably by investors (Albuquerque et al., 2020). This underscores the importance of incorporating ESG (Environmental, Social, Governance) metrics in firm valuation during crises. Fourth, COVID-19 provides a natural experiment to test theories of market efficiency, investor behaviour, and risk pricing. For example, several studies have used high-frequency data to analyse how markets incorporate pandemic-related news into prices (Engle, 2021). Others have investigated how firm characteristics such as leverage, cash holdings, and board diversity influenced stock returns during the crisis (Papanikolaou and Schmidt, 2020).

Understanding the varied impact of COVID-19 is also essential for policy formulation and crisis management. Governments and central banks implemented massive stimulus programs, including The Coronavirus Aid, Relief, and Economic Security (CARES) Act¹ in the U.S., to stabilize markets and provide liquidity. Central banks slashed interest rates and engaged in asset purchases to prevent a financial meltdown. Evaluating the effectiveness of these interventions requires a detailed understanding of how firms and investors responded across sectors and timeframes (Baek, Mohanty, & Glamboosky, 2020). From a corporate strategy perspective, COVID-19 has prompted firms to reevaluate their risk management, supply chain dependencies, and digital transformation strategies. Companies are increasingly incorporating scenario planning and stress testing into their operations. Thus, examining COVID-19's impact helps businesses prepare for future systemic shocks—whether from pandemics, climate change, or geopolitical tensions.

The COVID-19 pandemic has left a lasting imprint on human life and the financial ecosystem. The massive disruptions to economic activity and investor sentiment resulted in severe losses across global stock markets and exposed deep vulnerabilities in corporate structures. The crisis has underscored the need for multidimensional analyses that go beyond aggregate trends to understand heterogeneity in firm responses, the role of policy, and the relevance of non-financial factors. By studying the impacts of COVID-19 on stock markets and companies, researchers, investors, and policymakers can better equip themselves to mitigate the effects of future global crises.

¹ The Coronavirus Aid, Relief, and Economic Security (CARES) Act was enacted in the United States in March 2020 as a large-scale fiscal response to the economic fallout of the COVID-19 pandemic. The Act provided emergency financial support to households, businesses, and state and local governments through measures such as direct stimulus payments, enhanced unemployment benefits, and lending programs for firms, aiming to stabilise economic activity and financial markets during an unprecedented crisis.

1.2 Research Background and Motivation

The outbreak of COVID-19 had a profound and heterogeneous impact on global stock markets. Notably, the first wave of the pandemic triggered a far more severe reaction in financial markets compared to subsequent waves. During the initial months of 2020, markets around the world experienced unprecedented levels of volatility and sharp declines in valuation. For instance, the S&P 500 dropped more than 30% from mid-February to late March 2020 (Zhang, Hu, & Ji, 2020), and similar crashes occurred across Europe and Asia. This extreme market response can be attributed to the high level of uncertainty and lack of information surrounding the virus at the time. Investors were reacting not only to declining earnings expectations but also to fears of systemic collapse, inadequate health infrastructure, and government inaction (Baker et al., 2020).

In contrast, the second wave of COVID-19, although more infectious and deadly in many regions, elicited a more muted response from stock markets. This relative market resilience during the later waves can be explained by increased preparedness, the availability of fiscal and monetary interventions, and better investor understanding of the pandemic's dynamics. For example, governments introduced large-scale stimulus packages, central banks engaged in asset purchases, and investors had begun to price in the expected path of recovery (Fahlenbrach et al., 2021). By this time, firms and markets had also started adapting to the "new normal" of remote work, altered consumption patterns, and digital service delivery.

Importantly, the pandemic's impact was not uniform across firms, even within the same industry. Despite being in identical sectors, firms experienced widely differing stock price responses and financial performance. This divergence underscores the critical role of firm-level characteristics in determining resilience to external shocks. Research has shown that firms with stronger balance sheets, lower leverage, more cash reserves, and access to external finance were better able to withstand the economic fallout of the pandemic (Ding et al., 2021). For

example, large retail chains with robust e-commerce platforms performed better than smaller competitors without digital infrastructure.

Several studies have sought to identify which firm-specific factors contributed to greater resilience during the pandemic. Albuquerque et al. (2020) highlight that firms with strong environmental, social, and governance (ESG) practices experienced less negative stock returns during the crisis. Similarly, Ding et al. (2021) emphasize that firms with global supply chains, high operating leverage, or poor corporate governance structures were more vulnerable to disruption. Additionally, the ability to rapidly adjust operations—such as shifting to remote work or digital sales—proved essential for resilience. In this context, it is crucial to investigate the role of firm characteristics in shaping financial outcomes during pandemics. Such analysis helps policymakers, investors, and managers understand the sources of corporate resilience and guides strategic decision-making in future crises. Exploring questions such as “What makes some firms more resistant to shocks such as COVID-19?” not only contributes to academic understanding but also enhances real-world preparedness for systemic risks. The following research question is asked in the first empirical chapter.

RQ1. Which firm-level characteristics most strongly explain cross-sectional differences in stock market performance during the COVID-19 pandemic?

RQ2. To what extent did firms’ financial flexibility, governance quality, and adaptability to operational disruptions mitigate downside risk during pandemic-induced market stress?

Most early empirical research on COVID-19's economic consequences focused almost exclusively on the first wave of the pandemic, primarily due to its unprecedented nature and immediate global financial disruption. For instance, Ramelli and Wagner (2020) conducted a seminal study examining the cross-sectional shifts in U.S. firm performance during the onset of the pandemic. They observed that firms with a global footprint, especially those heavily

reliant on trade with China, were disproportionately affected. This result aligns with broader theories on global supply chain interdependence, where shocks in one part of the system can propagate quickly across borders. Firms with high corporate debt and low cash reserves also exhibited poor market performance during this period, highlighting the significance of internal financial resilience in times of crisis.

This phenomenon is supported by broader literature on global economic spillovers. Hanif et al. (2020) argue that the interconnectedness of modern economies makes even localized health or economic shocks capable of causing worldwide disruptions. The COVID-19 pandemic, characterized by abrupt declines in consumer confidence, contraction in demand, and suspension of business activities, revealed the fragility of many economies and companies. As a result, firm success across various markets and sectors became heavily dependent not just on industry trends, but also on the ability to adapt business operations to rapidly changing external conditions.

While early studies focused on immediate firm-level responses, subsequent research explored market volatility during different waves of the pandemic. For example, Szczygielski et al. (2021) and Uddin et al. (2021) investigated how recurring waves of COVID-19 influenced investor behaviour and asset price movements. They found that COVID-related news—such as infection surges, lockdowns, and vaccine rollouts—triggered coordinated shifts in investor sentiment, leading to either widespread selloffs or market rallies. These patterns often occurred even when firms' operations were not directly affected by the virus countermeasures, indicating the dominance of behavioural finance mechanisms in driving volatility during the crisis.

However, a critical gap in the literature remains: none of the studies have examined whether the cross-sectional relationships between firms persisted across multiple COVID-19 waves. This paper aims to fill that gap by analysing how companies' performance and return correlations evolved over time, and what firm characteristics influenced this evolution. To

investigate this, I draw upon two competing theoretical frameworks: the “business model hypothesis” and the “learning hypothesis”, as outlined by Fahlenbrach et al. (2012). The business model hypothesis suggests that a company’s structural attributes—such as how it generates revenue and adds value—are relatively rigid, making some firms inherently more vulnerable to crises. This would imply that performance outcomes are persistent across crisis episodes; firms that performed poorly in the first wave should continue to underperform, resulting in positively correlated returns across COVID-19 waves.

Conversely, the learning hypothesis posits that companies and markets can adapt by assimilating lessons from earlier disruptions. Such learning may involve strategic pivots, investments in digital infrastructure, or more robust supply chain management. If firms learned from the first wave and adjusted accordingly, I would expect to see negative correlations in returns across waves—that is, firms that fared poorly initially might outperform in subsequent waves due to improved resilience and better crisis management. Testing these two hypotheses helps us understand not only how firm-specific attributes influence crisis response, but also whether companies and investors evolve their strategies over time in response to repeated external shocks. Understanding these dynamics is essential for corporate risk management, investor strategy, and policy formulation in a post-pandemic world. The following research question is asked in the second empirical chapter.

RQ1. Do firm-level stock return responses to COVID-19 persist across successive pandemic waves, or do they change as firms and investors learn from earlier shocks?

RQ2. Which firm characteristics explain the evolution of return correlations across COVID-19 waves, and do these patterns support the business model hypothesis or the learning hypothesis?

Although the body of academic literature on the economic and financial consequences of COVID-19 has expanded rapidly, a notable gap remains in understanding how firm-level COVID-19 risk and firm-level political risk were jointly priced in financial markets during the pandemic. Most studies have focused either on macro-level risks, sectoral analysis, or broader market volatility (Baker et al., 2020; Zhang, Hu & Ji, 2020), but no studies have explored how these two specific forms of risk (covid risk and political risk) intersected at the firm level and influenced stock returns. This thesis fills that void by empirically examining the relationship between quarterly stock returns in the U.S. and firm-specific measures of COVID-19 exposure and political risk.

The significance of this research lies in the unique and interrelated nature of pandemic-related health and political risks. COVID-19 triggered simultaneous crises across public health, economic activity, global trade, and governance systems, making it a complex and multifaceted event (Gormsen and Koijen, 2020). As firms navigated pandemic-related disruptions including lockdowns, supply chain breakdowns, labour shortages, and shifts in consumer demand, they also faced heightened political uncertainty. For instance, governments introduced rapid fiscal stimulus, altered tax regulations, and imposed trade restrictions in ways that were often unpredictable and unevenly applied across sectors (Baldwin and Tomiura, 2020).

Understanding how financial markets priced these risks is critical for several reasons. First, it helps clarify whether investors differentiate among firms based on their unique exposures to pandemic-related and political uncertainty. Second, it offers insight into the risk-return trade-offs that were amplified during the crisis. If firm-level COVID-19 and political risks were reflected in stock prices, it implies that investors were attentive to idiosyncratic risk factors—and not merely responding to market-wide shocks. Third, it can inform both investor strategy and policy formulation, particularly regarding corporate disclosure and risk communication during crises.

Political risk during the pandemic was especially salient. Sudden regulatory changes, shifting health mandates, and partisan conflict over stimulus measures introduced high levels of uncertainty. According to Baker et al. (2020), political risk was among the most volatile economic policy concerns during the early months of COVID-19, surpassing even the levels observed during the 2008 financial crisis. For firms, especially those in trade-dependent sectors like manufacturing or energy, evolving political decisions—such as border closures and export bans—posed serious operational risks (Baldwin & Tomiura, 2020). These risks were not uniform. Large multinational corporations may have been better equipped to adapt to policy shifts than small and medium enterprises (SMEs) with limited financial buffers and less diversified supply chains (Juergensen, Guimón, & Narula, 2020).

Moreover, COVID-19 introduced firm-specific health-related risks, including employee safety concerns, changes to workplace norms, and reputational challenges tied to crisis response. As shown by Hassan et al. (2021), firms that disclosed more COVID-related risk in their earnings calls experienced larger declines in market valuation, indicating that investors actively processed this information. This thesis addresses the following research questions in the third empirical chapter.

RQ1. Were firm-level COVID-19 risk and firm-level political risk priced in U.S. stock returns during the COVID-19 pandemic?

RQ2. Did investors differentiate across firms based on heterogeneous exposures to pandemic-related health risk and political uncertainty, beyond aggregate market conditions?

This thesis, therefore, addresses an important but overlooked area by examining how both political and COVID-related risks were priced by markets at the firm level, using a dataset of U.S. quarterly stock returns. The findings will contribute to understanding the heterogeneous impact of systemic crises, the role of political stability in financial markets, and the ability of investors to assess complex and interacting risk sources during turbulent times.

1.3 Theoretical Framework: Firm Sensitivity to Systematic Risk During COVID-19

This thesis is grounded in asset pricing and corporate finance theories that emphasise firms' heterogeneous exposure to systematic macroeconomic risk. Rather than viewing COVID-19 as an isolated health shock, the pandemic is conceptualised as a compound macroeconomic risk factor that simultaneously affected aggregate demand, production capacity, financial conditions, and policy uncertainty. Prior research shows that such large-scale crises generate substantial variation in firm-level outcomes depending on structural characteristics and exposure to economy-wide risks (Baker et al., 2020; Gormsen and Koijen, 2020). Firms differed markedly in how these risks translated into cash-flow volatility and expected returns, providing the theoretical foundation for the research questions examined in this thesis

First, firms differ in their demand sensitivity to macroeconomic conditions. Standard asset pricing theory predicts that firms whose revenues are more cyclical—such as those producing discretionary goods or services—exhibit higher exposure to aggregate demand shocks. During COVID-19, lockdowns, income uncertainty, and shifts in consumer behaviour disproportionately reduced demand for non-essential products, amplifying cash-flow risk for cyclical firms (Nicola et al., 2020; Ding et al., 2021). In contrast, firms operating in essential sectors or with more stable demand faced relatively muted revenue shocks. This heterogeneity in demand cyclicalities is a central channel through which COVID-19 risk affected firm-level returns (Ramelli and Wagner, 2021)

Second, firms vary in their operating leverage, determined by the proportion of fixed versus variable costs. Firms with high fixed operating costs experience greater earnings volatility in response to revenue shocks, as costs cannot be easily adjusted downward. COVID-19 intensified this mechanism by constraining firms' ability to scale down labour, renegotiate contracts, or adjust production in the short run (Ding et al., 2021; Barry et al., 2022). By

contrast, firms with more flexible cost structures were better positioned to absorb revenue declines, reducing their exposure to systematic risk during the crisis

Third, financial leverage further amplifies firms' sensitivity to macroeconomic shocks. High leverage magnifies the impact of cash-flow volatility on equity holders and increases exposure to tightening financial conditions. During the pandemic, revenue shortfalls combined with heightened uncertainty raised refinancing and default risks, particularly for firms with high debt and limited liquidity (Giroud and Mueller, 2017; Ding et al., 2021). Consistent with this mechanism, cash holdings and unused credit capacity played a critical role in mitigating downside risk and supporting firm resilience during COVID-19 (Fresard, 2010; Ramelli and Wagner, 2021)

Building on this framework, the thesis extends the analysis across multiple COVID-19 waves, recognising that exposure to systematic risk may persist if driven by relatively rigid firm characteristics (the business model hypothesis) or evolve if firms and investors adapt based on prior experience (the learning hypothesis; Fahlenbrach et al., 2012). Finally, country-level policy stringency is incorporated as an institutional dimension that shapes the transmission of macroeconomic risk by constraining economic activity and limiting firms' ability to adjust demand, costs, and financing (Ozili and Arun, 2020; Chen and Yeh, 2021). Together, this integrated framework provides a coherent theoretical grounding for the research questions and empirical analyses developed throughout the thesis.

1.4 Scope of the study

This study examines firm-level resilience, return dynamics across pandemic waves, and the pricing of COVID-19 and political risk within a clearly defined empirical scope. The primary focus is on publicly listed firms, ensuring the availability of high-quality financial, market, and

textual disclosure data. The analysis spans multiple countries and industries in the first two empirical chapters, while the third chapter concentrates specifically on the United States, reflecting the depth and consistency of earnings conference call data required to construct firm-level COVID-19 and political risk measures.

In terms of geography, the cross-country analyses include a selected sample of developed and major emerging economies where COVID-19 had a substantial economic and market impact and where firm-level data coverage is sufficiently dense. Countries with very limited numbers of listed firms are excluded to ensure statistical reliability. Industry coverage is broad, encompassing all major non-financial sectors, while financial firms are excluded due to their distinct regulatory environment and balance-sheet structures.

The temporal scope covers the period from late 2019 through 2022, allowing the study to capture the first wave and subsequent waves of COVID-19, as well as evolving policy responses and market adaptation. Stock performance is measured using buy-and-hold returns, quarterly returns, and accounting-based outcomes, depending on the research question. Overall, this carefully defined scope allows the thesis to balance breadth and depth, providing robust and generalisable insights while remaining closely aligned with the data and research objectives of the study.

1.5 Main findings and Contribution

The first empirical chapter examines which firm characteristics are associated with stock market underperformance during the COVID-19 crisis. Using a probit framework, where the dependent variable distinguishes between the lowest- and best-performing firms, I document several robust and economically meaningful relationships. Firm size, measured by total assets, is positively associated with the likelihood of belonging to the lowest-performing group. This finding suggests that larger firms were more vulnerable during the initial phase of the pandemic,

potentially due to greater operational complexity, higher fixed costs, or stronger exposure to global supply chains. In contrast, cash holdings are negatively related to the probability of poor performance, indicating that internal liquidity buffers provided effective protection against heightened uncertainty, consistent with the precautionary role of cash during systemic crises (Chang and Yang, 2022).

I further show that capital expenditure and market beta are positively associated with underperformance, implying that firms with aggressive investment strategies or greater exposure to systematic risk were particularly susceptible to the pandemic shock. Executive compensation, however, is negatively related to the likelihood of poor performance, suggesting that incentive structures may have supported more effective managerial responses during the crisis. These results are reinforced by OLS estimations, which reveal a negative association between firm size and returns and a positive association between cash holdings and returns. This extends the literature linking financial structure—especially liquidity and leverage—to firm resilience (Fresard, 2010; Giroud and Mueller, 2017). I also document a negative relationship between capital expenditure and returns, alongside positive associations between executive compensation, ownership concentration, and performance, reinforcing governance-based theories of value creation (Murphy, 2013; Rau, 2015). Collectively, this chapter contributes by demonstrating that pre-pandemic firm characteristics significantly shaped cross-sectional differences in firm performance during the first COVID-19 wave.

A second key contribution of this chapter is the analysis of government policy responses, specifically COVID-19 stringency measures, at the firm level. While earlier studies such as Chen and Yeh (2021) and Ozili and Arun (2020), focus on aggregate market effects, I examine how policy strictness affected individual firms. Subsample analyses reveal that firms operating under more stringent restrictions experienced significantly poorer performance. Moreover, firms in the lowest performance tier are closely aligned with epidemiological indicators such

as COVID-related fatalities and infection rates. These findings suggest that firm-level outcomes were strongly linked to both policy severity and underlying public health conditions.

The third contribution relates to corporate governance. I document a strong negative association between weak governance and firm performance during the crisis. This finding is novel, as prior governance studies largely focus on normal market conditions (La Porta et al., 2000; Hooper et al., 2009; Leuz, Nanda, and Wysocki, 2003). The results indicate that high-quality governance—characterised by transparency, accountability, and managerial alignment with shareholder interests—enhanced firm resilience during the pandemic. Strong governance likely facilitated access to capital and enabled more effective strategic adjustments under stress.

Finally, this chapter contributes by examining alternative performance measures beyond stock returns, including ROA, ROE, and Tobin's q . The results show that total assets are positively associated with ROA, while higher debt levels are linked to weaker operating performance, reflecting increased financial burdens during a revenue-constrained environment. Cash holdings, although beneficial for downside protection, are negatively related to ROA, highlighting the opportunity cost of excess liquidity when profitable investment opportunities are limited. I also find that closely held shares, firm age, and capital investment are positively related to ROA, whereas market beta and brand exposure are negatively related. COVID-19 policy stringency further exerts a dampening effect on ROA, reinforcing the costs of restrictive public health measures. Together, these findings provide a comprehensive view of how financial structure, governance, and policy environments jointly shaped firm performance under extreme stress.

The second empirical chapter extends the literature by analysing firm performance across multiple COVID-19 waves rather than focusing exclusively on the initial shock. While prior

studies emphasise the first wave (e.g., Ramelli and Wagner, 2021; Hanif et al., 2020), little is known about the persistence of firm-level performance across subsequent waves. This chapter fills that gap by examining return correlations across different pandemic phases.

The first major contribution is the empirical test of the business model and learning hypotheses. By analysing return correlations across consecutive and non-consecutive waves, I assess whether firms adapted over time or whether structural characteristics dominated performance. The results reveal persistent positive correlations across waves, providing stronger support for the business model hypothesis and suggesting limited scope for rapid firm-level adaptation.

Second, I show that pre-pandemic firm characteristics explain return variation differently across waves. Variables such as firm size, leverage, cash holdings, capital expenditure, and governance display heterogeneous effects depending on the pandemic phase. This longitudinal perspective highlights that the relevance of firm fundamentals evolves as the nature of the crisis changes, underscoring the importance of wave-specific analysis.

Third, the chapter contributes cross-country evidence, demonstrating that return correlations vary systematically across national contexts. Countries with stringent lockdowns, such as China, exhibit distinct patterns compared to countries with more relaxed responses, such as India. These findings illustrate how national policy environments interact with firm-level dynamics.

Fourth, I provide sectoral evidence showing substantial industry-level heterogeneity. While sectors such as consumer discretionary, industrials, telecommunications, basic materials, and real estate exhibit consistent positive return relationships during later waves, healthcare and technology show weaker or insignificant patterns. This highlights that pandemic-induced shifts in demand and operating conditions did not benefit all sectors uniformly.

Collectively, these findings advance the crisis finance literature by linking macro-level pandemic shocks to persistent micro-level performance patterns across time, demonstrating that firm performance during COVID-19 was shaped by enduring structural characteristics, policy environments, and sectoral positioning rather than short-term learning alone.

The third empirical chapter advances the asset pricing literature by providing novel evidence that firm-level COVID-19 risk and political risk were jointly priced during the pandemic. Using text-based measures derived from earnings conference calls (Hassan et al., 2019, 2023), I show that firms with greater exposure to COVID-19 risk earned higher stock returns, consistent with standard risk–return trade-offs (Sharpe, 1964). This approach offers a forward-looking and firm-specific perspective on risk pricing during an unprecedented crisis.

A key contribution is the identification of time variation in risk pricing. Risk premia associated with COVID-19 exposure are strongest in 2020, when uncertainty and volatility were most pronounced, illustrating how investor responses evolved as information accumulated. This finding enhances understanding of how markets process novel risks over time.

Another important contribution is the incorporation of firm-level political risk during a global health crisis. While political risk has been studied in normal periods, this chapter demonstrates that it became particularly salient during COVID-19, as government interventions, regulatory changes, and trade policies directly affected firm outcomes. Political risk is shown to be positively priced, underscoring its relevance during periods of heightened uncertainty.

Methodologically, the chapter validates the robustness of these findings using alternative performance measures. While COVID-19 and political risks are priced in equity returns, their association with accounting performance (ROA) is weaker, highlighting the distinction between forward-looking market valuations and backward-looking operational outcomes (Jiang and Xin, 2022).

Finally, by focusing exclusively on COVID-19 and conducting wave-by-wave analysis, this chapter provides a more granular and targeted assessment than studies that pool multiple epidemics or treat the pandemic as a single event. The use of earnings call transcripts further demonstrates the informational value of corporate communication during crises and contributes to the growing literature integrating text analytics with asset pricing. Together, these contributions deepen our understanding of how complex, overlapping risks were internalised by financial markets during one of the most severe global shocks in modern history.

This thesis employs a multi-method empirical strategy tailored to each research question, combining cross-country firm-level analysis, intertemporal return correlations, and text-based risk measurement. In the first empirical chapter, firm resilience during the initial COVID-19 wave is analysed using cross-sectional regressions and probit models. Firms are classified into performance quantiles based on buy-and-hold returns, allowing the study to identify which pre-pandemic firm characteristics predict extreme underperformance. Ordinary least squares (OLS), probit estimation, quantile regressions, and extensive robustness checks are used to ensure consistency. This methodology directly supports the finding that cash holdings, governance quality, and financial structure significantly explain heterogeneity in firm performance during the crisis.

The second empirical chapter adopts a wave-based panel framework, examining correlations in firm-level stock returns across successive COVID-19 waves. By comparing return relationships across waves and conditioning on firm, country, and industry characteristics, the analysis tests the competing business model and learning hypotheses. The persistence of positive return correlations provides empirical support for the business model hypothesis, indicating structural rigidity rather than adaptive learning.

The third empirical chapter uses earnings conference call transcripts and applies established text-based measures of firm-level COVID-19 and political risk. These risk measures are linked to quarterly stock returns using panel regressions with firm and time fixed effects. The methodology underpins the central finding that both COVID-19 and political risk were positively priced, particularly during 2020, reflecting investor demand for risk compensation during periods of heightened uncertainty.

Taken together, these contributions not only fill existing gaps in the risk-pricing literature but also offer practical implications for investors, policymakers, and corporate managers seeking to understand how market expectations respond to large-scale, multidimensional crises such as the COVID-19 pandemic.

Chapter 2

2. Literature Review

The COVID-19 pandemic has emerged as one of the most significant global disruptions in recent history, profoundly affecting public health, economic systems, and financial markets. Unlike previous pandemics, the scale and speed of COVID-19's impact were magnified by globalization, dense interconnectivity of markets, and rapid information dissemination. This literature review synthesizes a growing body of research that explores the multifaceted effects of COVID-19 on financial markets, corporate resilience, and broader economic structures.

Scholars have examined the pandemic through multiple lenses, including firm-level performance, market volatility, government policy responses, and investor sentiment. Existing studies compare COVID-19 with earlier pandemics to assess long-term consequences, while others focus on the immediate financial volatility and its relationship with national characteristics, firm fundamentals, and uncertainty indices (Ding et al., 2021, Uddin et al., 2021). Researchers also explore the role of media coverage, corporate social responsibility, and cultural factors in shaping market outcomes.

Moreover, the literature captures how various sectors and regions responded to the crisis, revealing both vulnerabilities and sources of resilience. By reviewing these contributions, this chapter aims to identify common themes, methodological approaches, and gaps in the understanding of how pandemics, especially COVID-19 affect financial systems and economic behaviour at multiple levels.

2.1 Earlier Pandemics

Several studies have explored the economic and financial effects of past pandemics to shed light on the potential long-term consequences of COVID-19. Barro et al. (2020), Correia et al.

(2022), and Lilley et al. (2020) analysed the Spanish Flu and found that high mortality led to a significant contraction in gross domestic product (GDP) and reductions in returns on equities and short-term government bonds. However, they also observed eventual economic recovery. Jorda et al. (2020), examining pandemics since the 14th century, showed that real interest rates remained depressed for decades post-pandemic, contrasting with the post-war recovery patterns.

Other research has linked financial market risks with pandemics. Lagoarde-Segot and Leoni (2013) argued that pandemics such as AIDS and malaria increased the probability of financial instability in developing countries. Wachter (2013) suggested that rare events like pandemics raise equity risk premiums due to their temporal unpredictability. Similarly, Bleakley (2007) found that the elimination of hookworm disease in the early 20th-century American South contributed to long-term economic growth.

Gupta et al. (2021) compared COVID-19 with earlier US pandemics, including those in 1918–19, 1957–58, and 1968. They concluded that COVID-19's economic impact stemmed less from the virus's lethality and more from the unprecedented public health restrictions, which caused widespread behavioural shifts and economic disruptions.

2.2 COVID-19

Baker et al. (2020) identify three forward-looking measures of economic uncertainty—stock market volatility, news-based indices, and subjective business expectations—to quantify the impact of COVID-19, estimating an 11% GDP decline by late 2020, largely driven by pandemic-induced uncertainty. Fernandes (2020) similarly outlines the global economic fallout, attributing major disruptions to lockdowns, travel bans, and market reactions unrelated to fatality rates.

Ozili and Arun (2020) assess stock market responses across the US, UK, Japan, and South Africa during the first wave, finding that stringent containment policies had a significant negative impact. Their findings align with Baker et al. (2020), who argue that COVID-19 led to unprecedented market dislocation, surpassing even the Spanish Flu in terms of financial disruption, due in part to more efficient information flows and stronger global economic linkages. Szczygielski et al. (2021) assess regional volatility using ARCH and GARCH models and introduce a Google Trends-based uncertainty measure. They find that COVID-19-related uncertainty increased volatility globally, except in Arab markets. Xu (2021) similarly shows asymmetrical stock return responses to COVID-19 developments in Canada and the US, attributing them to underlying uncertainty rather than mortality differentials.

Uddin et al. (2021) analyse stock market volatility in 34 countries, linking it to national economic characteristics. They complement earlier work by Baker et al. (2020) and Fernandes (2020), who found that country-specific factors such as policy responses helped mitigate volatility. Other studies extend this work. Akhtaruzzaman et al. (2022) and Umar & Gubareva (2021a, 2021b) use the Media Coverage Index (MCI) to examine the effect of pandemic news on ESG and Islamic stock indices, finding strong associations with market volatility. Gubareva and Umar (2020) further apply wavelet analysis to reveal strong dependency patterns between media intensity and bond market fluctuations.

The MCI has also been used in studies of cryptocurrency (Umar et al., 2021), commodity markets, and sustainability. Bolton et al. (2020) draw parallels between the COVID-19 crisis and climate change, while He and Harris (2020) view the pandemic as a catalyst for more authentic corporate social responsibility (CSR) initiatives.

2.3 Characteristics of COVID-19

COVID-19 is highly contagious, with respiratory droplets and close contact identified as the primary transmission routes (Bourouiba, 2020). Age, pre-existing health conditions, and socioeconomic status have been linked to increased risk of severe outcomes (Wu & McGoogan, 2020). Public health responses varied by country, influenced by health infrastructure, political decisions, and cultural norms. Research shows that non-pharmaceutical interventions like lockdowns, mask-wearing, and social distancing were effective in curbing virus spread and protecting healthcare systems (Chu et al., 2020; Flaxman et al., 2020). Coordinated, evidence-based responses proved essential to mitigating mortality and limiting economic fallout (Gostin & Wiley, 2020). Barrot et al. (2024) find that state-mandated business closures lowered mortality rates, particularly in contact-intensive regions, though firms and workers bore substantial economic costs.

2.3.1 Economic disruption of Covid

The pandemic led to widespread economic disruptions, including recessions, labour market instability, and global supply chain breakdowns. Nicola et al. (2020) highlight that sectors such as tourism, entertainment, and retail suffered the most. Vulnerable populations—low-income workers, women, minorities, and those in informal employment—faced disproportionate hardships (Alon et al., 2020; McKibbin & Fernando, 2020).

Governments implemented fiscal and monetary policies to cushion the impact, including stimulus packages and social protection schemes (Blanchard et al., 2020). Auerbach and Gorodnichenko (2020) evaluate the effectiveness of these interventions, noting mixed success in protecting jobs and reducing inequality. Baldwin and Tomiura (2020) stress the need for international coordination to address long-term damage to the global economy.

Social changes have been equally profound. The pandemic altered norms, behaviours, and relationships. Studies report increases in stress, anxiety, and loneliness (Brooks et al., 2020) and examine how trust, risk perception, and cultural values influenced compliance with health measures (Bavel et al., 2020). Pre-existing disparities were exacerbated, particularly for vulnerable populations (Yaya et al., 2020; Van Lancker & Parolin, 2020), underlining the need for socially equitable policy responses (Marmot et al., 2020). Governance and political trust were also tested. Hale et al. (2020, 2021) document the effects of leadership and communication on policy effectiveness and civil liberties. The pandemic also highlighted the importance of international institutions like the WHO and World Bank in coordinating global responses (Kickbusch et al., 2020; Ghebreyesus, 2021).

2.3.2 Turbulence in financial markets

COVID-19 triggered severe stress in financial markets, including an unexpected liquidity crisis in the US Treasury market (He, Nagel, & Song, 2022). The pandemic also exposed the fiscal vulnerabilities of advanced economies. Augustin et al. (2022) show that sovereign default risks rose significantly in countries with limited fiscal space. Latif et al. (2021) and Phan & Narayan (2020) report that market uncertainty caused extreme volatility, with significant losses in the banking, tourism, and hospitality sectors (Herwany et al., 2021). Other industries—communication services, consumer goods, and energy—exhibited strong correlations with pandemic dynamics.

Uddin et al. (2021) found that countries with robust economic structures experienced less volatility. Ramelli and Wagner (2021) note that US firms with high international exposure, particularly to China, performed poorly early in the pandemic. Firm-level characteristics such as cash reserves and debt levels influenced performance. Using earnings call data, they further

analyse investor concerns. Huang et al. (2021) show that firms with strong brand value experienced better returns and reduced risk.

Ding et al. (2021) assess global firms and find that those with stronger balance sheets and CSR track records outperformed. However, companies with entrenched leadership struggled. Darmouni and Sutherland (2024) highlight capital reallocation as firms sought to use capital from competitors amid production disruptions. Barry et al. (2022) show that firms with greater organisational flexibility—workplace, investment, and financial—adapted more effectively to the crisis. Huq et al (2025) show that firms reduce leverage during covid 19. Okasha et al (2025) showed how COVID-19 has impacted Fintech firms’ environmental, social and governance (ESG) performance.

2.4 Gaps in the literature

I address several gaps in the literature in this thesis. While a substantial body of research has examined the economic and financial consequences of COVID-19, several critical questions remain unanswered. Most notably, the literature lacks a comprehensive understanding of which firm-specific characteristics best predict company performance during the pandemic. Moreover, little is known about whether the stringency of lockdown measures or the quality of country-level governance contributed to differences in firm outcomes across markets.

Existing studies provide valuable insights but have limitations. Ramelli and Wagner (2021), using US data, show that firms with high international exposure, especially to China, underperformed, and that leverage and cash holdings were key predictors of stock market performance. However, their focus is restricted to the US, limiting generalizability. Huang et al. (2021) find that brand capital significantly improved firm returns and reduced risk during the pandemic, yet they, too, examine only US firms. Ding et al. (2021) adopt a broader approach using data from 61 countries and 6,700 firms. Their findings suggest that firms with strong

capital buffers, low leverage, and solid CSR performance outperformed peers, while entrenched executives and weak ownership structures were linked to worse outcomes.

Ding et al. (2021) study the marginal sensitivity of weekly firm-level stock returns to changes in contemporaneous COVID-19 case growth, interacting weekly changes in infections with pre-pandemic firm characteristics in a difference-in-differences framework. In contrast, this thesis adopts a performance-based approach, asking whether firm characteristics measured before the pandemic can explain ex post realised firm performance over the COVID-19 period, using buy-and-hold returns and performance quantiles. Rather than modelling short-horizon reactions to epidemiological news, the focus here is on cumulative resilience versus vulnerability, which captures a different economic concept.

In the second empirical chapter, I address the following gaps. Although a growing body of research has examined the impact of COVID-19 on financial markets, most studies have focused on the initial wave of the pandemic, leaving subsequent waves underexplored. For instance, Ramelli and Wagner (2021) investigate cross-sectional performance of US firms during the first wave and find that firms with international exposure, particularly to China, initially underperformed. They also highlight corporate debt and cash holdings as key performance indicators. While valuable, their analysis remains confined to the early phase and a single country context.

Research by Hanif et al. (2020) emphasizes the interconnectedness of global economies, showing how localized shocks can trigger broader economic downturns, erode consumer confidence, and depress investment. Other studies, such as Szczygielski et al. (2021) and Uddin et al. (2021), analyse market volatility across different COVID-19 waves and show that investor reactions to pandemic-related news can lead to coordinated shifts in stock prices—even among firms not directly affected by the virus. These reactions can result in widespread rallies or sell-offs, linking firm returns across sectors and countries.

However, the literature has yet to explore whether firm-level returns are systematically related across different waves of COVID-19. In particular, there is little evidence on the cross-sectional correlation of firm performance across waves. I aim to fill this gap by analysing whether firm performance in early waves predicts outcomes in later ones.

This study also tests two competing explanations. The “business model” hypothesis (Fahlenbrach et al., 2012) suggests that vulnerable firms consistently underperform across crises, implying positive return correlation across waves. In contrast, the “learning hypothesis” posits that firms adapt over time, leading to negative return correlations. By evaluating these competing mechanisms, I provide new insights into corporate resilience and investor learning during recurring global shocks.

In the third empirical chapter, I address the following gap in the literature. Although the literature on COVID-19 and financial markets has grown rapidly, there remains a notable gap concerning the pricing of firm-level risks. Specifically, to the best of our knowledge, no existing study jointly examines whether firm-specific COVID-19 risk and firm-specific political risk were priced into stock returns during the pandemic. While previous research has separately explored macroeconomic uncertainty, market volatility, or general sentiment, the intersection of these two firm-level risks and their financial implications remains unexplored. This chapter addresses this gap by analysing the relationship between quarterly stock returns in the U.S. market and firm-level exposure to both COVID-19 and political risk.

Understanding the pricing of these risks is critical, given the complex and overlapping challenges posed by the pandemic—ranging from public health and economic instability to policy uncertainty and political disruption. These risks influence firm performance, investor expectations, and market behaviour. By examining how these risks were reflected in equity prices, this chapter offers insights into how markets processed firm-specific information during a period of heightened global uncertainty.

A key contribution of this chapter is the use of firm-level risk measures derived from earnings conference calls. Hassan et al. (2023) employ natural language processing (NLP) to quantify COVID-19 risk from the language used in earnings calls, capturing real-time concerns expressed by firm management and analysts. This approach provides a more nuanced and timely signal than traditional regulatory filings (e.g., Loughran & McDonald, 2011). Similarly, Hassan et al. (2019) developed a firm-level political risk measure based on the same textual data. By combining these innovative measures, this study provides a more comprehensive understanding of risk pricing during the COVID-19 crisis and highlights how firm-level narratives influence investor behaviour during periods of systemic uncertainty.

Chapter 3

What characteristics made firms more resilient during Covid- 19?

3.1. Introduction

Originating in Wuhan, China, Covid-19 spread rapidly over the world and claimed many lives. According to the Covid dashboard at Johns Hopkins University, 6.7 million people had died worldwide as of January 22, 2023. Coronavirus (countermeasures) has had a devastating economic impact on several countries (Kriti et al., 2023). Though the impact of Covid-19 is felt in all parts of the globe, the severity is not the same. The impact of Covid-19 on different stock markets was different. Most importantly, the impact of the first wave of Covid-19 on the stock markets was much more severe compared to the second wave of Covid-19. Likewise, the impact of Covid-19 on different companies from the same sector was different. In this chapter, I address several important questions. Do firm characteristics make companies perform differently? What firm characteristics make firms more resilient to Covid-19?

The literature on Covid-19 is huge, and it is growing. Despite the large literature, my contribution is in several areas. First, I address the question whether firm characteristics measured before the Covid-19 help predict the performance of the companies during the pandemic. There are studies that concentrate on the US market. Ramelli and Wagner (2021), for instance, examined the cross-sectional changes in US businesses during the Covid-19 epidemic. They found that businesses with an international orientation, particularly those who have a greater trading relationship with China, underperformed at first. Key performance metrics included cash balances and corporate debt. Based on information from US firms, Huang et al. (2021) report that companies with higher brand value have greater equity returns, lower market risk, and lower business risk during the coronavirus pandemic than other companies. According to Huang et al. (2021), the impact of brand equity differs from that of corporate social responsibility during Covid. The US evidence does not apply to the rest of the world automatically, as there are lots of differences in institutional settings, culture and financial characteristics of the US firms and firms from other countries. For instance, Bates et

al. (2009) address the question of why US firms hold more cash. They find that the typical company has enough cash on hand to pay off all debt. As organisations' cash flows grow riskier, cash ratios rise. Additionally, businesses evolve they invest more heavily in R&D and maintain lower inventories and receivables. Although the precautionary motive for retaining cash is a key factor in explaining the rise in cash ratios, agency conflicts are not consistently shown to be a factor. There are notable differences between the cash holdings, leverage of US firms and other countries (Bates et al. (2009), Fan et al, (2012)) Hence, I use cross-country data to address what firm characteristics at the end of 2019 help predict the performance of firms during the pandemic.

Although Ding, Levine, Lin and Xie (2021) used data from all around the world, they examined the stock market reaction to the growth of weekly Covid cases. There are a few fundamental differences between their approach and mine. They address the question "the reaction of stock returns to Covid-19 cases..." (p 802), while I address the question whether pre-pandemic firm characteristics can explain the performance of companies using buy-and-hold returns (BHRs). Ding et al. (2021) link the weekly rise in Covid instances using weekly market return data. I use the BHRs for the whole period. They make use of a challenging to comprehensive interaction between two continuous variables, such as the size and growth rate of Covid-19 weekly cases. Also, they interact with the weekly growth rate of Covid cases with the firm's fundamentals pre-pandemic. In this case, the growth rate of Covid varies while the firm fundamentals are the same and repeated. Instead, I use the firm fundamentals before the pandemic and try to explain the performance of companies using those firm fundamentals. Ding et al.'s (2021) sample includes many countries that have only five firms or ten firms. I include a smaller number of countries where Covid had a much larger impact, and the number of firms is higher.

I use probit models to examine what characteristics are associated with the bottom performing quantiles of returns during Covid. My probit model findings are quite interesting. My results indicate a positive relationship between total assets and the lowest performing group. A one standard deviation change in size at the sample mean is connected to a 12.14% higher likelihood of belonging to the lowest performing group. This effect is substantial and important economically. A one standard deviation shift (18.56%) in cash at the sample mean (14.12%) is related to a 4.24% reduced likelihood of belonging to the lowest performing group. Cash acts as a protection against Covid. Capex and beta are positive and significant. Compensation is negative and significant. Our OLS results are in line with the probit results. The findings indicate a negative relationship between total assets and returns. The returns are associated with a drop by 8.715% with a one standard deviation increase in size. Cash is also beneficial and important. If cash grows by one standard deviation, it increases returns by 5.776%. These results are in line with other studies linking company performance to financial characteristics, such as cash holdings (Fresard, 2010) and debt levels (Giroud and Mueller, 2017). Capex displays a negative correlation. Compensation and closely held stock are positive and significant. My results are consistent with the idea that executive compensation policies can influence corporate performance (Murphy, 2013; Rau, 2015). My findings are in sharp contrast to the notion that entrenched executives destroy firm value (Gompers et al., 2003; Bebchuk et al., 2009). To sum up, my first contribution is to show that pre-pandemic characteristics help quantify the variation in performance of companies during the first wave of Covid.

This chapter is closely related to Ding et al. (2021) in that both studies examine how pre-pandemic firm characteristics shape stock market outcomes during the COVID-19 crisis and share several consistent findings, particularly regarding the importance of financial flexibility and cash holdings. However, this chapter makes a distinct contribution by adopting a different conceptual and empirical perspective. Whereas Ding et al. (2021) focus on firms'

short-term sensitivity of weekly returns to contemporaneous COVID-19 case growth, this thesis takes a performance-based approach, analysing whether pre-pandemic firm characteristics explain cumulative, ex post firm performance during the pandemic using buy-and-hold returns and performance quantiles. This allows the study to identify firms that experienced extreme underperformance rather than those merely exposed to weekly pandemic news. In addition, the chapter extends the governance dimension by explicitly examining executive compensation and ownership concentration, and it analyses policy stringency in terms of longer-horizon performance consequences rather than short-run return reactions. Finally, differences in findings on firm size are reconciled by recognising that size may have different implications for short-term return sensitivity versus cumulative crisis performance. Overall, the chapter complements and extends Ding et al. (2021) by shifting attention from short-term exposure to realised firm resilience over the course of the COVID-19 crisis.

Second, I contribute to the literature by documenting that the likelihood that the returns will belong to the lowest performing group increases with increasing Covid stringency. According to Chen and Yeh (2021), the government's response to policy has a favourable effect on the stock market's recovery. Ozili and Arun (2020) looked at how economic activity affected the broad stock market index. However, the effects of stringency vary for various businesses and sectors. My subsample analysis (low Covid stringency vs high Covid stringency) shows that Covid stringency is negatively related to BHRs in the high stringency sample, which shows that government restrictions were partially responsible for the bad performance of the companies. I also show that the performance of the lowest performing group is strongly correlated with the number of fatalities per million and new cases per million. This demonstrates that returns falling into the bottom quartile are positively correlated with the severity of Covid.

Third, I document that the likelihood of a group of companies functioning poorly is significantly impacted negatively by governance. I am the first to document that governance matters for a good performance during the Covid. Prior research has revealed that governance has an impact on performance such as share price returns (La Porta et al., 2000). Hooper et al., (2009) show a positive association between measures of stock market performances and governance at a country level. Leuz, Nanda, and Wysocki (2003), suggest that better governance may lead to more precise financial statements and increased arbitrage, which may lead to stock prices that more closely reflect a company's essential principles. Good governance facilitates businesses' access to capital for initiatives with high net present value (NPV). All these studies were done under normal market conditions. I extend the literature under the crisis of Covid that stocks perform better when governance is of good quality.

Fourth, I contribute to the literature by using measures of alternative performances—return on assets (ROA) as in Wintoki et al. (2012), return on equity (ROE) and Tobin's q. The result for ROA shows that total assets are positive and significant. A change of total assets by one standard deviation increases ROA by 10.90%. Debt is negatively related to ROA. A higher level of debt decreases ROA, probably because the company needs to pay interest and principal repayments for debt. An increase of debt by one standard deviation is associated with a decrease in returns by 4.03%. Since cash and ROA are inversely correlated, storing cash during a recession has a large opportunity cost. The returns would be reduced by 5.34% for a one standard deviation rise in cash. Closely held shares, log (firm age), and capex have a favourable relationship with ROA. Beta and brand have a detrimental impact on ROA. The return on assets decreases when Covid stringency increases. The returns are associated with a drop by 1.54% for every standard deviation rise in the Covid stringency.

My heterogeneity analysis provides some interesting results. While company size is negatively related to returns for small firms, it has a positive association for large firms. This

demonstrates that the findings indicating business size is inversely correlated with returns for the entire sample are driven by the smaller firms. Additionally, Covid stringency and returns are inversely correlated, meaning that tighter restrictions reduce returns. The fact that capex is inversely correlated with returns across all subsamples indicates that investment value vanished during Covid, and as a result, performance is inversely correlated with investment. Returns and compensation are strongly correlated, hence during COVID-19, companies with higher-paid executives outperformed those without.

As an alternative technique of estimation, I use quantile regression. Quantile regression minimises the sum of absolute residuals, as opposed to OLS, which minimises the sum of squared residuals. Most of the findings are consistent with OLS results. Some findings are in line with my examination of the subsample. I have discovered that total assets have a negative effect on returns for quantiles 1-3 (4 quantiles in total). The impact is positive, but marginally significant, for quantile 4. This outcome is in line with those of larger firms using OLS. In every quantile, cash is significant and beneficial. In the first three quantiles capex and beta are negative. The results of the first three quantiles show positive and significant compensation. In all the quantiles, Covid stringency is negative and significant.

My study has some practical significance. During times of market turbulence, like the Covid-19 epidemic, investors and traders must make wise choices about which firms to invest in or trade. Investors can find potentially resilient or high-performing firms by understanding the corporate traits that are linked to stock price success. Long-term investing plans can benefit from understanding the corporate traits that influenced stock price performance during Covid-19. Investors can spot businesses that have proven their capacity for innovation, adaptation, and success in difficult circumstances. This information may help investors make decisions about businesses that have solid fundamentals, competitive advantages, and the potential for long-term, sustainable development. Businesses across several industries faced considerable

uncertainty and dangers as a result of the Covid-19 epidemic. Investors may more accurately identify and manage the risks connected with their investments by looking at the firm features that are related to Covid-19 stock price performance. They can identify businesses that may be more able to withstand crises in the future if they have sound fundamentals. The Covid-19 epidemic provided as a timely reminder of the value of corporate disaster planning. Companies may gain important lessons and improve their crisis management plans by looking at the correlation between corporate traits and stock price success during this crisis. They are able to identify weak spots and take steps to improve their supply chains, financial positions, operations, and general resilience.

The rest of the chapter is organised as follows. Section 3.2 provides a review of the literature and develops hypotheses based on the gaps in the literature. Section 3.3 describes the data and methodology. In section 3.4, I present some summary statistics. In section 3.5, I discuss the empirical results. Section 3.6 conducts further analysis. Finally, section 3.7 concludes this chapter.

3.2.1 Review of Literature and Hypotheses Development

The Covid-19 pandemic has had a significant impact of the companies in the world financial markets (Latif et al., 2021). Financial volatility might result from the market uncertainties brought on by Covid-19 (Latif et al., 2021; Phan & Narayan, 2020). Markets might become incredibly volatile as a result (Zhang, Hu, & Ji, 2020). The largest losses were incurred by the banking sector (Herwany, Febrian, Anwar, & Gunardi, 2021). The leisure and hospitality sectors experienced a significant decline. The pandemic had a strong correlation with the industries of communication services, consumer discretionary goods, industrial goods, energy, and materials. The association between the real estate sector and consumer staples was moderate, but the relationship between the utilities sector and those two sectors was either weak

or moderate. In all three sets of links, healthcare and information technology were linked together.

Huo and Qiu (2020), He et al. (2020), and Tan et al. (2021) all analyse the sectoral effects of COVID-19 in the Chinese stock market, yet they differ meaningfully in their analytical focus, time horizons, and interpretation of sectoral resilience. Huo and Qiu (2020) adopt a narrow event-study approach centred on the lockdown announcement, concluding that pharmaceutical and biotechnology firms benefited from strong positive abnormal returns, while technology-related sectors such as electronics and media also displayed short-term resilience. In contrast, He et al. (2020) employ a broader event-study framework that captures greater cross-sectoral heterogeneity, identifying transportation, mining, and utilities as the most severely affected industries, while healthcare, education, and information technology were relatively insulated. Tan et al. (2021) further extend the literature by examining both short- and longer-run dynamics, showing that although medical supply and pharmaceutical sectors rebounded quickly, sectors dependent on mobility and social interaction—such as tourism and cultural industries—experienced persistent underperformance. While all three studies consistently document superior performance in healthcare-related industries and pronounced losses in mobility-intensive sectors, their conclusions diverge with respect to technology and media industries. The more optimistic assessment in Huo and Qiu (2020) appears driven by short-term market reactions, whereas the more cautious findings of He et al. (2020) and Tan et al. (2021) suggest that technological resilience was uneven and highly sensitive to subsector composition and the time horizon considered.

Uddin et al. (2021), Ramelli and Wagner (2021), and Huang et al. (2021) examine the financial market consequences of COVID-19 from different but complementary perspectives, varying in their level of analysis, data, and interpretation of firm and country characteristics. Uddin et al. (2021) adopt a cross-country approach, analysing stock market volatility across 34

nations during mid-2020 and linking COVID-induced volatility to national economic characteristics. Their findings suggest that country-level fundamentals—such as economic strength and institutional capacity—help dampen volatility, thereby extending earlier work by Baker et al. (2020) and Fernandes (2020), which focused primarily on aggregate uncertainty and market disruption. While informative, this macro-level focus abstracts from firm-level heterogeneity and provides limited insight into why firms within the same market experienced markedly different outcomes.

By contrast, Ramelli and Wagner (2021) shift attention to the firm level, examining cross-sectional variation in U.S. stock returns during the early phase of the pandemic. They document that firms with greater international exposure, particularly to China, underperformed, highlighting the role of global supply chain linkages. Their analysis further underscores the importance of balance-sheet characteristics, such as cash holdings and leverage, and enriches the empirical framework by incorporating information from earnings conference calls. However, their exclusive focus on U.S. firms limits the generalisability of the findings and does not account for cross-country institutional or policy differences.

Huang et al. (2021) also concentrate on U.S. firms but introduce a distinct dimension by emphasising intangible assets, specifically brand value. They show that firms with stronger brands experienced higher equity returns and lower risk during the pandemic, suggesting that reputational capital can act as a buffer in times of crisis. While this complements the financial and operational channels highlighted by Ramelli and Wagner (2021), it raises questions about whether such intangible advantages would play a similar role in different institutional settings or during prolonged crisis periods. Taken together, these studies illustrate the multifaceted nature of COVID-19's market impact, but they also reveal a fragmented literature in which macro-level volatility, firm-level financial exposure, and intangible assets are often examined in isolation rather than within an integrated framework.

Using information from 61 nations and 6,700 businesses, Ding et al. (2021) assess the severity of the impact of the coronavirus on stock prices. The dependent variable used by Ding et al. (2021) is the weekly stock return of certain companies for the weeks t and $t-1$. They also utilise the weekly increase in confirmed COVID cases. In terms of how the stock market reacted, companies with a better capital basis, unutilized credit capacity, less leverage, less short-term leverage, and higher profitability beat their competitors. Moreover, they discovered that companies who had stronger pre-epidemic CSR performance fared better during the pandemic. However, during the epidemic, businesses with more firmly established executives do poorly.

According to Baker et al. (2020), the high market reaction to COVID-19 is a result of the more aggressive government measures to the pandemic. Prior studies evaluating how the government acted during different pandemic stages found a strong correlation between the government's response to COVID-19 and stock market volatility (Zaremba et al., 2020). On the other hand, Narayan et al. (2021) discovered that country lockdowns, pandemic stimulus packages, and travel restrictions all had a favourable impact on the excess returns of the stock market.

The majority of countries' stock markets have experienced a string of significant losses and volatility since the outbreak of the virus. As a result, various studies have looked for explanations and provided information on variables that affect stock market volatility, such as infection rates, fatality rates, government actions (blockades, stimulus packages), consumer behaviour, and investor apprehensions. In separate research, Ozili and Arun (2020) looked at the many explanations for why a health emergency like the COVID-19 pandemic may have such a negative impact on the world economy. They found that whereas foreign embargoes and travel restrictions had a detrimental effect on economic activity, constraints on domestic mobility and increased fiscal policy expenditures had a favourable influence. Baker et al. (2020)

assert that the market's significant response to the disease epidemic was brought on by the government's forceful response to COVID-19. They advise additional research into the role and importance of government operations during a pandemic. An important link between COVID-19-related government activity and stock market volatility was found in earlier research assessing government behaviour during various pandemic phases (Zaremba et al., 2020). More recent studies have reinforced these findings: for example, Benlagha and Hemrit (2025) show that while containment and economic support policies in Asian emerging markets generally reduced volatility, stringent lockdown measures increased it; similarly, Al-Sharkas et al. (2024) report that stringent government actions boosted volatility across 34 economies, even when sometimes improving returns. Evidence from developed and emerging economies also suggests that volatility increased significantly during the pandemic relative to pre-pandemic levels (Khan et al., 2024). Sector-level studies in India further highlight that COVID-19 shocks generated persistent volatility across different industries, underlining the long-lasting influence of the pandemic on stock market dynamics (Patel, 2024). Travel restrictions, pandemic stimulus plans, and political embargoes, on the other hand, all have a positive impact on stock market excess returns, claim Narayan et al. (2021). In addition to Baker et al. (2020) and Fernandes (2020), Uddin et al. (2021) show that state-level characteristics lessen COVID-induced volatility. The research of Baker et al. (2020), Fernandes (2020), and Uddin et al. (2021) was expanded upon by Badar (2021) by showing a link between COVID-induced uncertainty and national culture. Many cultures react differently to COVID-19 exposure. Badar (2021) investigated if national culture of the nation under study has an impact on stock market reactions. He makes the case that the cultural history of a country will determine how the coronavirus affects its stock market.

Though there exists a large literature on Covid, there are many unanswered questions in the literature. There is a gap in the literature in terms of what company characteristics can

predict company performance during Covid, whether lockdown stringency can explain some company performance during Covid, and whether country-level governance can explain company performance during Covid. In the next section, I develop our hypotheses based on the gaps in the literature.

Ramelli and Wagner (2021) analyse the cross-sectional variations of US companies during the Covid-19 pandemic. They discovered that companies with an international focus, especially those with greater exposure to trade with China, initially underperformed. Corporate debt and cash holdings were identified as key performance indicators. Ramelli and Wagner (2021) analyse only US data, and they use cash and leverage data to explain the performance of the stocks in the US. They also use the conference calls of analysts to examine the impact of Covid. Huang et al. (2021) find that companies with more brand value have better equity returns, lesser market risk, and lesser business risk during the coronavirus pandemic than other firms, based on data from the US companies. Huang et al., (2021) find that brand equity is different from corporate social responsibility during Covid.

Ding et al. (2021) examine the severity of the effect of coronavirus on stock prices using the data from 61 countries and 6,700 firms. Ding et al. (2021) use the dependent variable, as the weekly stock return of individual firms for the weeks t and $t-1$. They also use the growth in confirmed Covid cases on a weekly basis. They use difference in difference estimation procedure using Covid 19 cases in that week for that country. They interact with the firm characteristics which is taken at pre-Covid with the weekly increase in Covid cases. Firms with a stronger capital base, credit capacity that was unused, less leverage, less short-term leverage, and higher earnings outperformed their peers in terms of stock market reaction. They also find firms with better pre-pandemic CSR performance performed better during the pandemic. Furthermore, firms with more entrenched executives perform worse during the

pandemic. They also find that firm ownership structure is correlated with the performance of firms during the coronavirus pandemic.

3.2.2 Hypothesis Development

I postulate that firm characteristics before the Covid crisis help predict the performance of the companies during the pandemic. I use the following firm characteristics to predict firm performance during the pandemic. Larger companies are better positioned in the market as they have more earning assets, have a diversified business, and have better negotiation power. There is a large literature examining the difference between large and small firms, that finds that information asymmetry is lower for large firms, and they are less risky (Fama and French, 2015). I expect that larger firms performed better during Covid. Leverage increases the financial risk of the firms as the firms need to make payments to service debt. Consequently, as the cash flows suffer during a crisis, the firms with higher leverage are more likely to perform badly during the Covid pandemic. On the other hand, a higher leverage might be a way to make managers more disciplined resulting in them having less control over the firm's cash flow. As managers are more disciplined if the leverage is higher, it might imply better performance during Covid.

Holding a larger amount of cash has advantages and disadvantages. Cash holdings are either favourably or adversely correlated with performance. On the one hand, cash provides flexibility to invest in good projects by reducing the chance of underinvestment when external capital is expensive (Myers and Majluf, 1984). On the other hand, too much cash encourages overinvestment in projects that are not as profitable (Richardson, 2006), makes executives entrenched (Jensen, 1986; Shleifer and Vishny, 1989), and grants more control (Kalcheva and Lins, 2007). How cash holdings affect the performance of the firms during Covid is an empirical question. To ensure that the returns on their capital expenditures are proportional, businesses carefully select their capital projects. However, there is still substantial

disagreement over how capital expenditure choices affect businesses' financial success (Kerstein and Kim, 1995). Capital expenditures before the Covid may not produce good returns because of uncertainty (Key, 2022). Hence, higher capital expenditure before Covid may relate negatively to returns.

Brand capital is an intangible asset that captures how well-known a company's products are among customers (Dada, 2025). Brand capital is an important asset for the firm because it aids businesses in boosting sales through, for instance, enhanced consumer loyalty or visibility. How brand capital is related to the performance during Covid is an empirical question. There is little evidence, according to Fahlenbrach and Stultz (2011), that during the financial crisis of 2007-08, banks with CEOs whose incentives were less closely correlated with those of their shareholders performed poorly. Together with the UK's regulator, the FSA (2009), and the Walker Report (Walker, 2009) examined the issues with top-level managers' compensation in the banking industry and made a number of recommendations for reforms to payment structure. Since executive remuneration was tied to the performance during the financial crisis of 2007-08, I examine the impact of compensation during the performance of companies during Covid. CEO duality is an important corporate governance phenomenon, and empirical studies have used this to assess the performance of companies and banks (Krause and Semadeni, 2013). As CEO duality represents a concentration of power at the firm level, this might destroy value. Ultimately, this is an empirical question of whether CEO duality is related to the company's performance during the Covid.

I utilise the variable "ownership concentration" as a proxy for agency issues (Jensen and Meckling, 1976). If a company's ownership is highly concentrated, the asymmetric information problem and, consequently, the agency problem between stockholders and executives, are likely to be greater. The information asymmetry and, thus, the agency costs

between managers and shareholders are likely to be larger if a firm's ownership is heavily concentrated (Jensen and Meckling, 1976). The influence of ownership concentration may also be seen in the competing interests of minority and controlling shareholders, which are frequently systematically linked to business decisions made by an organisation. During a crisis, I expect that higher agency costs will lead to a distorted performance. Therefore, I consider ownership concentration, which is calculated as the number of shares closely held divided by the total number of common shares outstanding.

Though there exist studies which examine the firm characteristics before Covid and the share price performance during Covid there are still gaps in the literature. Some studies were based on the US market (e.g. Ramelli and Wagner (2021) and Huang et al. (2021)). As Covid was a global pandemic (except for Africa), I include data from the countries that were severely affected by Covid. Though Ding et al. (2021) used data from across the globe, they used weekly stock return data and related the weekly growth in Covid cases. They use the interaction between two continuous variables (e.g., size and growth rate of Covid-19 weekly cases), which is difficult to interpret. But, using cross-country data, I ask the question whether the pre-Covid firm characteristics can explain the stock price performance of the companies across the globe. Knowing the answer is important for companies as they can build on those characteristics to avoid bad performance during future crises. I measure the share price return for the companies for the whole period of Covid and test whether the performance of the companies is related to the financial characteristics of the companies. Some of the company characteristics may help predict the performance of the worst performing companies. It is important to know what firm-level characteristics are associated with the worst performance. This knowledge will help us to take precautionary measures for those companies when a health or other crisis breaks out. Also, investors know in advance what sort of companies to avoid during a health crisis. Thus, I propose:

H1a. Company characteristics before the pandemic helps predict the worst performing companies (in terms of stock returns) during pandemic.

H1b. The stock market performance of the companies during the Covid-19 pandemic is related to the company characteristics (pre-pandemic).

Government policy responses such as social distancing, resulted in an economic shutdown, which impacted financial markets as well as companies. The Covid induced uncertainty and government policy measures wreaked havoc on a variety of industries, including recreation and entertainment, travel, commerce, transportation, and finance. Imposed lockdown measures included travel bans, leading to people's movement being severely restricted. Growing economic uncertainty affected everyone. With travel bans affecting the aviation sector, restrictions on public gatherings shut down the restaurants, cancellation of sporting events, concerts and the entertainment industry (Narayanan et al., 2020). Some of the sectors saw really good prospects during the times of Covid. For example, with 15.8 million new subscribers, Netflix was up 32%. Zoom Technologies' stock was up by more than 1,500%. In just a few weeks, Amazon recruited 80,000 new employees.² However, I do not know how the government's actions impacted different companies differently.

On the one hand, Chen and Yeh (2021) show the impact of government policy response has a positive impact on stock market recovery. Covid affected nearly every sector of the economy in the United States, and the Federal Reserve unveiled several quantitative easing (QE) measures to help the economy and regain market trust. Following the announcements of quantitative easing, Chen and Yeh (2021) indicate that market performance in most sectors began to rebound from the negative effects of Covid, implying that QE is successful in improving consumer morale. Furthermore, they find that the influence of QE in 2020 on stock

² Though a lot of these things have reversed now, such as Amazon fired a lot of employees (Bloomberg UK, 2023), but this does not affect our approach as we are interested in company performances during Covid.

performance is greater for sectors most impacted by the pandemic. On the other hand, Ozili and Arun (2020) illustrate how the coronavirus epidemic reverberated through large swaths of the global economy, and how policymakers' hasty reactions, in the interests of saving people's lives, caused and sustained economic downturns. Ozili and Arun (2020) examined the impact of economic activities on the aggregate stock market index. However, the impact of restrictions is different on different industries and companies.

The correlation between COVID-19 stringency standards and corporate success varies by country and industry. COVID-19 stringency rules relate to measures adopted by the government to contain the virus's transmission, such as lockdowns, social distancing recommendations, and travel restrictions. There are, however, notable outliers to this overall pattern. Companies in the IT and e-commerce industries, for example, have seen increased demand for these businesses' products and services, which has resulted in improved performance for many companies in these areas. In addition, the intensity of the pandemic in each nation influences the link between COVID-19 stringency requirements and firm performance. Countries with higher levels of infection and fatality rates may have taken tougher measures to prevent the virus's spread, which might have a bigger influence on company performance.

High COVID-19 stringency measurements have been linked to a deterioration in company performance, particularly in businesses that rely largely on in-person contacts. This is because the measures limit firms' capacity to function and produce income. Lockdowns, travel restrictions, and social distancing standards can all diminish demand for products and services, resulting in fewer revenues and profits. Stringency measures can also disrupt supply chains and cause delays in getting critical inputs, resulting in production delays and poorer productivity. Furthermore, cash flow issues can arise when businesses are unable to generate enough revenue to cover fixed costs such as rent and salaries.

Ding et al. (2021) further show that firm-level stock returns are positively associated with national policy responses to the pandemic, including containment and prevention measures, fiscal stimulus initiatives, and interventions by national authorities through the purchase of corporate debt, with larger-scale debt purchase programmes linked to stronger stock market performance. Governments made a few policies with far-reaching positive and negative effects for their economies, financial markets, industries as well as companies. It is an empirical question whether the government actions are positively or negatively related to returns during the pandemic. If government actions (e.g., Covid stringency) are related to the bad performance of the companies, then I expect that in the high stringency countries, the return performance is worse. On the other hand, I expect that in low-stringency countries, it might be positively related to company performance. Thus, I propose:

H2. Covid stringency is positively related to company performance.

Governance has been found to affect stock market returns in previous studies (La Porta et al., 1997, La Porta et al., 1998, La Porta et al., 2000). Public protections against insider expropriation, according to La Porta et al. (1996), can be traced in part to differences in the composition and effectiveness of capital markets across the globe. Better governance may result in more detailed financial statements (Leuz, Nanda, and Wysocki, 2003), as well as more information to the market (Morck, Yeung, and Yu, 2000), which could bring the stock price into line with the fundamental value of a firm. Governance improves companies' access to finance for positive NPV projects (La Porta et al., 1997, 1998, 2000, and 2002) and La Porta, Lopez-de-Silanes, and Shleifer (2006). Because of the challenge from the market for corporate control, firms located in nations with stronger governance are less likely to have their managers participate in value-destroying behaviours. Instead, they are more likely to carry out initiatives with positive NPV that improve shareholder wealth (Wurgler (2000), Shleifer and Wolfenzon

(2002), and Bekaert, Harvey, and Lundblad (2010)). Kaufmann et al., (2010) provide some governance benchmarks for 200 countries around the world, which were revised in 2020. The six indicators are Voice and Accountability, Political Stability and Absence of Violence/Terrorism Government Effectiveness, Regulatory Quality, Rule of Law and Control of Corruption as described in Kaufmann et al. (2010).

A stable and predictable regulatory framework, which may support returns, may be more likely to be advantageous for businesses operating in nations with high levels of voice and responsibility. Businesses are more likely to profit from a stable business climate, which can boost profits, when they operate in nations with high levels of political stability and low levels of violence and terrorism. Businesses are more likely to profit from a favourable business climate in nations with high levels of government efficacy, which can boost returns. Businesses operating in nations with strong regulatory standards could encounter less entrance hurdles and be able to run more effectively, which might support returns. A stable and open legal system, which can support returns, is more likely to be advantageous for businesses operating in nations with high levels of rule of law. Businesses located in nations with strong anti-corruption regulations may experience fewer corrupt activities and be able to run more successfully, which can support returns.

Through the timely allocation of resources and the implementation of policies to control the spread of the virus, effective governance can aid in the management of the pandemic crisis. Countries with strong governance institutions are more likely to be better prepared for crises and to respond faster and more effectively. Governments can give financial assistance to companies affected by the epidemic. Direct cash support, tax reductions, and other incentives may be included. Effective governance may assist in ensuring that these policies are applied equitably and openly, as well as ensuring that monies are allocated effectively. Effective governance may help to guarantee that information regarding the epidemic is disseminated to

the public and companies in a clear and open manner. This can assist in developing trust and confidence, which is critical for businesses performance throughout the epidemic.

Overall, the six governance indicators described in Kaufmann et al. (2010) can have a significant impact on return performance during the COVID-19 pandemic. Companies operating in countries with high levels of governance may be better positioned to manage risks and capitalize on opportunities, which can support returns. These governance indicators could explain how the individual companies in countries with better governance performed during the coronavirus pandemic. Hence, I propose:

H3. Companies in countries with better governance performed well during the Covid-19 pandemic.

3.3. Data and Methodology

3.3.1 Data

I use data from the countries which are severely affected by the Covid-19. I use the US, UK, China, Brazil, India, France, Germany, and Italy as our sample countries as these countries were seriously affected by Covid in terms of death rate (please see figure 1). For all of these countries I download the list of companies from Refinitiv. Then I exclude financial and utilities as financial firms have different balance sheets and both financials and utilities are part of regulated industries. In other words, the company characteristics are different for these two industries. After excluding financials and utilities, I have 15,444 companies in the sample. I use return and firm characteristics data from Refinitiv (all the variables are defined in Appendix A). Most of the variables that I use from Refinitiv have a good coverage, except for Carbon dioxide (Co2), Board size and ESG. These three variables have limited availability in Refinitiv. When I use these three variables, the number of observations drops significantly in the regressions.

To control for the severity of Covid lockdown, I use the Covid stringency index. The nine indicators used in the OxCGRT index are: school closures, workplace closures, cancelled public events, restrictions on gatherings, public transportation closures, stay-at-home requirements, restrictions on internal movement, international travel controls, public information campaigns. The scores are then combined to create a composite score that ranges from 0 (no measures) to 100 (strictest measures).

To control for the severity of Covid I use total deaths per million and new cases per million. I use this data from Oxford COVID-19 Government Response Tracker. I also use governance data as provided by Kaufman et al (2010), updated in 2020. The governance indicators are Voice and Accountability, Political Stability and Absence of Violence/Terrorism, Government Effectiveness, Regulatory Quality, Rule of Law and Control of Corruption. I use Refinitiv industry classification system which is 10 categories, and I use two-digit standard industry classification as in Ding et al. (2021).

3.3.2 Methodology

I calculate buy and hold returns from the weekly stock price indices for companies from 17 January, 2020 to 22 May, 2020 (as this was the first wave of Covid-19) as used in Ding et al. (2021). However, my methodology is very different from Ding et al. (2021). They have used the weekly return for those weeks (17 January, 2020 to 22 May, 2020). I use buy-and-hold returns for the whole of the sample period. Ding et al. (2021) use the weekly growth rate of Covid cases, while I am interested in whether the company performance in the first wave of Covid could be explained by the company characteristics before the pandemic.

$$BHR_{j,c,t} = \prod_{t=1}^T (1 + r_{j,c,t}) \dots\dots\dots(1)$$

Where $r_{j,c,t}$ is the weekly return for company j, in country c and week t.

Probit Regressions are used to predict who will be in the Bottom Performer Group as in Fahlenbrach et al. (2012). Fahlenbrach et al. (2012) used a probit model to predict the bottom

performing group in the context of the Global Financial Crisis. They offer probit regressions explaining whether a financial institution is in the lowest performing group during the financial crisis to further examine how bank attributes are connected with banks' crisis performance. I test a similar concept in the Covid-19 pandemic; hence, a probit model is suitable for my test. I form 4 quantiles, and the bottom performer group is the worst performing quantile by returns during Covid. The model's goal is to calculate the likelihood that an observation with a given set of attributes will fall into a certain category. As my objective is to examine whether the company characteristics can determine the bottom performing companies, as an appropriate model, I use Probit regressions. The following formula can be used to represent the Probit model:

$$\Pr(Y = 1|X) = \Phi(Z) = Z = \Phi(\beta_0 + \beta_1X_1 + \beta_2X_2 + \dots + \beta_nX_n) \dots \dots \dots (2)$$

where, given the explanatory variables X, Y is the dependent variable and measures the likelihood that the event will occur ($Y = 1$). In my model, Y is the probability that the firms are in the bottom performer group. Y is defined as 1 if the firm is in the bottom performer group and 0 if the firm is in the other group. I sort the buy and hold returns for period January 17, 2020 to May 22, 2020 and form quartiles. Quartile 1 is defined as the bottom performer group. X is the firm's characteristics. The cumulative standard normal distribution function is denoted by Φ . Z represents the linear combination of independent variables (X) with coefficients ($\beta_0, \beta_1, \beta_2 \dots \beta_n$).

I use ordinary least square regressions to test our hypotheses. OLS is the most appropriate model as I am interested in the cross-sectional variation of company returns using the 2019 pre-pandemic company characteristics. As my firms are drawn at a single point in time, I cannot use panel data techniques. Though I have cross country-data, country fixed effects are possible, but FE models will subsume country-level data (e.g., governance, Covid

stringency index etc). Beltratti and Stultz (2012) examined the cross-sectional performance of global banks during the Financial crisis of 2007-08. During that time, there is a substantial difference in the cross-section of big bank stock returns around the world. They utilise this variability to assess the significance of variables cited as contributing to banks' poor performance during the credit crisis. As I am examining the cross-sectional performance of companies during Covid-19, in line with Beltratti and Stultz (2012), the model I use is as follows:

$$BHR_{c,j,1st\ wave} = \alpha + \beta X'_{2019} + \lambda Covid\ Stringency\ index_c + \rho governance_c + \mu Total\ deaths\ per\ million_c + \gamma New\ cases\ per\ million_c + \delta_i + \varepsilon \dots \dots \dots (3)$$

Where $BHR_{c,i,1st\ wave}$ is the buy-and-hold abnormal return for country c, company j and time t. For time t I use the first wave of Covid return data from January 17, 2020 to May 22, 2020 as used in Ding et al. (2022). X'_{2019} includes pre Covid firm characteristics data as explained in the data appendix. δ_i is the industry fixed effects (time fixed effects is not possible as the data is drawn at a single point in time, country effects are possible but I cannot use Covid stringency index). For further analysis, I divide the sample by firm size, leverage, cash holdings, Investment, beta, agency cost and repeat model 3.

For robustness of our findings, I use accounting and market-based performance measures. I use ROA, ROE and Tobin's q for 2020 as dependent variables in separate regressions (same model as equation 3).

$$ROA_{c,j,2020} = \alpha + \beta X'_{2019} + \lambda Covid\ Stringency\ index_c + \rho governance_c + \mu Total\ deaths\ per\ million_c + \gamma New\ cases\ per\ million_c + \delta_i + \varepsilon \dots \dots \dots (4)$$

$$ROE_{c,j,2020} = \alpha + \beta X'_{2019} + \lambda Covid\ Stringency\ index_c + \rho governance_c + \mu Total\ deaths\ per\ million_c + \gamma New\ cases\ per\ million_c + \delta_i + \varepsilon \dots \dots \dots (5)$$

$$\text{Tobin's } Q_{c,j,2020} = \alpha + \beta X'_{2019} + \lambda \text{Covid Stringency index}_c + \rho \text{governance}_c + \mu \text{Total deaths per million}_c + \gamma \text{New cases per million}_c + \delta_i + \varepsilon \dots \dots \dots (6)$$

The statistical technique of quantile regression may be used to calculate the conditional quantiles of a response variable with the help of one or more predictor variables. Quantile regression estimates the conditional distribution of the response variable as opposed to typical linear regression, which estimates the conditional mean of the response variable. This allows for a more flexible and reliable analysis. It is especially helpful when the researcher wants to look at how the predictor variable or variables relate to the different parts of the distribution of the response variable.

Quantile regression calculates the regression slope by minimising the sum of absolute residuals, as opposed to the OLS technique, which does it by reducing the sum of squared residuals. I also use quantile regressions to further check our results. Think of a regression model with the structure of equation 3. The coefficients for different variables were calculated using the OLS regression technique, which minimises the squared sum of errors. QR calculates the conditional quantiles whereas OLS regression calculates the conditional mean. The p-th quantile of the distribution—BHR—that is a random variable is represented by the Q(p). P is a number between 0 and 1. The generic pth sample statistics quantile Q(p) may be solved as an optimal solution to minimise the sum of asymmetrically weighted absolute error terms with different weights for positive and negative residuals, depending on the quantile p that is chosen. Algorithms for linear programming can be used to determine the various parameter vectors for a given p. Since, BHR quartiles have different performances, hence, to estimate the impact of different firm characteristics in the different parts of the BHR distribution, I employ quantile regressions.

3.4. Preliminary analysis

3.4.1 Country level performance measures

I first discuss the country-level performance measures. The BHR in the first wave of Covid shows that only the US and France have a positive average buy and hold return, albeit very small (for the US 1.07% and France 3.43%). However, all the median BHRs are negative for all the countries that I consider. The lowest average BHR is calculated for Brazil (-40.96%) and the highest for France (3.43%). When I consider the BHR for the 2nd wave, most of the returns are positive and sizable. The highest is for France (45.89%) and the lowest is for China (35.32%). Looking at those BHRs for the second wave, it looks like the markets have recovered from the shock of Covid. (It is defined in the table Buy and hold return from weekly data for October 9, 2020 to June 18, 2021).

Table 1. Country level performance measures

	BHR	BHR 2nd wave	ROA	ROE	Tobins' Q
US					
N	2700	2896	2868	2475	2596
Mean	1.07	39.65	-14.01	-22.01	3.65
median	-18.97	18.19	1.28	2.31	2.26
Sd	622.48	70.46	33.75	62.41	4.54
p10	-53.49	-24.89	-78.63	-135.56	0.20
p90	29.72	132.32	12.64	28.78	10.28
UK					
N	880	920	945	873	893
Mean	-8.31	39.51	-9.68	-13.53	2.82
median	-24.01	20.39	1.43	2.10	1.69
Sd	128.78	68.41	29.60	51.11	3.74
p10	-57.14	-23.10	-57.41	-78.10	0.26
p90	25.99	126.18	13.96	27.64	7.08
Brazil					
N	200	241	265	224	198
Mean	-35.80	42.42	2.83	1.75	2.42
median	-40.96	20.25	5.06	8.96	1.56
Sd	23.90	74.49	14.41	41.08	3.31
p10	-63.14	-22.71	-11.82	-24.72	-0.15
p90	-0.57	123.20	14.67	34.38	7.18
China					
N	4289	3792	4291	4267	3428
Mean	-19.41	35.32	5.31	7.23	3.18
median	-22.85	15.03	5.47	9.07	2.35
Sd	22.42	69.24	11.22	23.84	2.85

p10	-40.63	-25.19	0.34	0.21	1.06
p90	3.97	122.86	15.71	24.82	6.14
France					
N	496	549	508	469	516
Mean	3.43	45.89	-5.72	-12.37	2.07
median	-1.50	28.24	2.49	5.59	1.38
Sd	39.81	73.60	22.33	50.35	2.80
p10	-12.50	-22.26	-36.99	-76.19	0.31
p90	13.79	140.62	8.83	20.12	4.52
Germany					
N	568	577	544	519	558
Mean	-1.20	39.52	-2.72	-4.72	2.89
median	-14.43	19.30	2.91	6.04	1.72
Sd	123.75	68.58	20.59	39.59	3.69
p10	-41.18	-21.81	-23.91	-43.84	0.23
p90	20.79	133.07	10.26	23.16	7.18
India					
N	3218	3740	2782	2531	2864
Mean	-18.66	39.33	3.68	4.58	1.75
median	-24.85	19.15	5.15	8.08	0.84
Sd	43.30	68.67	13.35	30.09	2.99
p10	-50.97	-23.14	-5.82	-8.86	-0.01
p90	12.26	127.54	14.35	24.74	4.34
Italy					
N	245	280	272	263	238
Mean	-18.93	35.57	2.10	2.85	2.32
median	-23.79	10.35	3.58	8.56	1.81
Sd	26.79	70.13	11.53	35.77	2.68
p10	-44.52	-31.17	-6.79	-26.58	0.45
p90	6.76	139.04	11.96	31.96	5.04

Table 1 reports the performance measures at the country level. I report buy-and-hold returns (BHR), Buy-and-hold returns 2nd wave, return on assets (ROA), Return on Equity (ROE) and Tobin's Q.

Then I consider the operating performance measures, ROA and ROE. They are negative for the US, UK, France, Germany and positive for the rest of the countries. The lowest average ROA and ROE are reported for the US. The highest average ROA and ROE are reported for China. When Tobin's Q is considered, our analysis finds that the average Tobin's q is highest for the US and lowest for India.

3.4.2 Descriptive statistics

I calculate the descriptive statistics for all the companies in our sample. I report mean, median, standard deviation, 10th and 90th percentile. The results show that the average BHR is -12.584% while the median is -21.645%. The standard deviation of those returns is 292.758% which shows that there are lots of variations in the returns across our sample. The average BHR for

the second wave of Covid is 38.51% with a median of 17.97%. The standard deviation is much lower than the first wave of Covid. The average ROA and ROE also show that they are negative. The average Tobin's q is 2.19.

Table 2. Descriptive statistics

Variables	N	mean	p50	sd	p10	p90
BHR	12596	-12.584	-21.645	292.758	-47.646	13.793
BHR 2 nd wave	13003	38.51	17.97	69.59	-24.17	128.64
ROA	12475	-51.11	4.25	612.84	-24.26	14.19
ROE	11621	-22.46	7.37	776.85	-40.53	25.57
Tobin's Q	11291	2.19	1.78	8.25	0.23	6.65
Log(total assets)	13127	5.28	5.32	1.07	3.90	6.58
Debt	13127	22.590	18.730	20.265	0.000	52.619
Cash	13127	14.122	7.569	18.567	0.314	36.763
Capex	13127	4.188	2.418	6.132	0.055	10.126
Brand capital	13127	0.841	0.012	3.783	0.025	1.505
Compensation	13127	22.673	2.235	61.673	1.126	81.471
CEO/chair duality	15443	0.126	0.000	0.332	0.000	1.000
log(CO2)	1357	5.229	5.207	1.140	3.870	6.732
logage	12917	3.938	4.001	0.331	3.498	4.270
Beta	12328	0.978	1.040	1.063	-0.042	1.912
Closely held shares	10366	40.989	45.310	29.735	0.000	77.920
Board size	3359	9.002	9.000	2.757	6.000	12.000
ESG	3360	40.051	36.375	20.414	15.955	70.765
Covid stringency	15431	75.366	75.460	5.527	66.670	81.940
Governance	15431	0.319	-0.110	0.672	-0.303	1.400
Total deaths per million	15431	155.386	3.298	221.366	2.629	418.297
New cases per million	15431	21.981	4.635	29.893	0.030	70.440

The table reports the descriptive statistics from US, UK, Germany, France, Italy, Brazil, India and China for which I could find data in the

Refinitiv. All the variable definitions are in Appendix A. I winsorize all the ratios and continuous variables at 2.5% tails to remove the effect of outliers.

The financial characteristics before the pandemic show that firms have an average debt ratio of 22.59% and cash ratio of 14.122%. The results show that though the companies had a moderate amount of debt, they are holding a lot of cash. Capital expenditure was on an average 4.188%. Compensation paid was 22.672%. CEO/Chair duality is 0.126. Beta was 0.978 which is very close to the market beta of 1. Closely held shares are found to be 40.989%, meaning that ownership is highly concentrated. Average board size is 9, with a standard deviation of 2.757. ESG is showing an average score of 40 with a standard deviation of 20. Average Covid stringency is 75 (out of 100) which is quite high, average total deaths per million is 155.386 and new cases per million is 21.98. The average of governance score 0.319.

3.4.3 Mean difference test for worst performers and best performers

I take the BHR for the first wave of Covid and divide it to form four quartiles. Quartile 1 is the worst performer and quartile 4 is the best performer. The results show that BHR for quartile 1 is 47.56% and for quartile 4 is 39.10% and the means are statistically different at 1% level. The BHR for the second wave results show that the quartile 1 average is 51.98% while the quartile 4 average is 65.52%. The accounting performance measures do not show evidence of mean difference across quartile 1 and 4. The mean difference test for company characteristics shows that the means are different for total assets, debt, cash, capex compensation, log(age), beta, Covid stringency, governance, and deaths per million.

Table 3. Mean difference test for worst performers and best performers during Covid

Variables	(1)	(2)	(3)	(4)	(5)
	Quartile 1	Quartile 2	Quartile 3	Quartile 4	mean diff Q1 vs Q4
BHR	-47.56	-28.34	-13.53	39.10	8.36***
BHR 2 nd wave	51.98	30.04	-3.90	65.52	6.89***
ROA	-7.06	1.10	-0.24	-66.36	-1.01
ROE	-23.86	-4.42	-2.54	-53.84	-1.00
Tobin's Q	2.01	2.64	1.84	1.98	-0.01
Log(total assets)	5.68	5.51	5.47	4.94	-13.60***
Debt	23.59	20.81	21.84	21.91	-3.19***
Cash	11.13	12.40	13.09	16.64	11.40***
Capex	4.69	4.42	4.03	3.54	-7.87***
Brand capital	0.84	0.67	0.78	0.99	1.36
Compensation	23.13	17.58	23.83	37.35	7.64***
CEO/chair duality	0.15	0.14	0.16	0.16	0.66
Log (C02)	5.32	5.27	5.23	5.08	-2.72***
Log(age)	4.00	4.01	4.01	3.94	-7.21***
Beta	1.19	1.13	0.98	0.84	-12.02***
Closely held shares	41.02	40.77	40.26	40.70	-0.39
Board size	8.89	9.09	9.29	8.76	-1.00
ESG	39.66	39.41	41.59	39.58	-0.08
Covid stringency	75.59	75.24	75.09	74.82	-5.42***
Governance	0.29	0.17	0.26	0.48	10.84***
Total deaths per million	153.99	116.42	138.59	191.01	6.52***
New cases per million	24.44	16.66	17.97	24.55	0.14

This table reports the quartiles formed based on the returns during the first wave of Covid. Quartile 1 is the worst performing group and Quartile 4 is the best performing group. Column 5 reports the mean difference t-test between the best performing (Quartile 4) and worst performing (Quartile 1) companies.

3.5. Empirical Results

3.5.1 Regressions predicting membership in the bottom performing group.

Whether a company's stock return will slip into the lowest quartile throughout the first wave of Covid is predicted using probit regressions. The dependent variable is equal to 1 if the BHR is in quartile 1, and zero otherwise. Using company characteristics in 2019, I estimate the probability that a company will fall into the worst performing category during Covid. Model 1 is without industry dummies and Model 2 is with industry dummies. I interpret the results of Model 2. The results show that total assets are positively related to being in the bottom performing group. Based on the sample mean, a change in size by one standard deviation is related to a 12.14% (0.023×5.28) larger probability of being in the bottom performer group. This effect is large and economically significant. The debt ratio is not significant. The cash is negative and significant. At the sample mean, a change in cash by one standard deviation is related to a 4.24 % ($-.003 \times 14.122$) lower likelihood of being in the group of poor performers. Cash acts as a shield in the Covid-19 crisis. Capex is positive and significant. From the sample mean, a change of one standard deviation in capex is related to a 2.93 % (0.007×4.188) larger likelihood of being in the group of poor performers. Probably the value of investment evaporated with Covid, hence I find that highly invested firms perform badly. Compensation is negative and significant. From the sample mean, a change in compensation of one standard deviation is related to a 2.26 % (-0.001×22.673) lower likelihood of being in the group of poor performers. Beta is positive and significant. Based on the sample mean, a change in beta by a standard deviation is associated with a 4.79% (0.049×0.978) larger likelihood of being in the group of poor performers. All these results support H1a.

The higher the Covid stringency, the more the chance that the returns will fall into bottom performing group. This result is consistent with H2a. Governance shows a significant negative impact on the returns, which is consistent with H3. Total deaths per million and new

cases per million are positively related to the performance of bottom performing group. This shows that the severity of Covid has a positive impact on prob of returns being in the bottom quartile.

Table 4. Probit Regressions Predicting Membership in the Bottom Performer Group

	(1)	(2)	(3)	(4)
Total assets	0.023*** (4.02)	0.033*** (4.23)	0.019 (0.59)	0.033 (0.77)
Debt	0.001 (0.47)	0.001 (-0.17)	0.001 (0.53)	0.001 (0.38)
Cash	-0.002*** (-5.79)	-0.003*** (-5.95)	-0.005** (-3.22)	-0.007*** (-3.71)
Capex	0.004*** (5.31)	0.007*** (5.56)	0.008** (2.71)	0.009* (2.01)
Brand	-0.002 (-1.24)	-0.003 (-1.80)	-0.004 (-1.50)	-0.006* (-2.17)
Compensation	-0.001*** (-3.74)	-0.001*** (-3.98)	0.001 (0.93)	0.001 (0.44)
Ceo chair duality	-0.029* (-2.13)	-0.016 (-0.84)	0.002 (0.08)	0.006 (0.16)
log(age)	-0.043* (-2.39)	-0.015 (-0.61)	-0.011 (-0.31)	0.019 -0.36
Beta	0.042*** (7.75)	0.049*** (6.55)	0.098*** (4.75)	0.121*** (4.37)
Closely held shares	-0.001 (-1.08)	-0.001 (-1.12)	0.001 (0.05)	-0.001 (-0.90)
Covid stringency	0.022*** (10.38)	0.019*** (7.26)	-0.016*** (-3.93)	-0.032*** (-5.91)
Governance	-0.160*** (-5.05)	-0.188*** (-4.53)	-0.158** (-3.03)	-0.341*** (-4.60)
total deaths per million	0.001*** (7.62)	0.001*** (6.39)	0.001*** (5.99)	0.001*** (6.88)
New cases per million	0.003*** (12.36)	0.004*** (10.12)	0.002*** (3.56)	0.002** (2.86)
Consumer Discretionary		-0.087*** (-3.84)		-0.11 (-1.85)
Health Care		0.139*** (6.11)		0.029 (0.47)
Energy		0.079* (2.45)		0.08 (0.90)
Industrials		-0.097*** (-4.33)		-0.140* (-2.41)
Consumer Staples		-0.168***		-0.078

		(-5.55)		(-0.93)
Telecommunications		-0.041		-0.017
		(-0.96)		(-0.15)
Basic Materials		-0.284***		-0.296***
		(-11.67)		(-4.23)
Real Estate		-0.291***		-0.297**
		(-8.56)		(-3.22)
log(CO2)			0.014	0.012
			(0.89)	(0.55)
ESG Score			-0.002	-0.001
			(-1.88)	(-1.08)
Board Size			0.005	0.005
			(0.97)	(0.74)
N	12256	9492	1322	1229
Pseudo R-sqr	0.23	0.25	0.12	0.10

The table displays the results of Probit regressions that forecast whether a company's stock return will fall into the bottom quartile during the initial wave of COVID. If the BHR is in quartile 1, the dependent variable is equal to 1; otherwise, it is equal to zero. I predict inclusion in the poorest performing category using company characteristics in 2019. In Appendix A, each variable is defined. The z-statistics in parentheses represent statistical significance at the 1%, 5%, and 10% levels, respectively.

The results in columns 3 and 4 include the additional firm characteristics like log(co2), ESG score and board size. In column 3, I do not use industry dummies, while in column 4, I include industry dummies. The results are similar to columns 1 and 2, except for Covid stringency. Covid stringency is loaded as negative as this is a much-restricted sample.

Overall, the above analysis shows that many company characteristics pre-pandemic help predict the performance of the company during the Covid. It is of interest to examine the cross-sectional variation of performance of the companies based on OLS regression, which I focus our attention on.

3.5.2 Cross sectional variation in returns

In this section, I examine the cross-sectional variation of returns during the first wave of Covid using the pre-pandemic characteristics. The results are reported in Table 5. Column 1 reports the results without industry dummies and column 2 reports the results with industry dummies. I interpret the results of column 2. The results show that total assets are negatively related to returns. Increase in size by a one standard deviation decrease the returns by 8.715% (-

8.145*1.07). Debt is positive and significant. If the debt increases by a one standard deviation the returns will increase by 2.816% (0.139*20.265). Cash is also positive and significant. If cash were to grow by one standard deviation, the returns rise by 5.776% (0.311*18.576). Capex shows a negative coefficient. If capex increased by one standard deviation, the returns fall by 4.672% (-0.762*6.132). Compensation is positive and significant. If compensation increased by one standard deviation, the returns rise by 4.317% (0.070*61.673). The lower the beta the higher the return. Closely held shares are positive and significant. An increase in closely held shares by a one standard deviation increase the returns by 2.944% (0.099*29.735). All these results support H1b.

Covid stringency, total deaths per million and governance are not significant in this specification. I do not find support for H2a and H3. New cases per million are negative and significant. It means that the number of new cases (severity of Covid) reduces the return.

Table 5. Regression explaining the variation in returns

	(1)	(2)	(3)	(4)
Total assets	-7.387** (-3.13)	-8.145*** (-7.43)	0.311 (0.18)	0.74 (0.28)
Debt	0.042 (0.72)	0.139** (3.09)	-0.016 (-0.39)	-0.026 (-0.41)
Cash	1.208 (1.25)	0.311*** (5.43)	0.349*** (3.62)	0.467*** (3.95)
Capex	-0.302 (-1.30)	-0.762*** (-4.51)	-0.29 (-1.75)	-0.217 (-0.89)
Brand	-0.159 (-0.99)	-0.083 (-0.37)	0.08 (0.67)	0.168 (0.97)
Compensation	-0.094 (-0.63)	0.070*** (4.37)	-0.001 (-0.05)	0.001 (0.06)
Ceo chair duality	-1.703 (-1.15)	-3.014 (-1.14)	0.51 (0.34)	1.506 (0.65)
log(age)	7.755 (0.69)	-3.567 (-1.03)	-2.982 (-1.46)	-4.265 (-1.29)
Beta	-2.621 (-1.59)	-1.682* (-2.01)	-7.078*** (-5.04)	-7.614*** (-4.91)
Closely held shares	0.015 (0.25)	0.099** (2.96)	0.028 (0.89)	0.064 (1.19)

Covid stringency	0.498 (0.61)	-0.50 (-1.81)	1.286*** (6.91)	1.831*** (5.33)
Governance	20.403 (1.36)	6.983 (1.78)	12.332*** (4.28)	18.574*** (3.94)
total deaths per million	-0.05 (-1.22)	-0.014 (-1.28)	-0.029*** (-5.47)	-0.044*** (-5.45)
New cases per million	0.077 (0.37)	-0.171*** (-4.26)	-0.097*** (-3.96)	-0.102* (-2.40)
Consumer Discretionary		5.633 (1.87)		5.103 (1.42)
Health Care		-9.675** (-3.18)		-4.094 (-1.11)
Energy		-5.493 (-1.29)		-3.941 (-0.72)
Industrials		6.425* (2.15)		10.639** (2.99)
Consumer Staples		15.466*** (3.72)		8.131 (1.59)
Telecommunications		1.416 (0.25)		-3.422 (-0.50)
Basic Materials		18.020*** (5.06)		18.491*** (4.06)
Real Estate		18.846*** (3.52)		17.803** (2.87)
log(CO2)			-1.495 (-1.76)	-2.279 (-1.70)
ESG Score			0.108* (2.16)	0.081 (1.08)
Board Size			-0.206 (-0.63)	-0.181 (-0.40)
constant	-45.584 (-0.47)	79.029** (3.19)	-90.326*** (-4.50)	-131.637*** (-4.11)
R-sqr	0.051	0.071	0.128	0.221
N	9477	5746	1211	1196

The table reports the regression results (OLS) for explaining the cross-sectional variation in returns during Covid using the firm characteristics before Covid (2019). The dependent variable is BHR during the first wave of Covid. Variable definitions are in Appendix A. Numbers in parentheses are t-statistics, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

The results in columns 3 and 4 include additional firm characteristics like log(co2), ESG score and board size. In column 3, I do not use industry dummies, while in column 4, I include industry dummies. The results are similar in columns 1 and 2, except that size is not

significant. Also, Covid stringency and governance are positive and significant. Total deaths per million and new cases per million are negative and significant.

3.5.3 Impact of Covid stringency on the share price returns

The results from the probit model findings show that higher Covid stringency is associated with the bottom performing quartile. The OLS results do not show any significance in the larger sample (columns 1 and 2, table 5). Hence, I perform a regression analysis (OLS) that uses company characteristics prior to Covid to explain how the Covid stringency index affected the cross-sectional volatility in returns. My logic is simple. If government action (such as Covid stringency) is associated with poor performance of the firms, then I anticipate that return performance is poorer in countries with strong Covid stringency. On the other hand, if Covid stringency is not associated with poor firm performance, I anticipate that it may not be significant in nations with lenient Covid stringency. High (low) Covid stringency is defined as being greater (lesser) than the cross-sectional average (75.00) for Covid stringency.

The COVID-19 stringency index assesses the rigour of government-imposed controls on the spread of COVID-19 in a certain country or area. The index is constructed using a series of metrics that represent the severity of limitations in areas such as social isolation, travel restrictions, and business and school closures. The nine indicators used in the OxCGR index are: School closures, Workplace closures, Cancelled public events, Restrictions on gatherings, Public transportation closures, Stay-at-home requirements, Restrictions on internal movement, International travel controls and Public information campaigns. The scores are then combined to create a composite score that ranges from 0 (no measures) to 100 (strictest measures).

The results are reported in Table 6. Column 1 reports the results for high Covid stringency and column 2 reports the results for low Covid stringency. I find interesting results. Covid stringency is negatively related to returns in the high Covid stringency sample. This means that in countries with high Covid stringency return is lower. On the other hand, the

Covid stringency index is not related to returns in the low Covid stringency sample. These results support H2a and reject H2b. The results show that government actions (Covid stringency) are partially responsible for the gloomy performance of companies in high stringency countries (only).

Due to the restrictions, companies that rely on in-person connections, such as those in the hotel, tourism, and retail industries, may see a decrease in demand for their products and services. Customers may be unable or unwilling to travel, dine out, or purchase in person, resulting in decreased revenues and profitability for these businesses. Companies' supply chains may be disrupted as a result of limitations on the movement of products and persons. This may create delays in getting critical inputs, resulting in production delays and poorer productivity. Companies may have cash flow issues if they are unable to produce enough income to meet fixed expenditures such as rent and salaries. This can result in reduced investment, layoffs, and possibly insolvency.

Table 6. Impact of Covid stringency on the Performance of companies

	High Covid stringency	Low Covid stringency
Total assets	-5.316*** (-6.32)	-10.883*** (-4.74)
Debt	0.208*** (6.52)	0.026 (0.27)
Cash	0.038 (0.70)	0.258** (2.45)
Capex	-0.522*** (-4.44)	-1.065*** (-2.83)
Brand	0.04 (0.16)	-0.188 (-0.51)
Compensation	-0.123 (-1.17)	0.059** (2.39)
Ceo chair duality	7.332*** (2.98)	-4.764 (-1.01)
log(age)	4.374 (1.30)	-4.08 (-0.67)
Beta	-1.886*** (-3.02)	-1.572 (-0.91)
Closely held shares	0.129***	0.132

	(5.52)	(1.46)
Covid stringency	-2.470***	0.154
	(-10.75)	(0.10)
Governance	13.922***	22.932*
	(6.95)	(1.89)
total deaths per million	-0.021	-0.025
	(-1.11)	(-1.56)
New cases per million	0.121	0.066
	(0.32)	(0.21)
Consumer Discretionary	3.994*	5.987
	(1.93)	(0.88)
Health Care	-6.907***	-12.759*
	(-3.28)	(-1.89)
Energy	-4.919*	-5.742
	(-1.69)	(-0.59)
Industrials	3.067	9.114
	(1.48)	(1.37)
Consumer Staples	10.397***	22.576**
	(3.73)	(2.32)
Telecommunications	1.313	1.781
	(0.34)	(0.13)
Basic Materials	14.607***	19.677**
	(6.02)	(2.41)
Real Estate	13.234***	24.860**
	(3.67)	(2.01)
constant	182.607***	26.75
	(8.63)	(0.29)
R-sqr	0.139	0.068
N	3457	2268

The table reports the regression results (OLS) for explaining the impact of Covid stringency index in the cross-sectional variation in returns during Covid using the firm characteristics before Covid (2019). The dependent variable is BHR during the first wave of Covid. High (low) Covid stringency is defined as if the Covid stringency is higher (lower) than average (75.00). Covid stringency for all the countries. Variable definitions are in Appendix A. Numbers in parentheses are t-statistics, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

3.6. Further Analysis

3.6.1 Alternative performance measures

As measures of alternative performances, I use return on assets (ROA), return on equity (ROE) and Tobin's q. While the first two are accounting based performance measures which are not affected by irrational behaviour or herding in the markets, the last one is based on market value

and replacement value. Column 1 describes the results for ROA. Total assets are positive and significant. The returns rise by 10.90% (10.19×1.07) for each unit of total asset that increased by one standard deviation. Debt is negatively related to ROA. Higher level of debt decreases ROA, because the company needs to pay interest and principal repayments for debt. A one standard deviation rise in debt result in a 4.03% (-0.199×20.265) reduction in ROA. Cash is negatively related to ROA, implying that the opportunity cost of holding cash is high during Covid. A one standard deviation increases in cash decrease the returns by 5.34% (-0.288×18.567). Capex, log(age) and closely held shares are positively related to ROA. Brand and beta are negatively related to ROA. The higher the Covid stringency, the lower the return on assets. The returns are associated with a drop by 1.54% (-0.279×5.527) for every standard deviation rise in the Covid stringency.

Column 2 describes the results for ROE. Total assets are positive and significant. A change in total asset by a one standard deviation increase the returns by 21.085% (19.706×1.07). Debt is negatively related to ROE. A higher debt level reduces ROE, and the business may have to make interest and principal payments on the loan. Increased debt by one standard deviation results in a 12.118% (-0.598×20.265) reduction in returns. Cash is negatively related to ROE, implying that the opportunity cost of holding cash is high during Covid. A one standard deviation increases in cash result in an 8.98% (-0.484×18.567) reduction in returns. Capex, log(age) and closely held shares are positively related to ROE. Beta is negatively related to ROE. The higher the Covid stringency the lower the return on equity. A one standard deviation increases in Covid stringency decrease the returns by 3.77% (-0.682×5.527).

Table 8. Alternative performance measures

	(1)	(2)	(3)
	ROA	ROE	Tobins'q
Total assets	10.190*** (34.14)	19.706*** (28.95)	-0.067 (-1.18)

Debt	-0.199*** (-16.17)	-0.598*** (-20.07)	-0.019*** (-7.91)
Cash	-0.288*** (-18.22)	-0.484*** (-14.24)	0.021*** (6.95)
Capex	0.151*** (4.12)	0.842*** (8.43)	0.019** (2.66)
Brand	-0.138* (-2.21)	-0.194 (-1.49)	0.050*** (4.14)
Compensation	0.001 (0.23)	-0.021* (-2.16)	0.006*** (7.11)
Ceo chair duality	-1.131 (-1.52)	-1.832 (-1.17)	0.341* (2.38)
log(age)	7.564*** (7.80)	16.035*** (7.84)	-0.129 (-0.69)
Beta	-1.022*** (-4.38)	-2.426*** (-4.82)	-0.054 (-1.20)
Closely held shares	0.029** (3.12)	0.050* (2.56)	-0.010*** (-5.29)
Covid stringency	-0.279*** (-3.63)	-0.682*** (-4.21)	-0.091*** (-6.12)
Governance	-2.535* (-2.30)	-3.273 (-1.40)	-0.608** (-2.87)
total deaths per million	0.013*** (4.30)	0.029*** (4.52)	-0.001 (-1.01)
New cases per million	-0.044*** (-3.95)	-0.112*** (-4.56)	-0.001 (-0.28)
Consumer Discretionary	-0.414 (-0.49)	-1.466 (-0.83)	-0.04 (-0.25)
Health Care	-0.211 (-0.25)	-1.331 (-0.74)	-0.061 (-0.37)
Energy	1.461 (1.23)	0.712 (0.29)	-0.174 (-0.76)
Industrials	-0.682 (-0.82)	-0.746 (-0.42)	-0.167 (-1.04)
Consumer Staples	0.21 -0.18	(1.44) (-0.59)	(0.13) (-0.59)
Telecommunications	-0.715 (-0.45)	-2.084 (-0.62)	-0.305 (-1.00)
Basic Materials	0.18 (0.18)	0.957 (0.46)	0 0.00
Real Estate	-0.78 (-0.52)	-2.085 (-0.66)	-0.167 (-0.58)
constant	-66.600*** (-9.61)	-123.938*** (-8.50)	11.195*** (8.40)
R-sqr	0.365	0.309	0.081
N	5885	5514	5865

The table reports the regression results (OLS) for explaining the cross-sectional variation in alternative performance measures during Covid using the firm characteristics before Covid (2019). The dependent variable is ROA, ROE and Tobin's in 2020. Variable definitions are in Appendix A. Numbers in parentheses are t-statistics, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

When I use Tobin's q in column 3, the impact of different variables is similar to ROA and ROE, albeit with smaller magnitudes (except for total assets which is not significant). For example, Debt would grow by one standard deviation and reduce Tobin's q by 0.385 (-0.019×20.265). Cash is positively related to Tobin's q, implying the market valuation of the cost of holding cash is different compared to ROA or ROE. Cash increased by one standard deviation result in a 0.389 (0.021×18.567) rise in Tobin's q. Capex, brand, compensation, CEO/chair duality are positively related to ROE. The higher the Covid stringency, the lower the Tobin's q. Tobin's q drop by 0.105 (-0.019×5.527) for every standard deviation rise in the Covid stringency.

3.6.2 Heterogeneity analysis

In this section, I examine different sub-samples to shed further light on the variation of cross-sectional returns depending on company characteristics. In Table 9, I divide our sample based on size, debt, and cash. Column 1 reports the results for small firms and column 2 reports the results for large firms. Column 1 and 2 shows some interesting results. While the impact of firm size is negative on returns for the small firms, it is positive for the large firms. This shows that our results for the whole sample, that firm size is negatively related to returns, are driven by the smaller firms. Also, Covid stringency is negatively related to returns, implying that higher restrictions decrease the return.

In columns 3 and 4, I divide our sample by debt. Column 3 reports results for low debt and column 4 reports results for high debt. Debt is significant and positively related only in the

high debt sample. So, our results for the whole sample, that debt is positively related to returns are driven by the high debt sample. In columns 5 and 6, I divide our sample by cash. Column 5 reports results for low cash and column 6 reports results for high cash. Cash is significant and positively related only in the high cash sample. So, our results for the whole sample, that cash is positively related to returns are driven by the high cash sample.

What is common in all the subsamples is that capex is negatively related to returns, implying that investment value evaporated during Covid, hence, performance is negatively related to investment. Compensation is mostly positively related to returns, meaning that firms with higher-paid executives performed better during Covid-19.

Table 9. Subsample analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	Small	Large	low debt	high debt	low cash	high cash
Total assets	-24.859*** (-7.50)	4.532*** (4.28)	-10.200*** (-4.76)	4.847*** (-4.47)	6.848*** (-4.58)	-10.714*** (-6.35)
Debt	0.058 (0.60)	0.122*** (3.98)	-0.101 (-0.40)	0.370*** (6.13)	-0.015 (-0.25)	0.351*** (4.98)
Cash	0.145 (1.42)	0.179** (3.23)	0.133 (1.56)	0.570*** (7.26)	-0.444 (-0.84)	0.215** (2.75)
Capex	-0.784* (-2.18)	0.611*** (-5.43)	-0.743* (-2.20)	0.663*** (-4.17)	-0.527* (-2.57)	-1.161*** (-3.93)
Brand	-0.321 (-0.71)	0.1 (0.64)	-0.545 (-1.28)	0.229 (1.06)	-0.066 (-0.23)	-0.02 (-0.06)
Compensation	0.140*** (4.61)	0.148*** (6.51)	0.066* (2.54)	0.052** (2.76)	-0.024 (-0.84)	0.109*** (5.44)
Ceo chair duality	-8.383 (-1.28)	-3.475* (-2.14)	-0.376 (-0.08)	-4.382 (-1.70)	-0.757 (-0.20)	-4.022 (-1.11)
log(age)	-6.799 (-0.94)	-0.062 (-0.03)	-7.446 (-1.17)	-0.442 (-0.13)	-3.06 (-0.71)	-2.838 (-0.49)
Beta	-0.085 (-0.05)	2.722*** (-4.57)	0.855 (0.69)	6.286*** (-5.72)	-0.171 (-0.12)	-2.690* (-2.54)
Closely held shares	0.165* (2.13)	0.03 (1.37)	0.209*** (3.63)	-0.033 (-0.92)	0.038 (0.77)	0.163*** (3.47)
Covid stringency	-0.367 (-0.53)	1.082*** (-6.03)	-0.727 (-1.43)	-0.349 (-1.26)	-0.658 (-1.70)	-0.191 (-0.40)

Governance	5.582 (0.59)	-1.344 (-0.50)	2.701 (0.35)	8.314* (2.21)	8.397 (1.52)	6.177 (1.05)
total deaths per million	-0.022 (-1.03)	-0.008 (-0.89)	0.009 (0.43)	-0.034** (-3.18)	-0.013 (-0.81)	-0.016 (-1.10)
New cases per million	-0.278** (-3.03)	0.172*** (-6.36)	-0.102 (-1.25)	0.212*** (-5.63)	0.184*** (-3.42)	-0.164** (-2.64)
constant	173.874** (2.72)	28.324 (1.75)	117.106** (2.59)	38.144 (1.53)	88.079** (2.65)	67.292 (1.61)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
R-sqr	0.069	0.107	0.07	0.11	0.049	0.094
N	2289	3434	2725	2998	3014	2709

The table reports various sub-samples regression results (OLS) for explaining the cross-sectional variation in returns during Covid using the firm characteristics before Covid (2019). The dependent variable is BHR during the first wave of Covid. Small (large) is lower (higher) than median size. Low (high) debt is lower (higher) than median debt ratio. Low (high) cash is lower (higher) than median cash ratio. Variable definitions are in Appendix A. Numbers in parentheses are t-statistics, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 10 reports the results for subsamples based on capex, beta and agency problems. Column 1 reports the results for low capex firms and column 2 reports the results for high capex firms. Capex is negative and significant in both the samples. Total assets are also significant and negative in both samples. Compensation is positive and significant in both samples. When I divide the sample according to beta, debt, compensation and governance are positive and significant. However, beta loses significance in both samples. When I divide the sample according to agency costs, most of the variables are significant in the high agency cost sample. Closely held shares are not significant in the low agency cost subsample.

The variables total assets, cash, and new cases per million are significant in all the subsamples. Debt and compensation are mostly significant across sub-samples.

Table 10. subsample analysis

	(1) Low Capex	(2) High Capex	(3) Low Beta	(4) High Beta	(5) Low agency	(6) High agency
Total assets	-8.389***	-5.724***	-8.674***	-6.961***	-8.351***	-8.386***

	(-4.51)	(-4.77)	(-5.34)	(-4.46)	(-4.82)	(-5.80)
Debt	0.216**	0.03	0.181**	0.068	0.083	0.187**
	(3.01)	(0.62)	(2.63)	(1.13)	(1.27)	(3.01)
Cash	0.235**	0.384***	0.407***	0.193*	0.261*	0.296***
	(2.78)	(5.10)	(4.72)	(2.49)	(2.50)	(4.34)
Capex	-5.589**	-0.298*	-0.499	-0.983***	-0.610*	-0.852***
	(-2.71)	(-1.97)	(-1.82)	(-4.58)	(-2.56)	(-3.55)
Brand	-0.222	0.123	0.314	-0.771*	-0.105	-0.115
	(-0.69)	(0.40)	(1.02)	(-2.31)	(-0.28)	(-0.43)
Compensation	0.075**	0.081***	0.100***	0.042	0.002	0.076***
	(2.86)	(4.64)	(4.18)	(1.91)	(0.04)	(4.45)
Ceo chair duality	-6.344	-0.191	-5.14	-2.348	3.911	-4.632
	(-1.30)	(-0.08)	(-1.22)	(-0.69)	(0.79)	(-1.52)
log(age)	-1.574	-2.924	-3.966	-1.777	1.553	-6.583
	(-0.26)	(-0.85)	(-0.81)	(-0.36)	(0.28)	(-1.51)
Beta	1.716	-5.233***	-2.626	-0.18	-0.191	-3.201**
	(1.19)	(-6.29)	(-1.63)	(-0.13)	(-0.16)	(-2.76)
Closely held shares	0.107	0.077*	0.069	0.141**	0.178	0.262***
	(1.81)	(2.37)	(1.27)	(3.22)	(1.72)	(3.48)
Covid stringency	-1.070*	-0.115	0.217	-1.252**	-1.132**	0.975*
	(-2.16)	(-0.43)	(0.52)	(-3.14)	(-2.94)	(2.10)
Governance	8.261	7.14	12.843*	0.885	-3.231	18.268**
	(1.17)	(1.88)	(2.35)	(0.14)	(-0.51)	(3.27)
total deaths per million	-0.005	-0.028**	-0.028*	0.021	0.02	-0.036**
	(-0.25)	(-2.68)	(-2.11)	(1.08)	(1.12)	(-2.66)
New cases per million	-0.231***	-0.111**	-0.165**	-0.201**	-0.262***	-0.192***
	(-3.32)	(-2.75)	(-2.99)	(-3.10)	(-4.11)	(-3.41)
	116.875*					
constant	*	33.145	32.738	118.061***	102.144**	-17.74
	(2.65)	(1.37)	(0.85)	(3.40)	(2.77)	(-0.46)
Industry FEs	Y	Y	Y	Y	Y	Y
R-sqr	0.063	0.102	0.079	0.071	0.065	0.1
N	2878	2845	2379	3344	2824	2899

The table reports various sub-samples regression results (OLS) for explaining the cross-sectional variation in returns during Covid using the firm characteristics before Covid (2019). The dependent variable is BHR during the first wave of Covid. Low (high) capex is lower (higher) than median capital expenditure. Low (high) beta is lower (higher) than market beta of 1. Low (high) agency is higher (lower) than median closely held shares. Variable definitions are in Appendix A. Numbers in parentheses are t-statistics, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

3.6.3 Developing vs Developed countries.

As there are fundamental differences between developing and developed countries in this section, I repeat the regressions for analysing the BHR. In column 1, I use the whole sample but use a dummy for developing countries. The results show that developing dummy is negative and significant (coeff=-46.082 and t=-4.09). This result shows that developing countries BHR

are more negative compared to the developed countries. The other variables show a similar relationship with our baseline regression in Table 5. In column 2, I use the developing countries only. The results show that total asset, cash, capex and compensation is negatively related to BHR. In column 3, I use the developed countries. Total asset, Capex, CEO-chair duality are negative and significant. One note of caution is that, as I have only 7 countries in our sample, 4 of them developed and 3 are developing, I need to be careful in explaining the difference.

Table 11. Developing vs developed countries.

	(1)	(2)	(3)
	Whole sample	Developing	Developed
Developing	-46.082*** (-4.09)		
Total assets	-8.204*** (-7.86)	-3.665** (-3.27)	-11.531*** (-5.25)
Debt	0.132* (1.93)	0.177*** (5.70)	0.05 (0.36)
Cash	0.265* (2.23)	-0.093* (-1.93)	0.267 (1.60)
Capex	-0.781*** (-8.91)	-0.489** (-3.35)	-1.091*** (-4.23)
Brand	-0.135 (-1.43)	-0.034 (-0.21)	-0.109 (-0.96)
Compensation	0.062** (2.70)	-0.887** (-3.20)	0.057* (2.15)
Ceo chair duality	-2.096 (-1.33)	6.521*** (4.26)	-4.672** (-2.56)
log(age)	-2.701 (-0.95)	3.184 (1.15)	-2.676 (-0.75)
Beta	-1.733 (-0.79)	-2.898** (-2.32)	-0.839 (-0.22)
Closely held shares	0.145** (2.83)	0.153*** (6.48)	0.093 (0.74)
covid stringency	-0.467* (-2.28)	3.873*** (10.46)	2.189*** (3.99)
Governance	-27.259*** (-3.57)	-210.333*** (-11.53)	46.742** (2.89)
total deaths per million	0.006 (0.44)	+	-0.046** (-2.38)
New cases per million	-0.265*** (-8.41)	+	-0.144 (-1.61)

constant	113.885*** (4.06)	-364.852*** (-10.61)	-121.569** (-2.95)
R-sqr	0.054	0.072	0.048
N	9492	5432	4062
Country FE	No	No	No
Industry FE	Yes	Yes	Yes
Cluster robust SE	Industry	Industry	Industry

The table reports various sub-samples regression results (OLS) for explaining the cross-sectional variation in returns during Covid using the firm characteristics before Covid (2019). The dependent variable is BHR during the first wave of Covid. Developing is a dummy which equals one for China, India and Brazil. Numbers in parentheses are t-statistics, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

3.6.4 Fixed effects and clustered standard errors

In this section, I use country and industry fixed effects regressions and also use country and industry and country-industry clustered robust standard errors. In column 1, I use the country fixed effects and country clustered robust standard errors. The results show that total assets and compensation are negatively related to the BHR. When I use industry fixed effects and industry clustered standard errors in column 2, total assets, capex are negatively related and debt, cash and compensation are positively related. When I use country and industry fixed effects and country-industry fixed effects in column 3, the results are qualitatively similar to column 2. I conclude that fixed effects and robust standard errors do not change our results.

Table 12. Fixed effects and clustered standard errors

	(1)	(2)	(3)
Total assets	-7.715*** (-6.10)	-8.145*** (-8.36)	-8.745*** (-4.96)
Debt	0.046 (0.47)	0.139* (2.05)	0.146*** (4.65)
Cash	1.160* (2.02)	0.311** (2.75)	0.277*** (2.99)
Capex	-0.332 (-1.70)	-0.762*** (-8.54)	-0.809*** (-4.54)
Brand	-0.207 (-1.14)	-0.083 (-0.89)	-0.104 (-0.89)
Compensation	-0.109** (-3.19)	0.070** (2.92)	0.074*** (3.10)
Ceo chair duality	-0.325 (-0.12)	-3.014 (-1.65)	-1.457 (-0.59)

log(age)	9.754 (1.42)	-3.567 (-1.20)	-2.832 (-1.02)
Beta	-2.866 (-1.55)	-1.682 (-0.77)	-1.866 (-1.10)
Closely held shares	0.069 (0.97)	0.099* (1.92)	0.139** (2.49)
covid stringency		-0.500* (-2.29)	
Governance		6.983** (2.47)	
total deaths per million		-0.014 (-0.89)	
New cases per million		-0.171*** (-8.34)	
constant	-14.98 (-0.69)	82.670*** (3.64)	40.037*** (2.77)
R-sqr	0.041	0.047	0.045
N	9492	9492	9492
Country FE	Yes	No	Yes
Industry FE	No	Yes	Yes
Cluster robust SE	Country	Industry	Country and Industry

The table reports country and industry fixed effects regression results and clustered (country and industry) standard errors for explaining the cross-sectional variation in returns during Covid using the firm characteristics before Covid (2019). The dependent variable is BHR during the first wave of Covid. Country fixed effects are not possible in models 1 and 3. as covid stringency, governance, total deaths per million and new cases per million are country level variables.. Numbers in parentheses are t-statistics, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

3.6.5 Quantile regression results

Unlike the OLS method, which derives the regression slope by minimising the sum of squared residuals, quantile regressions accomplish it by minimising the sum of absolute residuals. I use quantile regressions to quantify the influence of various company characteristics in the various parts of the BHR distribution since I have seen that our BHR quartiles perform differently.

The results for quantile regressions are reported in Table 11. Most of the results are similar to what I find in OLS. Some results are consistent with my sub-sample analysis. I have found that for quartile 1-3, the impact of total assets is negative on the returns. However, for quartile 4, the impact is positive, albeit marginally significant. This result is consistent with the results of large firms using OLS. Cash is positive and significant in all the quantiles. Capex

and beta are negative in the first three quantiles. Compensation is positive and significant in the first three quantiles. Covid stringency is negative and significant in all the quantiles. The magnitude of the coefficient shows that it has the most impact on quantile 4 returns. Though the magnitude of the coefficients is different (which is expected) across quantiles, the results from quantile regressions are qualitatively similar to OLS regressions, which shows that my findings are robust.

Table 13. Quantile regression

	(1)	(2)	(3)	(4)
	Quantile 1	Quantile 2	Quantile 3	Quantile 4
Total assets	-1.216** (-2.94)	-2.719*** (-4.04)	-4.606*** (-5.88)	1.662* (1.71)
Debt	-0.008 (-0.48)	0.058* (2.09)	0.103** (3.20)	-0.104** (-2.61)
Cash	0.150*** (6.92)	0.304*** (8.66)	0.258*** (6.30)	0.098* (1.93)
Capex	-0.140* (-2.20)	-0.377*** (-3.64)	-0.566*** (-4.69)	-0.107 (-0.71)
Brand	0.102 (1.21)	0.179 (1.31)	0.025 (0.16)	-0.071 (-0.36)
Compensation	0.038*** (6.35)	0.058*** (5.90)	0.067*** (5.84)	0.022 (1.58)
CEO chair duality	0.099 (0.10)	-0.251 (-0.15)	0.106 (0.06)	-3.738 (-1.60)
log(age)	3.549** (2.72)	-0.792 (-0.37)	-3.759 (-1.52)	6.605* (2.16)
Beta	-2.056*** (-6.51)	-3.834*** (-7.45)	-3.291*** (-5.49)	-0.431 (-0.58)
Closely held shares	0.02 (1.58)	0.025 (1.23)	0.062* (2.56)	-0.011 (-0.38)
Covid stringency	-0.720*** (-6.91)	-0.448** (-2.64)	-0.743*** (-3.76)	-1.065*** (-4.36)
Governance	2.219 (1.50)	10.448*** (4.33)	7.502** (2.67)	-4.912 (-1.41)
total deaths per million	-0.022*** (-5.35)	-0.027*** (-4.18)	-0.021** (-2.72)	-0.015 (-1.59)
New cases per million	-0.164*** (-10.82)	-0.191*** (-7.76)	-0.131*** (-4.56)	-0.092** (-2.59)
constant	9.447 (1.01)	25.933 (1.71)	95.877*** (5.42)	-20.576 (-0.94)

Pseudo R-sqr	0.0568	0.0815	0.085	0.097
N	1430	1430	1430	1430

The table reports the quantile regression results for Quantile 1(0.25), quantile 2(0.50), quantile 3 (0.75) and quantile 4(1.00) to explain the stock returns during the first wave of Covid. I use firm characteristics in 2019 to as explanatory variables. All variables are defined in Appendix A. Numbers in parentheses are t-statistics, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

3.7. Conclusion

This study addresses the question whether firm characteristics before the pandemic help explain the performance of the companies during the first wave of Covid. My contribution to the existing substantial body of literature is in several areas. I start by addressing the issue of whether firm traits assessed before Covid-19 aid in forecasting the performance of the businesses during the epidemic. Studies that focus on the US market are available. Because US companies and firms from other nations have many different institutional arrangements, cultural norms, and financial features, the US findings do not necessarily apply to the rest of the globe. For instance, the reason American corporations store more cash is discussed by Bates et al. (2009). They find that the average business has sufficient cash on hand to settle all debt. Cash ratios increase when organisations' financial flows become riskier. Businesses also change with time; they spend more money on research and development and keep fewer receivables and inventories on hand. Agency conflicts have not been reliably proven to be a problem, despite the fact that they provide a crucial explanation for the growth in cash ratios. The cash holdings and leverage of American companies and those of other nations vary substantially. I thus examine which business characteristics at the end of 2019 aid in predicting the success of companies throughout the Covid-19 pandemic by using cross-country data.

I find size, cash, capital expenditure, compensation, beta, and closely held shares help predict the performance of the companies during the Covid pandemic. I find that larger firms are not guaranteed a better performance during the Covid pandemic. In fact, I document that on average, smaller firms performed better. My analysis shows that “cash is king”, and hence

higher cash protects firms during a time of health crisis. I also find that the value of investment (capex) evaporated during the time of Covid. The companies with higher-paid executives performed better during times of crisis. Companies with concentrated ownership (fewer agency problems) performed better during the Covid pandemic. High risk companies (beta) performed worse during the crisis. All the above findings have implications for the companies.

I also examine the impact of country-level factors on the performance of the companies. I have found that the Covid stringency of government policy impacts the performance of the companies. I document that higher Covid stringency is related to lower buy-and-hold returns. I show that countries with better governance performed better. The severity of Covid in terms of total deaths and new cases per million has an impact on the returns.

I use alternative performance metrics—ROA, ROE and Tobin's q. The share price return may be subject to herding behaviour and panic in the markets, while the accounting measures are not prone to these problems. Most of my findings were documented using the BHR hold in these settings. I also use some heterogeneity analysis, which shows the sensitivity of my results. I use different fixed effects regression and alternative clustered standard errors and our results survive. I use quantile regression, which shows that my results are robust to alternative estimation methods.

My work has some policy implications for companies and governments. Investors and traders must choose wisely whether companies to invest in or trade during times of market instability, such as the Covid-19 pandemic. By studying the business characteristics associated with successful stock price performance, investors may identify companies that may be resilient or high performing. Understanding the company characteristics that affected stock price performance during Covid-19 might be useful for long-term investment planning. Investors can identify companies that have demonstrated their ability to innovate, adapt, and succeed in challenging conditions. Investors may find this information useful in deciding on

companies with strong fundamentals, competitive advantages, and the potential for long-term, sustainable growth. I document that cash is useful and significant in covid. These findings are consistent with prior research relating corporate success to financial factors, including cash holdings and debt levels (Fresard, 2010; Giroud and Mueller, 2017). Capex has an inverse correlation with the return during the covid. Positive and important factors include compensation and closely held stock. My findings support the idea that CEO remuneration practises might affect business success (Murphy, 2013; Rau, 2015). Our results run counter to the idea that entrenched leaders undermine corporate value (Gompers et al., 2003; Bebchuk et al., 2009). All these findings imply that companies need to hold cash, invest moderately, and pay their executives well.

The Covid-19 outbreak presented significant risks and uncertainties to businesses in a variety of sectors. I find that consumer staples, basic materials and real estate performed better during Covid-19. By examining the business characteristics that are associated with this time period's stock price performance, investors may be better able to recognise and manage the risks associated with their investments. If a company has robust fundamentals, it can identify organisations that may be better equipped to endure crises in the future. The Covid-19 pandemic served as an important wake-up call to the need for business catastrophe preparation. By examining the relationship between company characteristics and stock price performance throughout this crisis, businesses may learn crucial lessons and enhance their crisis management strategies. They are able to identify weak areas and take action to strengthen their operations, supplier networks, financial standings, and overall resilience.

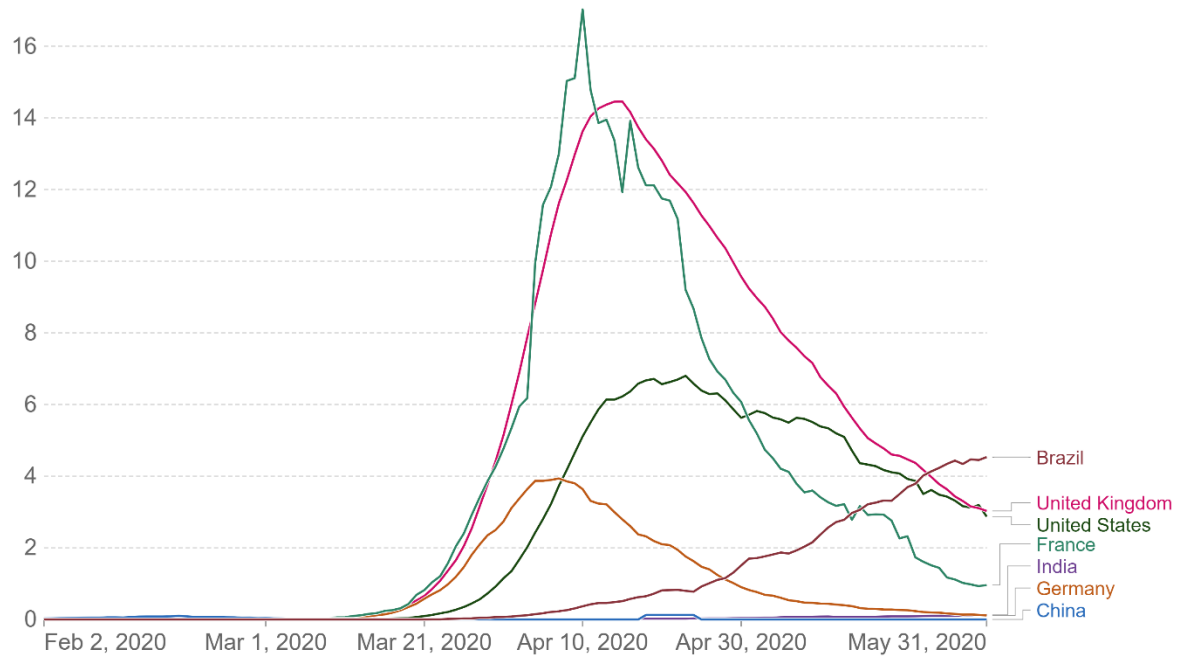
Firm size does not provide companies with any protection against a crisis like Covid. Why larger firms performed worse needs to be investigated further and subject to future research. But cash seems to provide an extra layer of protection from Covid crisis. However, holding a lot of cash has an opportunity cost, hence this needs to be interpreted

cautiously. Government actions have a negative impact on company performance. Hence, in the future, governments need to weigh the benefits of the restrictions against the cost of such action. This needs more research as well.

Figure 1: Severity of Covid 19 around our sample period

Daily new confirmed COVID-19 deaths per million people

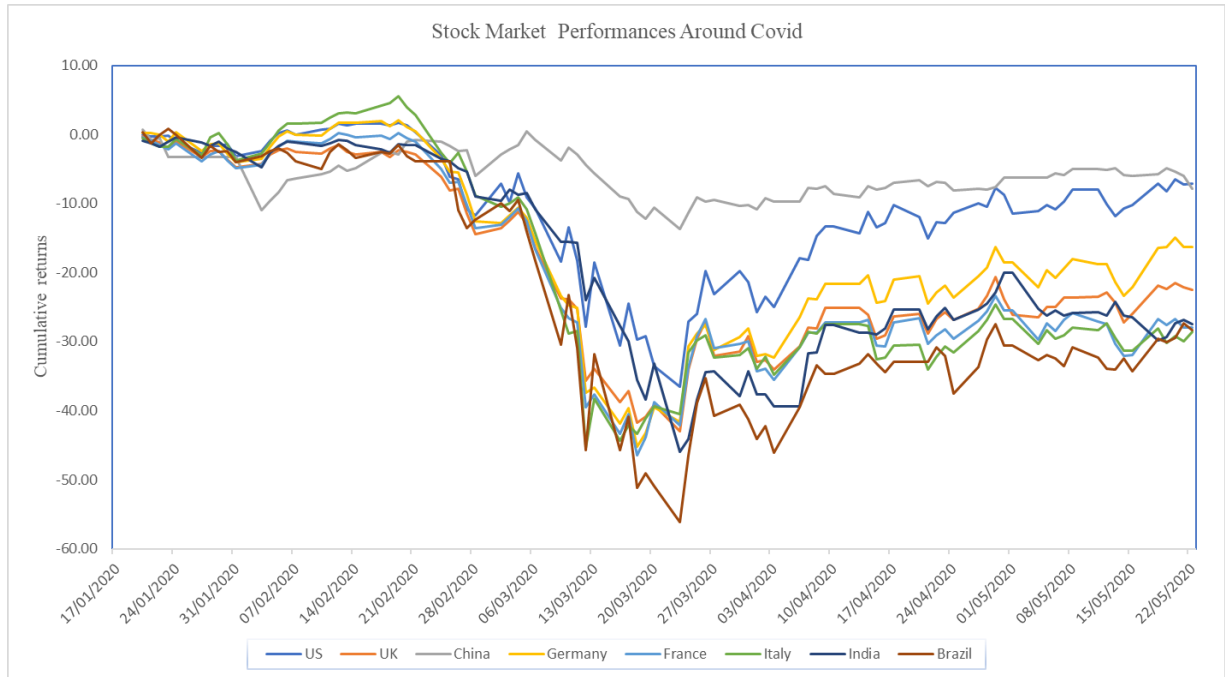
7-day rolling average. Due to varying protocols and challenges in the attribution of the cause of death, the number of confirmed deaths may not accurately represent the true number of deaths caused by COVID-19.



Source: WHO COVID-19 Dashboard

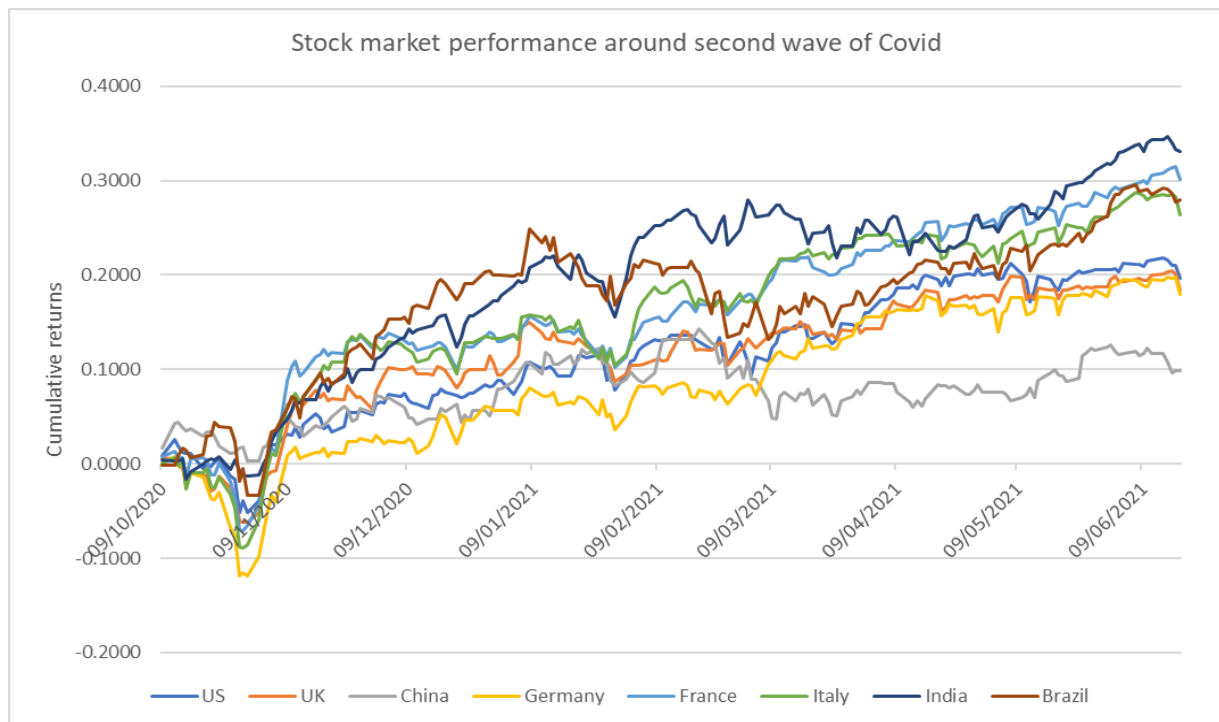
CC BY

Figure 2. Stock market performance around Covid 19 first wave



Source: Drawn by myself based on Refinitiv data

Figure 3 Stock market performance around Covid 19 second wave



Source: Drawn by myself based on Refinitiv data

Chapter 4

Are Covid-19 returns related across waves? Testing business model and learning hypotheses.

4.1. Introduction

Covid-19 turned into a global pandemic and had a severe impact around the world. Much research has been conducted to examine the different impacts of Covid-19. Covid-19 had a few waves (Polat et al, 2023) in terms of casualties. The virus was first discovered in December 2019 in Wuhan, China. The first wave of infections in different regions of the world, including Europe and the United States, began in early 2020 because of its rapid spread to other nations. Some areas saw a decrease in cases throughout the summer after initiating lockdowns and containment measures. As a result of an increase in infections in several places, a second wave began in the middle of 2020. The autumn and winter of 2020 saw a large rise in Covid-19 infections across several nations, leading to the greatest infection rates and hospitalisations to that moment. During the summer of 2021, incidences of infections of the extremely contagious Delta form spiked in several regions of the world. This variation was linked to more hospitalisations, which raised more worries. The nature of the waves was different, and it was affecting different countries at different points in time. Though the literature on Covid is large and it is still growing, to the best of my knowledge, no paper has examined the relationship among waves. I fill the gap in the literature and examine the relationship of Covid-19 waves in this chapter.

Most of the previous studies focus on the first wave of the covid. For example, Ramelli and Wagner (2021) looked at the cross-sectional shifts in US companies during the Covid-19 pandemic. They discovered that initially, companies with an international focus, especially those with significant trade ties to China, underperformed. Corporate debt and cash balances were important performance indicators. Because of the deep interdependence of the world's economies, localised economic shocks can have a significant impact elsewhere (Hanif et al. 2020). Economic downturns, diminished consumer confidence, and decreased investment can

all be attributed to COVID-19 waves. These elements may affect how well companies succeed across a range of markets and sectors. Some other studies examined the market volatility during different Covid waves. According to Szczygielski et al. (2021) and Uddin et al. (2021), COVID-19 waves might cause significant market volatility, which can have an impact on investor attitudes and actions. The stock values of several companies and industries may shift in a coordinated manner because of investor reactions to virus-related news and events. Even if their particular operations are not directly impacted by the virus, worries over COVID-19's global effects might trigger market-wide selloffs or rallies and linked returns across enterprises. However, no studies have examined the cross-sectional relationship among companies in different Covid waves. I fill this gap in the literature.

Understanding cross-wave correlation in firm-level stock returns is important because it reveals whether firms' responses to repeated systemic shocks are driven by persistent structural characteristics or by adaptation and learning over time. The COVID-19 pandemic was not a single, isolated event but a sequence of waves that differed in severity, policy responses, and market expectations. Examining how firm performance in one wave relates to performance in subsequent waves allows us to assess whether firms that were vulnerable early in the crisis remained vulnerable later, or whether they were able to adjust their operations, financing, or strategies to improve resilience.

From a theoretical perspective, cross-wave correlation speaks directly to competing explanations of crisis performance. A positive correlation in returns across waves supports the business model hypothesis, which argues that firms' exposure to systematic risk is largely determined by relatively rigid features such as demand cyclicalities, operating leverage, and financial structure. In this case, repeated shocks reveal the same winners and losers. In contrast, weak or negative correlations are consistent with the learning hypothesis, under which firms

and investors adapt based on experience, leading to re-ranking of firm performance across waves.

From an empirical standpoint, focusing only on the first wave risks overstating the permanence of early outcomes. Cross-wave analysis allows researchers to distinguish between temporary dislocation and structural vulnerability. Finally, understanding cross-wave correlation has practical relevance for investors and policymakers, as it informs portfolio allocation, risk management, and the design of targeted support measures during prolonged crises rather than one-off shocks.

A key proposition that I test in this paper is the “business model” hypothesis (Fahlenbrach et al. 2012). It entails making informed assumptions or estimates about how your firm will function, add value, and make money. This hypothesis suggests that the business model of a business cannot be changed and if a business is susceptible to crisis, it will perform badly during the crisis. The business model hypothesis implies that the returns across the waves are positively correlated. I also test a competing hypothesis which is the “learning hypothesis” (Fahlenbrach et al. 2012). The assumptions and expectations that a person, organisation, or society has on the knowledge and lessons that may be learned through dealing with a crisis are referred to as learning hypotheses for a crisis. Whether they are social, economic, environmental, or health-related, crises frequently offer chances for growth and adaptation. The learning hypothesis implies that the returns across the waves are negatively correlated.

A wave describes an increase in the number of unwell individuals, a typical peak in disease, followed by a sharp or prolonged fall in infections that eventually returns to baseline. I define the waves according to the confirmed deaths in each country. The beginning is when Covid deaths started to rise for at least three weeks (and then reached a peak) and the end is when Covid cases declined until the deaths flattened out. I do not rely on confirmed cases as initially at the beginning of the pandemic the testing of covid was not widespread. I also did

not rely on stringency measures to define a wave as the stringency was high in most of the Covid time and governments took time (policy lag) to adjust stringency measures. I also did some robustness checks using the definition of waves following Polat et al. (2023) and Ifitimie et al. (2021).

I test two competing hypotheses—business model and learning hypotheses. My prediction is that companies cannot change their business models or companies learn from previous experiences. As the Covid waves are a few months apart, hence my hypothesis testing period is closer for consecutive waves (i.e., first and second) and a bit longer for non-consecutive waves (i.e., fourth and first wave). The results show that the first and second wave returns are not correlated. Probably, the sudden shocks of covid in the first wave make things unpredictable and hence the first wave returns are not related to the second wave returns. The results also show that the buy-and-hold returns for the second and third waves are negatively correlated. Then I examine the relationship between the fourth and the other waves. The results show that the buy-and-hold return for the fourth wave is positive and significantly related to the buy-and-hold return of the second and third waves. As the waves of Covid are too close to each other, it is difficult to change business models, hence the returns are positively correlated.

In terms of the characteristics before the pandemic that explain the cross-sectional variation of returns, I find that total assets, Capex and CEO/chair duality are negatively related to the first wave returns and debt and cash are positively related to the first wave returns. In terms of the characteristics before the pandemics that explain the cross-sectional variation of returns for the second wave, I find that total assets, cash, and beta are negatively related to the returns, and debt, capex, CEO/Chair duality and closely held shares are positively related to the returns. The results for the buy-and-hold return for the third wave results for the characteristics show that total assets, cash, age, and closely held shares are negatively related to third wave returns and compensation is positively related to the third wave returns. When I

use the buy-and-hold return for the fourth wave as the dependent variable, I find that debt and closely held shares are positive and significantly related to fourth wave returns. I also find that cash, brand, capex, and CEO/Chair duality are negatively related to the fourth wave returns. Hence, I find evidence that certain characteristics before the pandemic can explain the performance of the companies during different waves of the pandemic. This is more in line with the business model hypotheses.

I rerun my baseline regressions at the country level. Most of my results are consistent with the baseline estimations. The fourth wave is mostly negatively correlated with all other waves since most of the countries have a negative correlation. India shows a positive correlation for the fourth and other waves. China shows a negative correlation among the fourth, third and second waves. As China imposed heavy lockdown measures and maintained a strict distancing policy, the returns show a negative relationship. On the other hand, India is a densely populated country, and India did not impose very strict lockdown measures, which might be a reason for positive correlations across the returns during different waves.

The findings demonstrate that returns for consumer discretionary, industrials, telecoms, basic materials, real estate, and other industries are significant and positive during the fourth wave and all subsequent waves. Surprisingly, technology does not appear to be related to waves. One would think that since online shopping and remote work were so popular in the first wave, technology and e-commerce companies would have shown a positive correlation with other waves, but this is not the case. There is a negative correlation across waves in health care, but it is not significant. When I look at the link for several industry categories, I find compelling evidence in support of the business model theory.

Governmental lockdown procedures, which were used to stop the spread of Covid-19, can have a substantial effect on business profits and financial performance. Since I have four waves in my sample, it provides a natural laboratory to test whether lockdown measures are

related to returns for companies in different waves. To test whether the stringency measures are related to buy-and-hold return, I use the change in stringency measure for the whole duration of a wave and relate it to the buy-and-hold returns for that wave. The results show that the change in the stringency measures is not significantly related to first wave returns. The results show that the change in the stringency measures is negative and significantly related to second wave returns. The higher the stringency measures the lower the buy-and-hold returns for the second wave. The results show that the change in the stringency measures is positive and significantly related to third and fourth wave returns. The lower the changes in stringency (less strict) measures the higher the buy-and-hold returns.

Even though Covid was a worldwide epidemic, its progression and degree of severity varied according to the country. I define the waves in accordance with the literature and perform many robustness tests. To trace the pandemic evolution, I follow Polat et al. (2023) and Ifitimie et al. (2021), I define the waves by following them: the first wave on January 17, 2020, through May 22, 2020, the second wave on July 1, 2020 through October 15, 2020, the third wave on November 1, 2020 through March 31, 2021, and the fourth wave on December 1, 2021 through January 19, 2022. Our results remain qualitatively the same but in some instances, they are slightly different. Global news and events, such as natural disasters, health crises (like COVID-19), or geopolitical tensions, can have a significant impact on the financial markets. These occurrences have the potential to affect market expectations and investor mood, which could cause linked changes in returns as investors make portfolio adjustments in reaction to fresh information. The degree to which the values of several assets move in tandem is referred to as correlation in asset prices. While assets with negative correlations move in the opposite direction, those with significant positive correlations typically move in the same direction. When common factors like development of covid impact asset values, there can be correlated movements in returns. I have conducted other robustness tests by excluding China,

India and India and China. My decision to exclude China and India from the robustness checks is grounded in methodological considerations aimed at ensuring the generalizability and robustness of my findings. The results are qualitatively similar to the whole sample analysis.

This chapter addresses a clear gap in the COVID-19 and crisis-finance literature by moving beyond the dominant focus on the first wave of the pandemic to examine whether firm-level stock returns are systematically related across multiple COVID-19 waves. While existing studies document substantial cross-sectional heterogeneity in firm performance during the initial shock, they provide little evidence on whether these differences persist, reverse, or dissipate as the crisis unfolds. As a result, the literature lacks a dynamic understanding of firm resilience under repeated and prolonged systemic shocks.

The chapter adds to knowledge by introducing a cross-wave correlation framework that explicitly tests whether firm performance in one pandemic wave predicts performance in subsequent waves. This approach allows the study to distinguish between two competing explanations. Support for the business model hypothesis implies that relatively rigid firm characteristics—such as demand cyclicity, operating leverage, and financial structure—drive persistent exposure to systematic risk. Evidence in favour of the learning hypothesis, by contrast, would suggest that firms and investors adapt based on prior experience, leading to re-ranking of performance across waves. By empirically evaluating these hypotheses, the chapter advances theory on how firms respond to recurring macroeconomic shocks.

The rest of the chapter is organised as follows. In section 4.2, I present a brief literature review and develop hypotheses. In section 4.3, I describe the data and methodology. Section 4.4 provides the descriptive statistics. Section 4.5 presents the empirical results. Section 4.6 provides some robustness checks. Finally, section 4.7 concludes.

4.2. Literature review and hypotheses development

In the literature review section, I describe the studies related to earlier pandemics and Covid-19.

4.2.1 Earlier Pandemics

Existing research has looked into how previous pandemics affected the economy. Only a few recent articles have re-examined earlier pandemics to get insight into the long-term consequences of the COVID-19 pandemic. Barro et al. (2020), Correia et al. (2022), and Lilley et al. (2020), for example, study mortality from the Spanish Flu pandemic. The consensus is that the pandemic resulted in a significant decrease in GDP and that high flu mortality rates resulted in a decrease in realised actual profits on equities and short-term government bills. In the long run, however, the economy was able to rebuild and recover from its previous state.

According to Lagoarde-Segot and Leoni (2013), the chance of a developing country's financial system failing increases as severe pandemics such as AIDS and malaria become more common. Those pandemics were relevant to the financial market. According to Wachter (2013), the chance of an extremely uncommon tragedy, such as a pandemic, significantly boosts the equity premium of the stock market. The temporal component of this event's likelihood causes both the high level of stock market volatility and the unpredictability of its excess returns. According to Bleakley (2007), the effective elimination of a pandemic of hookworm sickness in the American South, which began about 1910, contributed to increased economic and demographic development. Jorda et al., (2020) analyse the medium and long-term effects of a pandemic. They also examine how pandemics are different from other disasters. They have studied major pandemics since 1400 and use the real rates of return. The real rates of returns remain depressed for decades substantially which is exactly opposite to what happens after wars.

Gupta et al. (2021) compare the Covid-19 pandemic to the 1918-1919, 1957-1958, and 1968 health crises in the United States. They concluded that the financial market's negative

reaction to Covid-19 could not be linked solely to the fact that this virus caused death, because all past health crises were likewise lethal. They hypothesised that the government's restrictions on social distancing and business ventures, severe lockdowns, business closures, and travel bans, all of which caused significant economic damage and changes in human behaviour and attitude in nearly every aspect of daily life, had an adverse effect on the economy and that changing human behaviour was the root cause.

4.2.2 Covid-19

Baker et al., (2020) examine the Covid induced economic uncertainty. As no one was familiar with the disease hence it created massive uncertainty. They identify three forward-looking indicators of economic uncertainty—volatility based on the stock market, economic uncertainty based on newspapers, and the business expectation survey based on subjective uncertainty. They use these three indicators to measure the increase in uncertainty around the first wave of covid infections. Using those uncertainty factors they forecast the real GDP decline in the US market will be 11 percent as of the last quarter of 2020. The estimates suggest that 60 percent of the decline in the predicted output is related to covid-19 induced uncertainty. Fernandes (2020) provides the economic outcomes based on different scenarios of covid.

Fernandes (2020) finds that covid-19 virtually affected all the stock markets around the globe. The impact of social distancing, lockdown days, restrictions on movements, policy interventions to examine the impact on stock markets in four countries for the first wave of covid is examined by Ozili and Arun (2020) using the data from the US, the UK, Japan, and South Africa stock markets. They find that the increasing number of lockdown restrictions, international travel restrictions, and monetary policy interventions has a significant negative impact on the stock market indices in those countries. It is consistent with the findings in Baker et al., (2020) and Fernandes (2020), where they find that the impact is not related to the mortality rate of covid. Baker et al., (2020) asserted that covid-19 pandemic has an

unprecedented impact on the stock markets in comparison to the previous pandemics including the Spanish flu. The impact of covid-19 was so severe that it moved the stock market price back to 1900 and put the stock market volatility back to 1985. They argue various reasons for unprecedented stock market reactions—information transmission becomes much more efficient, economic linkages have increased to a significant extent.

Szczygielski et al., (2021) using the autoregressive conditional heteroscedasticity or generalized autoregressive conditional heteroscedasticity method, calculate the differential effect of COVID-19 associated volatility for six regional sector indices: Asia, Europe, Latin America, North America, Africa, and Arab markets. According to economic psychology, when people are confused about real events, they search for specific evidence more rigorously (Liemieux and Peterson, 2011). They develop a measure of uncertainty using Google search data for COVID-19-related words. They find that global COVID-19 instability has a detrimental influence on all regions' returns and that COVID-19 induced uncertainty has increased the volatility for all regions except Arab markets. This is consistent with Baker et al. (2020) who show that the impact of covid-19 induced uncertainty is related to the impact on the stock markets. Xu (2021) examines how stock returns react dynamically to sudden shifts in the COVID-19 scenarios, as well as the volatility that comes with a pandemic. Using daily data from Canada and the United States, they found that an improvement in COVID-19 cases has a negative impact on the stock market in general. Furthermore, for the rise and decline of covid cases in Canada, the stock return responses are not uniform. The asymmetry is due to the uncertainty of the pandemic. They report that the volatility has a negative impact on the US stock market. The magnitude, though, is insignificant. These results are puzzling in light of the fact that covid-19 fatality was much higher in the US as compared to Canada. However, these results are partially consistent with the fact that the mortality rate of covid-19 is not related to the stock market impact (Fernandes, 2020).

The Covid-19 epidemic had a substantial influence on global financial markets and firms (Latif et al., 2021). Financial volatility might be caused by market uncertainty triggered by Covid-19 (Latif et al., 2021; Phan & Narayan, 2020). As a result, markets may become extremely volatile (Zhang, Hu, & Ji, 2020). The financial industry suffered the most losses (Herwany, Febrian, Anwar, & Gunardi, 2021). The leisure and hospitality industries saw major declines. Communication services, consumer discretionary products, industrial goods, energy, and materials all showed a high association with the epidemic.

COVID-19, according to Uddin et al. (2021), induced volatility in 34 countries between July 1 and August 14, 2020. They investigate whether the volatility of a country's stock market is related to its economic characteristics. They add to the work of Baker et al. (2020) and Fernandes (2020) by linking COVID-induced volatility to national variables. Many researchers have used COVID-19 news-related indices for a variety of purposes. Akhtaruzzaman et al. (2022) and Umar & Gubareva (2021b) investigated the impact of the MCI on Environmental, Social, and Governance (ESG) indices and discovered that the MCI had a major effect on the volatility of the analysed ESG indices. Umar and Gubareva (2021a) investigated the MCI's impact on the volatility of Islamic equity indexes and discovered consistency between the MCI and Islamic stock movements. Gubareva and Umar (2020), for example, used the wavelet technique to investigate the influence and dependency of the Media Coverage Index (MCI) on the volatility and returns of 11 bond indexes.

Moreover, Umar et al. (2021c) investigated the dynamics of certain cryptocurrencies using the MCI, as well as additional research on the MCI's involvement in commodities markets, short stocks, and other areas. Bolton et al. (2020) discovered similarities between the COVID-19 viral health crisis and climate change, arguing that the issue has heightened interest in sustainability. Furthermore, the COVID-19 pandemic provides an excellent chance for corporations to embrace more true and authentic Corporate Social Responsibility (CSR) and

assist in tackling important global social and environmental concerns (He and Harris, 2020). Athira (2024) investigates the effect of the COVID-19 pandemic on firm performance using quarterly financial data from firms across 89 countries. The findings indicate a significant decline in firm performance during the pandemic period, with variations across different industries and regions. Factors such as revenue decline, reduced investment, and increased operational challenges contributed to the overall negative impact on firm performance.

4.2.3. Hypotheses development

COVID-19 is a highly infectious virus that has spread around the world since its original outbreak. There was a possibility of fresh waves of infection in other places as long as the virus circulated. There were a few waves of Covid-19 in different countries. People's mobility, including travel and migration, can help the virus spread across geographical borders, resulting in linked returns across companies in different waves.

Covid-19 waves in various nations can influence international trade and the general demand for products and services. Travel restrictions, lockdowns, and changes in consumer behaviour during epidemics can all have an impact on the demand for certain products or services. For example, if numerous nations have lockdowns at the same time, it might lead to decreased consumer spending, affecting businesses across borders. Similarly, if one nation is hit by a wave, it may restrict imports from other countries, hurting the returns of exporting enterprises in other locations.

The global economy is intricately interwoven, and economic shocks in one place can have far-reaching consequences (Hanif et al. 2020). COVID-19 waves can cause economic downturns, lower consumer confidence, and decreased investment. These factors can influence the performance of businesses in a variety of industries and regions. For example, if a key market has a severe COVID-19 outbreak, it may result in decreased demand for products or services, impacting the returns of enterprises that rely on that market.

COVID-19 waves can generate considerable market volatility (Szczygielski et al. 2021; Uddin et al. 2021), influencing investor attitudes and behaviour. Investors may respond to virus-related news and developments, resulting in linked changes in stock prices across different firms and industries. Concerns about the worldwide impact of COVID-19 might cause market-wide sell-offs or rallies, resulting in linked returns across firms, even if their individual activities are not directly affected by the virus.

Lockdowns, limits on non-essential firms, and stay-at-home orders are examples of public health measures that can have a direct influence on company operations. Ozili and Arun (2020) analyse the spillover mechanisms of the spread of the virus and the economic impact of Covid restrictions. When firms are forced to close or function at a reduced capacity, revenue and profitability might suffer. Companies in the hotel, leisure, entertainment, and retail industries are particularly sensitive to these tactics. If identical limits are imposed over different COVID-19 waves, the returns of enterprises in these industries can be connected. Ramelli and Wagner (2021) and Fernandes (2020) find Energy, Consumer Services, and Real Estate suffered during the pandemic.

Consumer behaviour and spending habits can be influenced by public health policies. During COVID-19 waves, consumers may restrict their discretionary spending, avoid crowded areas, and limit themselves to online shopping or critical purchases. This shift in consumer behaviour may have an impact on businesses in a variety of industries since changes in customer demand can affect revenue and profitability. Companies in the e-commerce, healthcare, and vital products sectors, for example, may have increasing demand, but those in the luxury goods or non-essential services sectors may see lower demand. If similar changes in consumer behaviour occur in multiple places at the same time throughout waves, they might lead to correlated returns.

Government assistance and stimulus programmes are frequently complemented by public health interventions targeted at minimising the economic effects of COVID-19. These initiatives may include cash support, tax relief, and corporate subsidies. The availability and efficacy of government assistance can have an impact on a company's financial health and resilience. If governments employ comparable support measures across various locations throughout COVID-19 waves, it can lead to correlated returns because enterprises benefit from or confront similar obstacles as a result of these policies.

The degree of connection in firm returns among COVID-19 waves might vary based on factors such as industry sector, geographical exposure, business structures, and individual company characteristics (Ding et al. 2021). Not all businesses will be affected similarly, and some may even see diverging performance throughout different waves based on their unique circumstances and adaptation to the changing environment. In many countries, there were several waves of coronavirus. In some countries, there were two waves and in other countries, there were three waves. In the United Kingdom, Covid had three waves. Some other countries like Italy, Germany, Portugal had four waves. The performance of the companies is not the same across the waves. For example, AstraZeneca and GlaxoSmithKline are both pharmaceutical companies. The performance of AstraZeneca is better in both waves of Covid compared to GSK. On the other hand, HSBC and Barclays are two leading banks in the UK. While Barclays performed worse than HSBC during the first wave of Covid, the performance reversed during the second wave of Covid. None of the previous studies examines whether the performance of the companies in the stock market is similar during the waves. Various waves could be related in terms of company performance.

It is possible that some elements of the business model that make a firm more susceptible to crises are either profitable or too expensive to modify. It outlines the anticipated expenditures and expenses related to operating the business. Both fixed costs (such as rent and

payroll) and variable costs (such as the cost of items sold and marketing expenses) are included in this. Current research has focused on elements of bank business models that have an impact on how well they performed during the current financial crisis (Adrian and Shin, 2009). Fahlenbrach et al (2012) provide evidence in favour of the business model during the global financial crisis.

According to growing amounts of financial literature, executives' and investors' prior experiences have an impact on their present-day actions and performance (Malmendier and Nagel, 2011; Malmendier, Tate, and Yan, 2011). Apple Inc. is a prime example of a business that initially struggled before becoming incredibly successful. Apple had serious financial issues in the 1990s and was viewed as being on the verge of bankruptcy by some. As a result, the learning hypothesis proposes that a firm changes its risk culture or its business model in response to a negative crisis experience to make future crises less likely.

Many times, business models are complex and comprise a number of different elements, including value propositions, client groups, revenue streams, distribution routes, and cost structures. Modifying any of these components necessitates collaboration and might affect other areas of the model as well. A new business model shift may necessitate consumer education, buy-in, and behavioural adjustments. Change-averse customers might make it challenging to swiftly switch to a new model. Abrupt modifications to the company model might call for large resources, such as cash outlays, technological advancements, and hiring or training of new employees. The process of obtaining and assigning these resources might take some time. In the short run (as the Covid waves were close to each other) it would be extremely difficult for the firms to change their business models. If business models remain unchanged, the returns across the waves would be positively related. Thus, I propose:

H1a. The returns for companies are significantly positively correlated across all four waves of Covid (Business Model hypotheses).

It might be possible that some correlations are significant, and some are not. If some are not significant, I reject the hypotheses for that pair.

On the other hand, a learning hypothesis in the context of business performance during the COVID-19 pandemic may be defined as the presumptions or convictions that companies have about how they can adjust and enhance their performance in light of the lessons they have learned from the difficulties presented by the epidemic. Companies think that using digital technologies and adjusting to remote work are crucial for preserving productivity and continuing operations in the face of disruptions. If this theory is correct, companies may spend money on tools for remote work, collaboration software, and training to improve their capacity for working remotely. Businesses think that creating a supply chain that is more adaptable and resilient is essential to enduring shocks brought on by world events. Companies may decide to reassess and diversify their supply networks, make technological investments for continuous monitoring, and create backup plans. Companies think that creating an organisational culture that is flexible and agile is essential to responding quickly to situations that are changing quickly. Companies may use agile approaches, expedite the decision-making process, and provide teams the flexibility to adapt quickly to changing circumstances. Early in the 1990s, IBM almost went out of business. The business had a number of difficulties at the time that put its existence and ability to compete in the technology sector in jeopardy. Since then, IBM's reinvention and comeback have been moulded by the lessons acquired from this near-death experience. In essence, the learning hypothesis for business refers to assumptions or forecasts about how a firm might gain information and understanding. The Learning hypothesis is essential to a business's development and expansion. This theory, as in Fahlenbrach et al., (2012), known as the learning hypothesis, holds that a company would alter its business model or risk culture in response to a negative crisis experience, making it less likely that it will

encounter one of these situations in the future. If the learning hypothesis is true, then I expect that company returns across waves are negatively related. Hence, I propose:

H1b. The returns for companies are significantly negatively correlated across all four waves of Covid (Learning hypotheses).

It might be possible that some correlations are significant, and some are not. If some are not significant, I reject the hypotheses for that pair.

According to Fernandes (2020) and Ramelli and Wagner (2021) real estate, consumer services, and energy all suffered during the epidemic. The COVID-19 pandemic caused a wide range of industry performance, which was attributed to a number of variables such as industry type, government laws, customer behaviour, and economic situations. During the pandemic, businesses that provide necessities like groceries, drugs, and healthcare tended to do rather well. Travel, hospitality, and entertainment are examples of non-essential businesses that suffered greatly when consumers cut back on their expenditure on luxuries. Raw resources and goods were scarcer in industries with worldwide supply chains, especially those that depended significantly on manufacturing in afflicted nations like China. Government assistance initiatives and stimulus packages have an impact on the success of many industries. While many industries benefited from government support, others did not. In response to the pandemic, the pharmaceutical and healthcare sectors were instrumental in driving innovation and increasing funding for vaccine development and medical research.

Several sectors performed rather well during the COVID-19 pandemic, owing to shifts in consumer behaviour and increased demand for products and services (Fernandes, 2020; Ramelli and Wagner, 2021). Due to physical store lockdowns and limitations, e-commerce witnessed a major increase in demand. As customers turned to online purchasing for a variety of items, online merchants, marketplaces, and delivery services saw increasing revenues. The healthcare industry, which includes medications, medical equipment, and telemedicine services,

was critical in fighting the epidemic. Demand for COVID-19 diagnostics, treatments, and vaccinations rose, resulting in growth in these industries.

During lockdowns, remote work and internet communication were critical. Collaboration tool providers, video conferencing platforms, and cloud service providers saw increased usage and demand. Streaming services, internet entertainment, and gaming platforms have also grown in popularity. Supermarkets and grocery stores stayed open as necessary enterprises, with increased demand for food, household goods, and personal care items. During the pandemic, online grocery delivery businesses experienced substantial development. For example, during the COVID-19 epidemic, Amazon saw substantial growth.

Demand for streaming services, video-on-demand platforms, and digital entertainment material increased as consumers spent more time at home. This shift helped companies in the entertainment business that could provide at-home entertainment alternatives. With school closures and the transition to remote learning, there has been a rise in demand for online education platforms and e-learning technologies. Companies that provide online courses, virtual tutoring, and educational technology solutions have grown significantly. For example, Zoom saw a huge growth during the pandemic.

Chen and Yeh (2021) investigate the consequences of these two big crises on diverse businesses and how various sectors responded to the challenges and uncertainties they brought. The research examines organisations' financial performance, tactics, and behaviours in reaction to the crises, with an emphasis on understanding the parallels and contrasts between the two events. The authors want to gain insight into the durability and flexibility of firms during times of economic downturn and uncertainty by analysing these industrial reactions. The study's findings may lead to a better understanding of how businesses navigate and recover from crises, which can aid policymakers, practitioners, and academics in developing measures to avoid negative consequences and enhance economic recovery.

Businesses with minimal entry barriers, dynamic client interaction, and strong technical innovation are common traits of industries where changing business models is comparatively easy (Porter, 1980). For example, in technology, e-commerce and trade, it is easy to change business models. These sectors gain from a variety of elements, including flexibility, technologically advanced solutions, and the capacity to react fast to client input. It's crucial to remember, though, that even within these sectors, certain businesses may have particular difficulties and possibilities due to their particular market positioning and competitive environment. Businesses in difficult-to-change business model industries may encounter institutional, legal, cultural, end user obstacles that impede quick transformation. Heavy machinery, oil and gas, real estates are some instances of businesses where it is often more challenging to change the business model. The study conducted by McKibbin and Fernando (2020) investigated the effects of COVID-19 on customer behaviour and its commercial consequences. As covid-19 returns could be positively related in some industries because of the nature of the industry. Industry channels will work for some industries but not for all. Ultimately, it is an empirical question for which of the industries the industry channel works. Hence, I propose:

H2a: For an industry, buy-and-hold returns for companies between all four waves are positively correlated (Business Model hypotheses).

H2b: For an industry, buy-and-hold returns for companies between all four waves are negatively correlated (Learning hypotheses).

I am talking about pairwise correlations. It might be possible that some correlations are significant, and some are not. If some are not significant, I reject the hypotheses for that pair.

During the COVID-19 epidemic, stringent measures including lockdowns, travel bans, and social distancing orders can significantly affect a company's profits. The degree to which

COVID-19 stringency measures affect different businesses varies. For example, lockdowns and travel restrictions had a greater negative impact on businesses in the hotel, tourist, and restaurant industries, which resulted in a precipitous drop in profits. In contrast, as more individuals used internet services during lockdowns, technology and e-commerce businesses stood to gain. Tight measures have the power to change customer behaviour. During lockdowns, businesses that offer necessities or have a strong web presence may see a rise in demand, which might result in better returns. Conversely, businesses in the discretionary sector can experience a decline in consumer spending. Tight measures have an effect on the earnings and profitability of a business. Some businesses may see a decline in sales and profitability, which would mean a decrease in investment returns due to decreased consumer activity and supply chain disruptions. Good news concerning the creation and distribution of vaccines can reassure investors and increase business profits. On the other hand, failures or doubts regarding the efficacy of vaccinations can cause market turbulence and lower profits.

Government policy measures such as social distancing, resulted in an economic shutdown, affecting both financial markets and businesses. Uncertainty caused by the Covid, and government policy actions wreaked havoc on a wide range of businesses, including recreation and entertainment, tourism, commerce, transit, and banking. Travel prohibitions were imposed as lockdown measures, severely restricting people's movement. Everyone was affected by the growing economic uncertainties. Travel bans hurt the airline business, limitations on public gatherings close down eateries, and cancellations of sporting events, concerts, and the entertainment industry (Narayanan et al., 2020).

In their discussion of the sectoral impact of COVID-19, Haleem et al. (2020) emphasised how lockdown measures had varying effects on different industries. Several factors can influence the impact of lockdown measures on share price returns for firms during the COVID-19 pandemic, including the specific industry, the duration and intensity of the

lockdowns, and the company's capacity to react to changing conditions. While lockdown measures can have both good and bad implications on share prices, they are only one factor among several that might affect individual company success. Lockdown methods have had diverse effects on various businesses. Travel, hotel, and retail sectors, which have encountered major limitations and closures, have usually had a negative impact on share values due to lower revenues and uncertainty about the recovery timescale. Sectors such as e-commerce, technology, healthcare, and online entertainment, on the other hand, had stronger favourable impacts on share prices as a result of the shift in customer behaviour towards remote services and online purchasing.

According to Chen and Yeh (2021), government policy responses have a favourable influence on stock market recovery. Covid impacted practically every area of the US economy, and the Federal Reserve announced multiple quantitative easing (QE) steps to aid the economy and restore market faith. According to Chen and Yeh (2021), following the announcements of quantitative easing, market performance in most industries began to recover from the negative impacts of Covid. Baker et al. (2020) talked about how COVID-19 affected the economy and how well government initiatives worked to lessen the effects. As the lockdown or stringency measures are different across the four waves of covid-19 I can test whether stringency measures have impacts on the four waves of Covid-19 returns. Hence, I propose:

H3a: Buy-and-hold returns for companies during the different waves of covid-19 are negatively related to lockdown measures during that wave.

H3b: Buy-and-hold returns for companies during the different waves of covid-19 are positively related to lockdown measures during that wave.

I am talking about four waves of covid, and restrictions placed during these four waves of covid. It is plausible that certain buy-and-hold returns will exhibit statistically significant correlations, while others may not. The hypothesis will be accepted for those returns showing significance within a given wave and rejected for those that do not. As a measure of lockdown restrictions, I use the sum of eight indicators of government containment and closure policies: closings of schools and universities, workplaces, cancellations of public events, limits on private gatherings, closing of public transport, orders to shelter-in-place, restrictions on internal movement between cities or regions, and restrictions on international travel.

4.3. Data and Methodology

4.3.1 Data

I use data from the countries that are severely affected by Covid-19. I use the US, UK, China, Brazil, India, France, Germany, and Italy as our sample countries. The selection of our sample countries was based on their significant impact and high death rates during Covid-19. These nations represent diverse regions, economic structures, and healthcare systems, providing a comprehensive perspective on the global implications of the pandemic. Our decision to include China in our sample, despite its comparatively lower Covid-19 death rate, is motivated by a holistic understanding of the pandemic's multifaceted impact. As a major global economic player, China's experience with Covid-19 has implications for international trade, supply chains, and economic resilience. Including China in our sample provides valuable insights into the interconnectedness of global economies and the broader economic implications of the pandemic. For all of these countries, I downloaded the list of companies from Refinitiv. Then, I exclude financial and utilities from our sample as the company characteristics are different for these two industries. After excluding financials and utilities, I have 15,444 companies in the sample. I use return and firm characteristics data from Refinitiv (all the variables are defined

in Appendix 2). Because of data availability, the sample size reduces further to around 12,000 observations.

To control for the severity of Covid lockdown, I use the Covid stringency index. The eight indicators used in the OxCGR index are: school closures, workplace closures, cancelled public events, restrictions on gatherings, public transportation closures, stay-at-home requirements, restrictions on internal movement, international travel controls, public information campaigns. The scores are then combined to create a composite score that ranges from 0 (no measures) to 100 (strictest measures). I use Refinitiv industry classification system which is 10 categories, and I use two-digit standard industry classification as in Ding et al. (2021).

4.3.2 Methodology

I calculate buy-and-hold returns from the weekly stock price indices for companies in seven countries in four different waves. As Figure 1 shows Covid-19 did not affect all the countries at the same time, hence I apply my own definitions of waves. I define a wave according to the following. The beginning is when covid cases started to rise for at least three weeks (and then reached a peak) and the end is when covid cases declined until the deaths flatten out. I do not rely on confirmed cases as initially at the beginning of pandemic the testing of covid was not widespread. It is difficult to define the waves according to the stringency index as the stringency measures are high throughout the whole period, and, as this is a policy tool, governments took some time to take actions and reduce/increase stringency measures. I am interested in the relationship among company performance in the four waves of Covid.

$$BHR_{j,c,t} = [\prod_{t=1}^T (1 + r_{j,c,t})] \dots \dots \dots (1)$$

Where $r_{j,c,t}$ is the weekly return for company j, in country c and week t.

I will mainly use regressions to examine the correlations. The sample period was from 09 March 2020 to 27 February 2022, beginning when the coronavirus began impacting nations before the WHO proclaimed it a global pandemic. This period was divided into four waves according to Table 1. I also conduct some robustness checks following Polat et al. (2023) and Iftimie et al. (2021) to track the pandemic evolution. Following them, the first wave is 17 January 2020-22 May 2020, the second wave is 1 July 2020-15 October 2020, the third wave is 1 November 2020-31 March 2021, and the fourth wave is 1 December 2021-19 January 2022. The dates for those fourth waves were chosen by monitoring the pandemic's progress (<https://coronavirus.jhu.edu/data/new-cases>) and concentrating on trends in the overall number of cases globally.

To test H1a and H1b, I use the following models:

$$BHR_{c,i,1st\ wave} = \alpha + \beta X'_{2019} + \delta_i + \omega_c + \varepsilon \dots \quad (2)$$

$$BHR_{c,i,2nd\ wave} = \alpha + \theta BHR_{c,i,1\ st\ wave} + \beta X'_{2019} + \delta_i + \omega_c + \varepsilon \dots \quad (3)$$

$$BHR_{c,i,3rd\ wave} = \alpha + \theta BHR_{c,i,1st\ wave} + \eta BHR_{c,i,2nd\ wave} + \beta X'_{2019} + \delta_i + \omega_c + \varepsilon \dots \quad (4)$$

$$BHR_{c,i,4th\ wave} = \alpha + \theta BHR_{c,i,1st\ wave} + \eta BHR_{c,i,2nd\ wave} + \lambda BHR_{c,i,3rd\ wave} + \beta X'_{2019} + \delta_i + \omega_c + \varepsilon \dots \quad (5)$$

Where $BHR_{c,i,k\ wave}$ is the buy-and-hold abnormal return for country c, company i and wave k. X'_{2019} includes pre-Covid firm characteristics data as explained in the data appendix. δ_i is the industry fixed effects and ω_c is the country fixed effects (time fixed effects are not possible as the data is drawn at a single point in time). ε is the error term.

Covid has already contaminated the company data in 2020; hence I use data from 2019 (pre-Covid). I use a similar regression like model 3, but the dependent variable would be the buy-and-hold return for the second wave, third wave and fourth wave of Covid.

To test hypotheses 2 I use the following model:

$$BHR_{c,i,2nd\ wave} = \alpha + \theta BHR_{c,i,1st\ wave} + \beta X'_{2019} + \delta_i + \varepsilon... \quad (6)$$

$$BHR_{c,i,3rd\ wave} = \alpha + \theta BHR_{c,i,1st\ wave} + \eta BHR_{c,i,2nd\ wave} + \beta X'_{2019} + \delta_i + \varepsilon... \quad (7)$$

$$BHR_{c,i,4th\ wave} = \alpha + \theta BHR_{c,i,1st\ wave} + \eta BHR_{c,i,2nd\ wave} + \lambda BHR_{c,i,3rd\ wave} + \beta X'_{2019} + \delta_i + \varepsilon... \quad (8)$$

Where $BHR_{c,i,j,kth\ wave}$ is the buy-and-hold abnormal return for country c, company i, and wave k. I repeat equation 6,7, and 8 nine times, for Refinitiv's ten major industry categories, to test hypothesis 2.

To test H3, I use the following model:

$$BHR_{c,i,wave\ k} = \alpha + \beta X'_{2019} + \lambda Covid\ stringency\ index_{c,wave\ k} + \delta_i + \varepsilon... \quad (9)$$

Where the BHR is the buy-and-hold return for country c, company i and wave k. Please note that buy-and-hold returns are at the company level and stringency index is at the country level.

4.3.3 Control variables

I use a number of control variables, mostly corporate characteristics, following the literature. Due to their greater negotiating strength, diversification of business, and earning assets, larger enterprises are in a stronger position in the market. Numerous studies comparing large and small businesses have found that big businesses are less hazardous and have less information asymmetry (Fama and French, 2015). Hence, I use Size. Because leveraged companies must make payments to repay their debt, it raises their financial risk. Therefore, the companies with more leverage are more likely to perform poorly during the Covid pandemic since cash flows deteriorate during a crisis. Hence, I use leverage. When external capital is expensive, cash lowers the risk of underinvestment, allowing flexibility in making quality investments.

However, excess cash leads to entrenchment of executives (Jensen, 1986; Shleifer and Vishny, 1989), stimulates overinvestment in less lucrative ventures (Richardson, 2006), and increases control (Kalcheva and Lins, 2007). Thus, in regressions, I control for cash. There is still substantial disagreement over how capital expenditure choices affect businesses' financial success (Kerstein and Kim, 1995). Capital expenditures before the Covid may not produce good returns because of uncertainty. I use Capex as a control. An intangible asset called brand capital measures how well-known a company's goods are among consumers. Brand capital is a valuable asset to the company since it helps firms increase sales by increasing customer loyalty or visibility, for example. An empirical inquiry pertains to the relationship between brand capital and performance during COVID-19. Fahlenbrach and Stultz (2011) claim there is minimal evidence that banks led by CEOs whose interests were less closely associated with those of their shareholders underperformed during the 2007–08 financial crisis. CEO duality is an important corporate governance phenomenon, and empirical studies have used this to assess the performance of companies and banks (Krause and Semadeni, 2013). I utilise the variable closely held shares as a proxy for agency issues (Jensen and Meckling, 1976).

4.4. Descriptive statistics

4.4.1 Country-level returns

The BHAR is shown in Figure 3. I report country-level returns in Table 1. The results show that the average mean (median) buy-and-hold return is negative for all the countries in the first wave of Covid. The lowest mean buy-and-hold return was reported for Italy (-0.129), and the highest was for France (-0.012). The median return was lowest for Brazil (-0.205) and highest for India (-0.061). The 10th percentile was lowest for Brazil (-0.519), and the highest return (90th percentile) was for India (0.351).

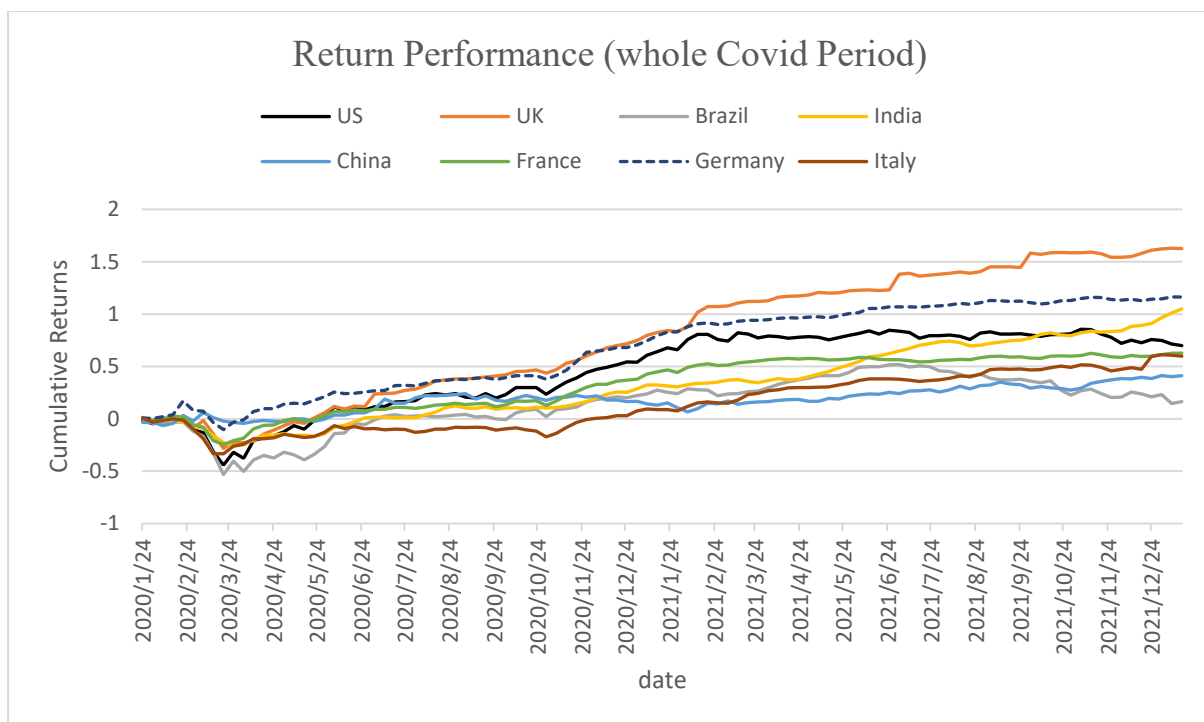


Table 1. Country Level descriptive statistics

	1stwave	2ndwave	3rdwave	4thwave	Covid Whole
US					
N	2576	2660	2868	3106	3139
mean	-0.024	0.068	0.565	0.014	0.585
p50	-0.102	0.013	0.303	-0.005	0.070
sd	0.630	0.440	1.836	0.337	10.223
p10	-0.429	-0.257	-0.099	-0.319	-0.596
p90	0.334	0.367	1.299	0.339	1.314
UK					
N	903	942	1011	1044	1044
mean	-0.025	0.719	0.003	0.067	0.825
p50	-0.172	0.287	-0.007	0.000	0.034
sd	1.094	6.488	0.235	1.748	7.869
p10	-0.508	-0.141	-0.216	-0.133	-0.537
p90	0.322	1.174	0.237	0.185	1.611
Brazil					
N	217	236	266	270	270
mean	-0.077	0.200	0.106	-0.050	-0.054
p50	-0.205	0.046	-0.011	-0.038	-0.274
sd	0.673	0.473	0.604	0.150	0.791
p10	-0.519	-0.118	-0.354	-0.225	-0.694
p90	0.280	0.677	0.567	0.135	0.730
China					

N	3511	3816	4002	4214	4213
mean	-0.048	-0.068	0.078	0.073	0.335
p50	-0.100	-0.111	0.015	0.053	0.097
sd	0.245	0.243	0.257	0.271	0.954
p10	-0.252	-0.308	-0.137	-0.140	-0.325
p90	0.220	0.209	0.351	0.264	1.189
France					
N	541	545	568	583	541
mean	-0.012	0.398	0.028	-0.055	0.326
p50	-0.141	0.257	0.002	-0.053	0.059
sd	0.888	0.786	0.276	0.267	1.284
p10	-0.412	-0.126	-0.216	-0.343	-0.514
p90	0.331	1.025	0.268	0.207	1.213
German					
N	586	609	623	645	645
mean	-0.027	1.011	0.135	0.012	2.539
p50	-0.145	0.175	0.063	-0.039	0.139
sd	1.140	13.144	0.490	0.790	46.274
p10	-0.399	-0.095	-0.152	-0.343	-0.454
p90	0.168	0.963	0.402	0.226	1.830
India					
N	3798	3884	3932	3962	3962
mean	-0.002	0.352	0.134	0.275	2.314
p50	-0.061	0.184	0.017	0.099	0.773
sd	0.659	0.603	0.506	0.564	7.743
p10	-0.378	-0.076	-0.125	-0.044	-0.129
p90	0.351	0.995	0.443	0.768	5.171
Italy					
N	243	259	272	303	303
mean	-0.129	0.283	0.196	0.164	0.487
p50	-0.181	0.162	0.091	0.000	0.084
sd	0.276	0.836	0.572	2.043	2.240
p10	-0.369	-0.084	-0.117	-0.219	-0.399
p90	0.149	0.527	0.557	0.326	1.463

This table reports the buy-and-hold returns for different countries in my sample for different waves of covid. The definitions of waves of covid are in appendix 4.1

For the second wave, the mean (median) buy-and-hold returns are all positive, except for China.

The average buy-and-hold return for the third wave is positive for all countries. The average buy-and-hold return is positive for all the countries except for Brazil and France. When I consider the whole Covid period, the buy-and-hold return is positive for all the countries except for Brazil.

4.4.2 Sample descriptive statistics

In this section, I describe the sample in terms of mean, median, standard deviation, 10th percentile, and 90th percentile. The results show that average (median) returns are negative for the first wave of Covid while it is positive for all other waves. The 10th percentile return is all negative for all four waves of covid and the 90th percentile return is all positive for all four waves. The standard deviation of return is a few times compared to the average returns showing that the returns are quite dispersed compared to their means. This shows a variation in the return performances across companies.

Table 2. Descriptive statistics

Variables	N	mean	p50	sd	p10	p90
1stwave	12375	-0.0266	-0.1011	0.6527	-0.3776	0.2877
2ndwave	12951	0.2252	0.0333	3.3858	-0.2396	0.6800
3rdwave	13542	0.1951	0.0462	0.9369	-0.1432	0.6023
4thwave	14127	0.1077	0.0313	0.7035	-0.1864	0.3973
Covidwhole	14117	1.0786	0.1722	11.9824	-0.4105	2.2442
Log(total assets)	13127	5.9839	6.1212	1.1328	4.4383	7.2741
Debt	15443	0.2128	0.1349	0.2842	0.0000	0.4945
Cash	15443	0.1200	0.0508	0.1785	0.0000	0.3295
Capex	15443	0.0356	0.0175	0.0585	0.0000	0.0922
Brand capital	15443	0.0072	0.0000	0.0350	0.0000	0.0104
Compensation	15443	0.3660	0.0000	1.4757	0.0000	0.5640
CEO/chair duality	15443	0.1264	0.0000	0.3323	0.0000	1.0000
logage	12917	3.9384	4.0012	0.3306	3.4979	4.2700
Beta	12328	0.9775	1.0400	1.0632	-0.0420	1.9120
Closely held shares	15443	0.2751	0.0877	0.3105	0.0000	0.7415
Δ stringency_1st	15441	60.97	72.67	21.20	37.03	81.94
Δ stringency_2	15441	-14.04	-16.67	9.73	-25.93	-2.78
Δ stringency_3rd	15441	-6.39	-10.18	11.57	-18.98	12.96
Δ stringency_4 th	15441	2.17	0.00	15.45	-7.41	21.24

This table reports the descriptive statistic for different variables that are used in this chapter. All the variable definitions in appendix 4.2.

The financial characteristics before the pandemic show that firms have an average debt ratio of 0.2128 and cash ratio of 0.1200. The results show that though the companies had a moderate amount of debt, they are holding a lot of cash. Capital expenditure was on an average 0.0356. Compensation paid was 0.3660. CEO/Chair duality is 0.1264. The Beta was 0.978 which is very close to the market beta of 1. Closely held shares are found to be 40.989%, meaning that ownership is highly concentrated.

I report the change in stringency measures for the four waves of Covid. The average change in stringency measure is positive (60.97) for the first wave of covid. This is expected as the governments across the countries put restrictions to control Covid. The average change in Covid stringency is negative for the second and third waves. The average change in stringency is positive (2.17) while the median is 0.

4.4.3 mean and median differences across waves

In the previous sections, I have shown that the mean (median) values are different for all four waves. In this section, I conduct mean (median) differences test across all the waves. I first conduct a joint test for the mean differences. Hotelling's t-squared statistic (T2) is a generalization of Student's t-statistic that is used in multivariate hypothesis testing. I find the Hotelling T2 value is 593.6 which is significant at 1%. I reject the null that the means are the same. Hence, I conclude that the means are different across the waves.

Table 3. Mean and median differences across waves

Wave	Istwave	2ndwave	3rdwave	4thwave	Hotelling T2 (p-value)
Mean	-0.027	0.225	0.195	0.108	593.6 (0.00)
Median	-0.101*	0.033*	0.046*	0.031*	

This table reports the mean and median differences across waves. *Signtest and signrank test shows pairwise medians are different at 1% level of significance.

Then I conduct a pairwise median difference test between the waves of Covid. I conduct signtest and signrank tests for the median differences. I find that all the medians are different across the waves.

4.5 Empirical Results

4.5.1 Relationship between waves of Covid

In this section, I examine the relationship between waves of covid. Columns 1-2 of Table 4 report the results where the dependent variable is the buy-and-hold return for the first wave. In

column 1 I did not cluster standard errors. In column 2, I use country and industry clustering. In both columns 1-2, I use the industry and country fixed effects. I did not use the other waves to check the relationship where the first wave is the independent variable, as the other waves had not happened yet. I use the firm level characteristics before covid and find that total assets, capex, are negatively related and debt, cash is positively related in this regression. Firms with more investment are negatively related to share price performance. Probably Investment value evaporated with the start of pandemic and lack of actions from managers at the beginning of the pandemic might be related negatively to performance. On the other hand, firms with more cash acts as a shield from the pandemic. In columns 3-4, I use the BHAR of the second wave as the dependent variable and use only the BHAR for the first wave. In column 4, I did not cluster standard errors. In column 5, I use industry clustering and in column 6, I use country and industry clustering. I find they are negatively related, but not significant. Irrespective of the clustering used, I find similar results for the second and first waves. I find that age is negatively related to the second wave returns. These results imply that younger firms performed badly in the second wave. I also find that debt and capex are positively related in this regression. This might imply that firms that have better discipline because of debt, have higher CEO control and high ownership concentration help them perform better in the second wave.

In columns 5-6, I use BHAR of the 3rd wave as the dependent variable and find that second wave and first wave returns are negatively related to third wave returns. The coefficient for the 1st wave is 0.005 and not significant. The coefficient for the 2nd wave is -0.049 and significant at 1% level if I use no clustering. Again, the third and second wave returns are negatively related which supports the learning hypotheses. Size is negatively related to 3rd wave returns and compensation is positively related to returns. Larger, established firms are negatively related to performance.

In columns 7-8, as the fourth wave is the last one to happen, I use the buy-and-hold return during the fourth wave as the dependent variable. The main independent variables are the buy-and-hold returns for the first, second and third waves. I find that the 4th wave is positively related to all other waves. The coefficients for the first, second and third waves are 0.00, 0.015, and 0.014 and all significant at the 5% level (when I did not cluster standard errors). Hence, I accept H1a. As the fourth wave is the last one that happened, nonetheless, the experience from other waves does not help companies have learned a lot, hence I find that fourth wave is positively related to all other waves. I find that capex, cash and brand are negatively related to fourth wave returns. I also find that debt is positively related to fourth wave returns.

Overall, I find that the fourth and other waves are positively related providing evidence for the business model hypothesis. I find limited evidence that the second and third waves are negatively related, providing evidence for the learning hypothesis. However, the results disappear when I use country and industry clustering. Clustering standard errors is more important for a panel data set (Petersen, 2009). As I have cross-sectional data which is pooled at a single point in time clustering per se is not very important in our case. Nonetheless, I report the results with no clustering, and with clustering to facilitate comparison.

Table 4. Relationship Across waves

	(1)	(2)	(4)	(5)	(7)	(8)	(10)	(11)
	1stwave	1stwave	2ndwave	2ndwave	3rd wave	3rd wave	4thwave	4thwave
1stwave			-0.000 (0.011)	-0.000 (0.013)	0.005 (0.016)	0.005 (0.007)	0.003 (0.004)	0.003 (0.006)
2ndwave					-0.049*** (0.018)	-0.049 (0.037)	0.015** (0.006)	0.015 (0.012)
3rd wave							0.014** (0.007)	0.014 (0.015)
Total assets	-0.048*** (0.007)	-0.048*** (0.010)	-0.010 (0.008)	-0.010 (0.014)	-0.068*** (0.013)	-0.068*** (0.020)	-0.024*** (0.005)	-0.024* (0.012)
Debt	0.158*** (0.021)	0.158*** (0.050)	0.080*** (0.024)	0.080** (0.037)	-0.020 (0.037)	-0.020 (0.024)	0.038*** (0.014)	0.038 (0.029)
Cash	0.076* (0.042)	0.076 (0.064)	-0.058 (0.047)	-0.058 (0.053)	-0.113 (0.073)	-0.113 (0.077)	-0.152*** (0.028)	-0.152*** (0.036)
Capex	-0.252*** (0.097)	-0.252** (0.118)	0.610*** (0.108)	0.610 (0.691)	-0.075 (0.169)	-0.075 (0.083)	-0.195*** (0.064)	-0.195* (0.099)
Brand	-0.057 (0.169)	-0.057 (0.128)	-0.147 (0.189)	-0.147 (0.130)	-0.359 (0.295)	-0.359** (0.153)	-0.083 (0.111)	-0.083 (0.078)
Compensation	-0.001 (0.005)	-0.001 (0.006)	0.003 (0.005)	0.003 (0.005)	0.016** (0.008)	0.016 (0.012)	-0.003 (0.003)	-0.003 (0.003)
Ceo chair duality	-0.000 (0.018)	-0.000 (0.018)	0.005 (0.020)	0.005 (0.025)	0.056* (0.032)	0.056 (0.061)	0.012 (0.012)	0.012 (0.008)
log(age)	-0.028 (0.024)	-0.028 (0.027)	-0.093*** (0.027)	-0.093** (0.043)	-0.057 (0.042)	-0.057 (0.040)	0.020 (0.016)	0.020 (0.022)
Beta	-0.009 (0.006)	-0.009 (0.012)	0.003 (0.007)	0.003 (0.008)	0.005 (0.010)	0.005 (0.008)	-0.000 (0.004)	-0.000 (0.004)
Closely held shares	-0.007 (0.022)	-0.007 (0.029)	0.046* (0.024)	0.046 (0.028)	-0.026 (0.038)	-0.026 (0.044)	-0.007 (0.014)	-0.007 (0.018)
constant	0.242** (0.117)	0.242** (0.113)	0.609*** (0.131)	0.609*** (0.171)	1.179*** (0.205)	1.179*** (0.145)	0.273*** (0.077)	0.273** (0.127)
Fixed effects	Ind & coun	Ind & coun	Ind & coun	Ind & coun	Ind & coun	Ind & coun	Ind & coun	Ind & coun
Clustering	No	Ind & coun	No	Ind & coun	No	Ind & coun	No	Ind & coun
Observations	9,827	9,827	9,826	9,826	9,825	9,825	9,825	9,825
R-squared	0.036	0.036	0.108	0.108	0.056	0.056	0.094	0.094

This table reports the relationship among the buy-and-hold returns of the second, third and fourth waves. The dependent variable is BHAR for the 1st wave in column 1, BHAR for the 2nd wave in column 2, BHAR for the 3rd wave in column 3 and BHAR for the 4th wave in column 4. All the control variables are pooled at the end of 2019 (before covid). All variables are defined in Appendix 2. All models include country and industry fixed effects. The t-statistics are calculated based on clustered (country and industry) adjusted standard errors and reported in parentheses. ***, ** and * represents significance at 1, 5 and 10 percent level, respectively.

In terms of the characteristics before the pandemic that explain the cross-sectional variation of returns, I find that total assets and capex are negatively related to the first wave returns and debt and cash are positively related to the first wave returns. The results show that the size of the firm, and capex reduce the return and higher leverage and cash increase the returns. Maybe large firms are more complex; hence their performance is not good in the pandemic. Cash acts as a shield in the pandemic as firms with more cash perform better in the first wave, but later, this relationship is reversed.

4.5.2 Relationship between the whole Covid period and different waves

In this section, I examine the relationship between the returns for the whole Covid period and the different waves. In column 1, I do not cluster the standard errors. In column 2, I use industry adjusted clustered errors and in column 3, I use country and industry adjusted clustered standard errors. I find that the returns across the different waves and the whole covid returns are positively correlated. The results are similar irrespective of the clustering used for adjusting the standard errors. In terms of the coefficients, the coefficient for the fourth wave is the largest, followed by the first wave, third wave and second wave. Due to the interconnection of financial markets and the effect of multiple factors, such as market circumstances, investor behaviour, and economic changes, the buy-and-hold return for the whole Covid-19 era may be related to returns for distinct waves of Covid-19.

Table 5. Relationship between whole covid period and different waves

	(1) covidwhole	(2) covidwhole	(3) covidwhole
4 th wave	3.214*** (0.175)	3.214*** (0.721)	3.214*** (0.543)
3 rd wave	1.199*** (0.067)	1.199 (0.901)	1.199 (0.860)

2 nd wave	1.187*** (0.102)	1.187** (0.372)	1.187*** (0.403)
1 st wave	1.505*** (0.118)	1.505*** (0.151)	1.505*** (0.161)
Total assets	0.140* (0.075)	0.140* (0.070)	0.140 (0.086)
Debt	0.112 (0.246)	0.112 (0.257)	0.112 (0.256)
Cash	-0.650 (0.477)	-0.650* (0.290)	-0.650** (0.274)
Capex	-0.284 (1.132)	-0.284 (0.593)	-0.284 (0.943)
Brand	-2.219 (1.938)	-2.219*** (0.349)	-2.219*** (0.495)
Compensation	-0.046 (0.049)	-0.046 (0.065)	-0.046 (0.062)
Ceo chair duality	-0.505** (0.199)	-0.505*** (0.149)	-0.505*** (0.157)
log(age)	-0.390 (0.281)	-0.390 (0.425)	-0.390 (0.379)
Beta	-0.090 (0.069)	-0.090 (0.063)	-0.090* (0.047)
Closely held shares	0.011 (0.234)	0.011 (0.294)	0.011 (0.331)
constant	1.275 (1.163)	1.275 (1.459)	1.275 (1.215)
Clustering	No	Industry	Industry& country
Observations	9,824	9,824	9,824
R-squared	0.096	0.096	0.096

This table reports the relationship among buy-and-hold returns of the whole covid period and the 1st wave, 2nd wave, 3rd wave and 4th waves. The dependent variable is BHAR for whole Covid period. All the control variables are pooled at the end of 2019 (before covid). All variables are defined in Appendix 2. The t-statistics are calculated based on clustered (country and the industry) adjusted standard errors and reported in parentheses. ***, ** and * represents significance at the 1, 5 and 10 percent level, respectively.

I am also interested in whether the pre-covid firm characteristics are related to the buy-and-hold return for the whole Covid period. I find that total assets are positively related to the whole Covid period returns. I also find that Cash, brand capital and CEO/ chair duality are negatively related to the whole Covid period return. Probably firms holding a lot of cash lacking investment opportunities, firms with larger brand values suffer profit shocks and firms with a lack of good governance (CEO/Chair duality) suffer the most in terms of the whole Covid pandemic.

4.5.3 Country-level variation in the relationship across waves

Due to a variety of observed and unobserved factors, such as variations in the waves' severity, government responses, healthcare systems, economic structures, and the makeup of industries within each country, the returns of companies during the COVID-19 fourth wave and other waves can, in fact, differ significantly between different countries. Hence in this section, I examine how COVID-19 fourth and other waves are related across firms vary by nation. As the fourth wave is the last one to happen, I use the buy-and-hold return during the fourth wave as the dependent variable.

In Table 6, I repeat my baseline regression at the country level. For most of countries, there is a significant relationship between the fourth and first waves. There is a negative relationship between the US, UK, France and Germany and a positive relationship in Brazil and India. For the fourth and second waves, I find a negative relationship for China and a positive relationship for Germany, India and Italy. For the fourth wave and third wave, I find a negative relationship for China. Most of the results show fourth and first waves are negatively related providing evidence for the learning hypothesis. However, for some countries, I find a positive relationship across waves. For example, India shows a positive relationship across waves, providing evidence for the business model hypothesis. On the other hand, China shows evidence of a negative relationship which is evidence for the learning hypothesis.

All things considered, the adversely related COVID-19 waves in China are probably caused by a combination of strict control measures, centralised response, public compliance, and a strong healthcare infrastructure, which contain outbreaks in various regions before they have a chance to spread widely. Overall, the positively correlated COVID-19 waves seen in India are caused by a number of factors, including high population density, mobility, varying control measures and healthcare facilities, and differences in testing and reporting procedures.

Table 6. Country level variation in the relationship across waves

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	US	UK	Brazil	China	France	Germany	India	Italy
	4 th wave	4 th wave	4 th wave	4 th wave	4 th wave	4 th wave	4 th wave	4 th wave
3 rd wave	0.003	0.194	-0.003	-0.205***	0.088	-0.092	0.069	0.121
	(0.005)	(0.141)	(0.018)	(0.014)	(0.098)	(0.054)	(0.064)	(0.343)
2 nd wave	-0.014	-0.000	0.004	-0.078**	-0.023	0.085*	0.093**	0.261**
	(0.014)	(0.005)	(0.018)	(0.030)	(0.028)	(0.042)	(0.029)	(0.087)
1 st wave	-0.027*	-0.018**	0.037**	0.009	-0.025	-0.194**	0.078**	0.011
	(0.012)	(0.007)	(0.012)	(0.070)	(0.015)	(0.070)	(0.026)	(0.200)
Total assets	0.030**	0.001	0.032**	-0.030*	0.002	0.034	-0.088***	0.026
	(0.013)	(0.011)	(0.010)	(0.014)	(0.010)	(0.028)	(0.009)	(0.105)
Debt	0.008	-0.024	-0.073**	0.014	0.014	-0.058	0.043	-0.228
	(0.028)	(0.016)	(0.030)	(0.014)	(0.057)	(0.083)	(0.048)	(0.207)
Cash	-0.071	-0.062*	0.139	-0.034	-0.064	-0.139	-0.465**	-0.388
	(0.041)	(0.030)	(0.112)	(0.039)	(0.136)	(0.145)	(0.180)	(0.389)
Capex	0.589**	-0.026	0.169	-0.181**	-0.185	-0.140	-0.551***	0.955
	(0.224)	(0.035)	(0.385)	(0.066)	(0.270)	(0.170)	(0.095)	(2.147)
Brand	-0.085	-0.081	0.142	0.585	-0.350	0.088	-0.877**	2.614
	(0.139)	(0.073)	(0.303)	(0.471)	(0.260)	(0.245)	(0.334)	(1.629)
Compensation	0.000	-0.004	-0.315**	-0.802*	-0.037	0.001	-0.267***	0.306*
	(0.003)	(0.005)	(0.101)	(0.360)	(0.028)	(0.080)	(0.037)	(0.157)
Ceo chair duality	0.043**	-0.017	0.003	-0.032**	-0.019	-0.065	-0.039	-0.294*
	(0.014)	(0.020)	(0.021)	(0.013)	(0.047)	(0.058)	(0.028)	(0.131)
log(age)	-0.012	-0.007	0.067	0.081**	0.161**	0.070	-0.017	0.129
	(0.027)	(0.014)	(0.051)	(0.025)	(0.053)	(0.051)	(0.057)	(0.084)
Beta	0.002	0.005	-0.006	-0.003	0.003	-0.090**	0.019	0.125
	(0.004)	(0.007)	(0.015)	(0.005)	(0.030)	(0.028)	(0.016)	(0.094)
Closely held shares	-0.064	0.026	0.032	0.033*	0.035	0.015	-0.021	-0.238
	(0.042)	(0.027)	(0.040)	(0.016)	(0.044)	(0.076)	(0.038)	(0.133)

constant	-0.122	0.058	-0.526*	-0.028	-0.701***	-0.395	0.907***	-0.647
	(0.198)	(0.062)	(0.236)	(0.169)	(0.214)	(0.216)	(0.244)	(0.694)
Clustering	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Observations	2,160	853	192	3,377	422	141	2,652	28
R-squared	0.038	0.066	0.132	0.059	0.060	0.207	0.060	0.475

This table reports the country level variation in the relationship between buy-and-hold returns of the first wave and other waves. The dependent variable is BHAR of the fourth wave. All the control variables are pooled at the end of 2019 (before covid). All variables are defined in Appendix 2. The t-statistics is calculated based on clustered (industry) adjusted standard errors and reported in parentheses. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively.

As far as the characteristics are concerned, total assets are significantly negatively related to the first wave returns for most of countries. As the largest samples are from the US, China and India, a lot of variables show a significant relationship with the fourth wave returns.

4.5.4 Industry-level variation in the relationship across waves

The make-up of the industries in each nation might also be important. Businesses in industries that were considered necessary during the pandemic, such as healthcare, technology, and e-commerce, may have fared better throughout both waves, whereas businesses in non-critical industries encountered more difficulties. To test industry-level variation, I use the buy-and-hold return during the second wave for different industries as the dependent variable and repeat my regressions. The results are reported in Table 7. The results show that for the second and first waves, consumer discretionary and industrials are significantly negatively related. Consumers often prioritise necessities over frivolous purchases during uncertain and recessionary times. Consequently, there is frequently less demand for businesses that provide consumer discretionary goods, such as luxury goods or recreational activities. Lockdowns, travel restrictions, and lower production capacity can cause disruptions in global supply chains that impact both the industrial and consumer discretionary sectors. These might be driving the negative correlations that I find in these two sectors. On the contrary Energy sector is positively related to these waves. Probably, the strong demand for energy during the lockdowns is responsible for this relationship.

In Table 8, I use the BHAR for the third wave as the dependent variable and examine the first and second waves as my main explanatory variables. The results show that the healthcare returns are negatively related to the third wave and the second and first waves. This may be because the healthcare sector was responsible for vaccination development and shows a certain degree of learning across waves. Consumer discretionary, industrials and basic

materials are negatively related across the third and first waves. In times of uncertainty and crisis, consumers frequently prioritise needs over frivolous purchases. As a result, companies that offer consumer discretionary goods, including luxury products or leisure activities, usually experience a decline in demand. Global supply chains can be disrupted by lockdowns, travel restrictions, and reduced manufacturing capacity, which can have an effect on both the industrial and consumer discretionary sectors. The negative correlations that I observe in these two areas may be caused by these.

The results show that the fourth wave and all other wave returns are significant and positive for consumer discretionary, industrials, telecoms, basic materials, real estate and others. Surprisingly, technology does not show any relationship among waves. When remote work and online shopping boomed in the first wave, one would expect technology and e-commerce firms may have shown some relationships across waves, but this is not the case. Health care shows a negative relationship across waves, but this is not significant. I find strong evidence for the business model hypothesis when I examine the relationship for different industry categories.

Table 7. Industry level variation in the relationship between the second and first wave

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Technology 2ndwave	Consumer Discretionary 2ndwave	Health Care 2ndwave	Energy 2ndwave	Industrials 2ndwave	Consumer Staples 2ndwave	Telecomm 2ndwave	Basic Materials 2ndwave	Real Estate 2ndwave	Other 2ndwave
1stwave	-0.037 (0.101)	-0.100*** (0.032)	0.001 (0.018)	0.058** (0.026)	-0.065*** (0.025)	-0.034 (0.034)	0.016 (0.029)	-0.001 (0.021)	0.109 (0.150)	-0.230 (0.372)
Total assets	-0.196*** (0.041)	-0.128*** (0.013)	-0.077*** (0.016)	-0.093*** (0.029)	-0.070*** (0.011)	0.016 (0.026)	-0.004 (0.023)	-0.031** (0.016)	-0.076* (0.043)	-0.096 (0.122)
Debt	-0.163 (0.148)	0.259*** (0.036)	0.160*** (0.060)	0.028 (0.112)	0.208*** (0.037)	0.232*** (0.085)	0.272*** (0.067)	0.040 (0.046)	-0.373** (0.183)	-0.305 (0.276)
Cash	-0.269 (0.237)	-0.450*** (0.080)	-0.046 (0.077)	-0.129 (0.236)	-0.453*** (0.078)	-0.341** (0.167)	-0.037 (0.138)	-0.654*** (0.124)	-0.581** (0.289)	-0.278 (0.736)
Capex	10.724*** (0.858)	0.192 (0.233)	-0.592* (0.332)	0.186 (0.495)	0.041 (0.111)	-0.880** (0.383)	-0.581 (0.529)	0.079 (0.240)	-0.913 (0.912)	-1.977 (1.313)
Brand	-0.412 (1.617)	0.506 (0.314)	0.071 (0.269)	0.763 (0.879)	-0.283 (0.454)	-0.712** (0.340)	-0.191 (1.050)	-0.252 (0.595)	0.316 (1.469)	-8.214 (31.683)
Compensation	-0.010 (0.025)	-0.018* (0.009)	-0.015** (0.007)	0.025 (0.020)	0.003 (0.008)	0.015 (0.021)	0.012 (0.017)	0.003 (0.016)	0.004 (0.029)	-0.037 (0.095)
Ceo chair duality	0.072 (0.111)	0.119*** (0.032)	-0.008 (0.040)	0.181** (0.082)	0.110*** (0.027)	-0.110* (0.058)	-0.032 (0.062)	0.131*** (0.049)	-0.058 (0.122)	-0.114 (0.919)
log(age)	-0.521*** (0.182)	-0.012 (0.044)	0.057 (0.061)	0.182* (0.110)	0.067* (0.036)	0.036 (0.078)	-0.164 (0.108)	-0.131* (0.067)	-0.229 (0.182)	-0.178 (0.562)
Beta	-0.008 (0.030)	-0.025** (0.010)	-0.014 (0.012)	-0.038 (0.036)	-0.034*** (0.012)	-0.036 (0.027)	-0.020 (0.029)	-0.011 (0.017)	-0.044 (0.054)	0.091 (0.123)
Closely held shares	0.357*** (0.136)	0.091** (0.037)	0.088 (0.055)	0.265** (0.119)	0.215*** (0.030)	0.237*** (0.072)	0.297*** (0.074)	0.241*** (0.051)	-0.089 (0.145)	-0.411 (0.397)
constant	2.975*** (0.749)	0.968*** (0.183)	0.326 (0.242)	-0.074 (0.436)	0.236 (0.159)	-0.060 (0.338)	0.599 (0.441)	0.916*** (0.268)	1.852** (0.767)	2.034 (2.137)
Observations	1,094	2,020	1,180	400	2,376	655	303	1,371	338	89
R-squared	0.155	0.103	0.041	0.079	0.081	0.076	0.143	0.044	0.061	0.074

This table reports the industry level variation in the relationship between buy-and-hold returns of the 2nd and first wave. The dependent variable is BHAR second wave for different industries. All the control variables are pooled at the end of 2019 (before covid). All variables are defined in Appendix 2. c ***, ** and * represents significant at 1, 5 and 10 percent level, respectively.

Table 8. Industry level variation in the relationship between the third, second and first waves

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Technology 3rdwave	Consumer Discretionary 3rdwave	Health Care 3rdwave	Energy 3rdwave	Industrials 3rdwave	Consumer Staples 3rdwave	Telecomm 3rdwave	Basic Materials 3rdwave	Real Estate 3rdwave	Other 3rdwave
2 nd wave	-0.002 (0.014)	-0.021 (0.025)	-0.098* (0.054)	-0.172 (0.334)	0.001 (0.025)	-0.008 (0.025)	0.019 (0.052)	-0.001 (0.027)	0.023 (0.024)	-0.049 (0.053)
1 st wave	0.130*** (0.046)	-0.185*** (0.035)	-0.116*** (0.033)	-0.061 (0.172)	-0.062** (0.031)	0.254*** (0.022)	0.009 (0.026)	-0.038* (0.021)	-0.065 (0.064)	0.179 (0.174)
Total assets	0.004 (0.019)	-0.038*** (0.014)	-0.077** (0.030)	-0.183 (0.195)	-0.029** (0.014)	-0.065*** (0.016)	-0.020 (0.021)	-0.003 (0.016)	-0.033* (0.019)	0.038 (0.057)
Debt	0.051 (0.067)	0.013 (0.041)	0.109 (0.111)	-0.096 (0.735)	0.036 (0.045)	0.069 (0.054)	0.061 (0.061)	0.097** (0.046)	-0.125 (0.079)	-0.010 (0.130)
Cash	-0.014 (0.108)	-0.097 (0.089)	-0.075 (0.143)	-1.806 (1.556)	-0.168* (0.097)	-0.107 (0.105)	-0.002 (0.122)	0.096 (0.126)	-0.198 (0.124)	0.199 (0.344)
Capex	0.018 (0.417)	-0.124 (0.259)	-0.846 (0.616)	-0.477 (3.254)	0.022 (0.136)	-0.520** (0.241)	-0.520 (0.472)	-0.176 (0.240)	0.057 (0.391)	-0.280 (0.623)
Brand	1.037 (0.735)	-0.032 (0.349)	-0.471 (0.498)	-1.795 (5.786)	1.015* (0.557)	-0.112 (0.214)	0.047 (0.935)	-0.154 (0.596)	-1.132* (0.629)	-5.666 (14.813)
Compensation	0.082*** (0.011)	0.116*** (0.010)	0.023* (0.013)	0.214 (0.131)	0.060*** (0.010)	0.019 (0.013)	0.054*** (0.015)	0.010 (0.016)	0.052*** (0.013)	0.080* (0.044)
Ceo chair duality	-0.046 (0.050)	0.006 (0.036)	0.012 (0.073)	0.873 (0.544)	-0.022 (0.033)	0.018 (0.037)	-0.027 (0.055)	0.059 (0.050)	-0.042 (0.052)	-0.774* (0.430)
log(age)	-0.057 (0.083)	-0.053 (0.048)	-0.283** (0.113)	0.192 (0.723)	-0.104** (0.045)	-0.023 (0.049)	-0.222** (0.096)	-0.096 (0.067)	-0.072 (0.078)	0.125 (0.263)
Beta	0.022 (0.014)	0.010 (0.011)	0.011 (0.022)	0.072 (0.239)	-0.019 (0.015)	-0.003 (0.017)	0.066*** (0.025)	-0.036** (0.017)	0.019 (0.023)	-0.017 (0.058)
Closely held shares	-0.198*** (0.062)	-0.144*** (0.041)	0.020 (0.101)	-1.004 (0.788)	-0.135*** (0.038)	-0.181*** (0.045)	-0.039 (0.068)	-0.161*** (0.051)	-0.083 (0.062)	0.062 (0.187)
constant	0.433 (0.343)	0.659*** (0.205)	1.773*** (0.450)	1.215 (2.868)	0.827*** (0.195)	0.697*** (0.212)	1.086*** (0.394)	0.664** (0.269)	0.653** (0.331)	-0.485 (1.005)

Observations	1,094	2,020	1,180	400	2,376	655	303	1,370	338	89
R-squared	0.087	0.108	0.040	0.034	0.043	0.235	0.116	0.024	0.110	0.120

This table reports the industry level variation in relationship between the buy-and-hold returns of the 2nd and first waves. The dependent variable is the BHAR for the Third wave for different industries. All the control variables are pooled at the end of 2019 (before covid). All variables are defined in Appendix 4.2.

***, ** and * represent significance at the 1, 5 and 10 percent level, respectively.

Table 9. Industry level variation in the relationship between the Fourth and other waves

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Technology 4 th wave	Consumer Discretionary 4 th wave	Health Care 4 th wave	Energy 4 th wave	Industrials 4 th wave	Consumer Staples 4 th wave	Telecomm 4 th wave	Basic Materials 4 th wave	Real Estate 4 th wave	Other 4 th wave
3 rd wave	0.036 (0.024)	0.059*** (0.016)	-0.017 (0.013)	-0.003 (0.003)	0.009 (0.013)	-0.075 (0.059)	0.074 (0.048)	0.010 (0.018)	0.034 (0.057)	0.349** (0.149)
2 nd wave	0.008 (0.011)	0.051*** (0.017)	-0.039 (0.024)	0.006 (0.022)	0.038** (0.016)	0.021 (0.037)	0.220*** (0.043)	0.069*** (0.018)	0.077*** (0.024)	0.139** (0.069)
1 st wave	0.036 (0.036)	0.107*** (0.025)	-0.012 (0.015)	-0.008 (0.011)	0.082*** (0.020)	-0.015 (0.036)	0.037* (0.021)	0.040*** (0.014)	0.042 (0.066)	0.140 (0.227)
Total assets	0.027* (0.015)	0.001 (0.010)	0.052*** (0.014)	-0.016 (0.013)	-0.009 (0.009)	-0.043* (0.024)	0.008 (0.017)	-0.014 (0.010)	0.013 (0.019)	0.028 (0.074)
Debt	-0.051 (0.052)	0.086*** (0.029)	-0.079 (0.050)	-0.046 (0.049)	0.067** (0.029)	0.189** (0.081)	0.015 (0.050)	0.074** (0.031)	0.047 (0.081)	-0.171 (0.168)
Cash	-0.234*** (0.084)	-0.218*** (0.063)	-0.085 (0.064)	-0.167 (0.103)	-0.327*** (0.062)	-0.362** (0.157)	-0.373*** (0.101)	-0.358*** (0.084)	-0.173 (0.128)	-0.889* (0.447)
Capex	-0.383 (0.324)	0.007 (0.182)	0.083 (0.274)	0.301 (0.216)	-0.178** (0.087)	-0.800** (0.363)	-0.156 (0.389)	-0.464*** (0.161)	-0.999** (0.399)	-0.380 (0.808)
Brand	-1.007* (0.571)	-0.481* (0.246)	-0.148 (0.222)	-0.169 (0.384)	-0.512 (0.360)	-0.440 (0.321)	-1.026 (0.768)	-0.725* (0.400)	-0.095 (0.645)	-10.580 (19.210)
Compensation	0.024*** (0.009)	-0.007 (0.008)	-0.011** (0.006)	-0.005 (0.009)	-0.003 (0.006)	-0.024 (0.020)	0.006 (0.012)	0.012 (0.011)	-0.003 (0.013)	-0.048 (0.059)
Ceo chair duality	-0.026 (0.039)	-0.069*** (0.025)	-0.063* (0.033)	0.067* (0.036)	-0.069*** (0.021)	-0.094* (0.055)	-0.087* (0.045)	-0.052 (0.033)	-0.079 (0.053)	0.687 (0.568)

log(age)	0.088 (0.064)	0.048 (0.034)	0.062 (0.051)	0.082* (0.048)	-0.049* (0.029)	-0.039 (0.073)	-0.050 (0.080)	-0.001 (0.045)	0.088 (0.080)	0.153 (0.341)
Beta	0.005 (0.011)	0.006 (0.008)	0.009 (0.010)	0.015 (0.016)	0.005 (0.010)	-0.028 (0.025)	0.036* (0.021)	-0.010 (0.011)	0.014 (0.024)	-0.032 (0.075)
Closely held shares	0.158*** (0.048)	0.113*** (0.029)	0.069 (0.045)	0.043 (0.052)	0.054** (0.024)	0.050 (0.069)	0.106* (0.056)	0.086** (0.034)	0.082 (0.064)	-0.132 (0.242)
constant	-0.404 (0.266)	-0.121 (0.145)	-0.473** (0.202)	-0.155 (0.190)	0.378*** (0.126)	0.615* (0.320)	0.215 (0.328)	0.240 (0.181)	-0.337 (0.340)	-0.274 (1.304)
Clustering	No	No	No	No	No	No	No	No	No	No
Observations	1,094	2,020	1,180	400	2,376	655	303	1,370	338	89
R-squared	0.035	0.058	0.062	0.039	0.043	0.061	0.217	0.065	0.093	0.218

This table reports the industry level variation in the relationship between the buy-and-hold returns of the 2nd and first waves. The dependent variable is the BHAR of the Fourth wave for different industries. All the control variables are pooled at the end of 2019 (before covid). All variables are defined in Appendix 4.2. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively.

In sum, some sectors show a negative relationship across the third wave and the previous two waves. Overall, the results are consistent with the results documented earlier (overall analysis). On the other hand, the fourth wave shows a positive relationship across a number of industries. Again, this is consistent with the overall regression results. One interesting finding is that consumer discretionary shows a significant relationship between the fourth and other waves. Consumer behaviour changes frequently have an impact on the consumer discretionary industries, which include non-essential goods and services. The Covid-19 pandemic's several waves may have caused changes in consumers' purchasing habits and priorities. For instance, during lockdowns and times of increased uncertainty, customers who saved a lot of money because they could not go out, may spend more on discretionary items and more on goods and services connected to healthcare. This might help consumer discretionary show a positive relationship between the fourth and other waves. The term "consumer discretionary" refers to a broad category of businesses that manufacture products and services that are not necessary for day-to-day existence but are frequently sought after by customers for amusement, pleasure, and leisure. As an example, consider Amazon.com, Inc. Amazon is a global technology firm that began as an online book retailer but has now grown to sell a variety of things, such as apparel, electronics, and household items. In addition, it provides cloud computing, artificial intelligence, and digital streaming services.

4.5.5 Stringency and returns across waves.

To stop the spread of the virus during the pandemic's initial wave, several nations imposed stringent and protracted lockdowns. These actions had a negative impact on the economy, resulting in decreased consumer spending, company closures, and supply chain disruptions. In this section, I examine whether the stringency changes are related to the buy-and-hold returns for companies. The results are reported in Table 10. In the first column, the dependent variable is the buy-and-hold return during the first wave and the main independent variable is the change

in the stringency measure from the beginning to the end of the first wave. The results show that the change in the stringency measures are not significantly related to first wave returns.

In column 2, I use the dependent variable the buy-and-hold return during the second wave and the main independent variable is the change in the stringency measure from the beginning to the end of the second wave. The results show that the change in the stringency measures is negative and significantly related to second wave returns. The higher the stringency measures the lower the buy-and-hold returns for the second wave.

Table 10. Stringency and returns across waves.

	(1) 1stwave	(2) 2ndwave	(3) 3rdwave	(4) 4thwave
Δ Stringency_1st	0.000 (0.000)			
Δ Stringency_2nd		-0.006*** (0.002)		
Δ Stringency_3rd			-0.002** (0.001)	
Δ Stringency_4th				0.006*** (0.000)
Total assets	(0.016) 0.144**	(0.014) 0.130**	(0.013) 0.029	(0.010) 0.050*
Debt	(0.045) 0.111**	(0.053) -0.291***	(0.020) -0.185*	(0.026) -0.176***
Cash	(0.043) -0.240	(0.082) 0.592	(0.094) -0.022	(0.026) -0.188**
Capex	(0.133) -0.071	(0.704) 0.269*	(0.119) -0.264	(0.077) -0.222**
Brand	(0.132) 0.002	(0.133) -0.003	(0.236) 0.054**	(0.071) -0.006
Compensation	(0.004) -0.033	(0.006) 0.093***	(0.017) 0.077	(0.005) -0.019
Ceo chair duality	(0.024) -0.035	(0.026) -0.025	(0.062) -0.090***	(0.011) 0.033
log(age)	(0.023) -0.007	(0.052) -0.021***	(0.022) 0.008	(0.023) -0.000
Beta	(0.011) 0.005	(0.005) 0.146**	(0.007) -0.158**	(0.003) 0.028**
Closely held shares	(0.030) 0.308*	(0.045) 0.727**	(0.051) 0.853***	(0.009) 0.084
constant	(0.151) 0.308*	(0.243) 0.727**	(0.138) 0.853***	(0.133) 0.084
Clustering	Industry	Industry	Industry	Industry
Observations	9,827	9,867	9,977	10,083
R-squared	0.014	0.039	0.019	0.079

This table reports the relationship between buy-and-hold return and changes in stringency across the covid waves. The dependent variable is the BHAR of the first wave, 2nd wave, 3rd wave and 4th wave. All the control variables are pooled at the end of 2019 (before covid). All variables are defined in Appendix 4.2. The t-statistics is calculated based on cluster (industry) adjusted standard errors and reported in parentheses. ***, ** and * represents significance at the 1, 5 and 10 percent level, respectively.

In columns 3 and 4, the dependent variable is the buy-and-hold return during the third wave and fourth wave, respectively, and the main independent variable is the change in the stringency measure from the beginning to the end of the third wave and fourth wave, respectively. The results show that the change in the stringency measures is negative and significantly related to third wave returns. As the restrictions imposed were very high for the second and third wave, hence, the relationship is negative with the returns. The higher the stringency the lower the returns. The stringency measures are positively related to the returns for the fourth waves. The lower the changes in stringency (less strict) measures the higher the buy-and-hold returns.

In sum, changes in stringency measures may have varying effects on different businesses. For instance, businesses in the travel, hospitality, and retail sectors might see more swings in returns in reaction to modifications to social distancing policies, lockdowns, and travel restrictions. On the other hand, businesses in sectors such as technology, healthcare, and e-commerce could not be as negatively impacted by lockdowns and remote work—in fact, they might potentially gain from increasing demand for their goods and services. Businesses that operate or have a large revenue exposure in areas with different levels of stringency measures may have different results. Companies operating in countries with less severe controls may have less volatility in their returns than those exposed to places with tougher lockdowns and containment measures.

4.6 Robustness checks

Since Covid was a global pandemic, its development in different countries was not the same and the severity was different for different countries. As our definitions of different waves were

based on the severity of Covid deaths, I might be missing other common trends for the markets. In this section, I define the waves following the literature and conduct several robustness checks. I follow Polat et al. (2023) and Iftimie et al. (2021) to track the pandemic evolution. Following them, the first wave is 17 January 2020-22 May 2020, the second wave is 1 July 2020-15 October 2020, the third wave is 1 November 2020-31 March 2021, and the fourth wave is 1 December 2021-19 January 2022.

4.6.1 Relationship between the fourth wave and other waves— Alternative definitions of waves

I look at the connection between the initial wave of COVID-19 and subsequent waves in this section. Column 1 presents the findings utilising the definitions of Iftimie et al. (2021) and Polat et al. (2023) for the buy-and-hold return for the first wave as the dependent variable. The buy-and-hold return for the first wave is the dependent variable in Column 1's results. Since the subsequent waves have not yet occurred, I did not utilise them to examine the connection in which the initial wave is the independent variable. Regression analysis using firm-level variables prior to COVID-19 reveals a negative relationship between total assets and age, whereas cash shows a positive relationship. I employ the BHAR second wave as the dependent in the second column and use only the BHAR for the first wave. They turn out to be positively correlated. The first wave of the BHAR coefficient is 0.026, and it is not significant. This does not align with theories about business models or learning. I also discovered that this regression shows a negative relationship between total assets, cash, age, and closely held shares. Large, mature firms with higher cash and ownership concentration perform badly in the second wave. This might be due to the fact that large firms are often complex organisations, and idle cash is of no use in the midst of the pandemic.

Using the BHAR third wave as the dependent variable in column 3, I discover that the second wave and the third wave returns are positively and negatively correlated. First wave coefficient is -0.192, significant at 1% level. At the 1% level, the coefficient for the second wave is 0.129 and not significant. Once more, this fits the theories around learning hypotheses. Third wave returns are negatively correlated with size, cash, and age, whereas returns are favourably correlated with debt, remuneration, and the CEO/Chair duality. In column 4, as the fourth wave is the last one to happen, hence, I use the buy-and-hold return during the fourth wave as our dependent variable. The main independent variable is the buy-and-hold return for the first, second and third waves. I find that the 4th wave is negatively related to all other waves. The coefficients for the first, second and third waves are -0.014, -0.010, and -0.006 and the last one is significant at 10% level. Hence, I accept H1b. This is consistent with the learning hypothesis.

These results are not very similar to when I use our definition of covid waves. Because the COVID-19 epidemic was worldwide in nature, its progression and intensity varied throughout nations. I may be overlooking other prevalent patterns for the markets (when I use the common time frames to define covid waves in each country) because I defined distinct waves based on the severity of Covid deaths in different countries.

Other factors that have an impact on returns across different waves of Covid are local economic conditions and investor sentiment. Economic indicators that affect market mood and patterns include GDP growth, inflation rates, interest rates, and employment statistics. A number of industries and asset classes are typically impacted by changes in macroeconomic conditions at the same time, which causes associated changes in returns. Market movements and herd behaviour can be influenced by investor sentiment and risk appetite. Investing in riskier assets and taking on more risk may be more common during optimistic times, which could cause associated changes in returns across many industries. On the other hand, investors

may seek out safer assets during uncertain or risk-averse times, which could result in correlated changes in returns away from riskier assets. The changes in results when I use alternative definitions could be affected by the common trends in economic conditions and investor sentiment.

Table 11. Robustness Check: Relationship among waves—Alternative definitions of waves

	(1) 1stwave_alt	(2) 2ndwave_alt	(3) 3rdwave_alt	(4) 4thwave_alt
3rdwave_alt				-0.006* (0.003)
2ndwave_alt			0.129 (0.131)	-0.010 (0.013)
1stwave_alt		0.026 (0.022)	-0.191** (0.074)	-0.014 (0.010)
Total assets	-0.033** (0.014)	-0.018* (0.010)	-0.127*** (0.031)	0.011 (0.012)
Debt	-0.003 (0.028)	0.001 (0.033)	0.142* (0.070)	0.064* (0.032)
Cash	0.239*** (0.085)	-0.099** (0.040)	-0.265* (0.132)	-0.204*** (0.063)
Capex	-0.060 (0.088)	0.064 (0.104)	0.589 (0.628)	-0.310*** (0.095)
Brand	-0.129 (0.109)	-0.185 (0.123)	0.025 (0.196)	-0.501*** (0.142)
Compensation	-0.004 (0.013)	0.007 (0.006)	0.053*** (0.019)	-0.012*** (0.002)
Ceo chair duality	-0.030 (0.022)	-0.030 (0.020)	0.171* (0.087)	-0.078*** (0.012)
log(age)	-0.075*** (0.021)	-0.059** (0.029)	-0.140*** (0.043)	0.027 (0.018)
Beta	-0.004 (0.012)	-0.003 (0.007)	0.005 (0.013)	-0.001 (0.005)
Closely held shares	-0.038 (0.035)	-0.082*** (0.025)	0.058 (0.044)	0.081*** (0.016)
constant	0.395*** (0.132)	0.567*** (0.114)	1.477*** (0.290)	-0.091 (0.147)
Clustering	Country & Industry	Country & Industry	Country & Industry	Country & Industry
Observations	9,824	9,824	9,824	9,824
R-squared	0.017	0.008	0.028	0.055

This table reports the relationship among buy-and-hold return of first, second, third and fourth waves —using alternative definition of waves. Following Polat et al. (2023) and Iftimie et al. (2021) to track the pandemic evolution, the first wave is 17 January 2020-22 May 2020, the second wave is 1 July 2020-15 October 2020, the third wave is 1 November 2020-31 March 2021, and the fourth wave is 1 December 2021-19 January 2022. The dependent variable is BHAR for the 2nd wave in columns 1 and 2, BHAR for the 3rd wave in column 3 and BHAR for the 4th wave in column 4. All the control variables are pooled at the end of 2019 (before covid). All variables are defined in Appendix 2. The t-statistics are calculated based on clustered (country and industry) standard errors and reported in parentheses. ***, ** and * represents significance at the 1, 5 and 10 percent level, respectively.

In terms of the characteristics before the pandemic that explain the cross-sectional variation of returns, I find that total assets, age, CEO/chair duality and closely held shares are negatively related to the fourth wave returns and cash is positively related to the first wave returns. These results are similar to the results when using our definitions of waves.

4.6.2 Country-level variation in the relationship across waves-- Alternative definitions of waves

In this section, I examine how Covid-19 fourth and other waves are related across firms and vary by country. In Table 10, I repeat our baseline regression at the country level. Using the alternative definition of waves, the US and China show a significant negative relationship between the fourth and all other waves. The UK and Italy show no significant relationship between the fourth and other waves. These results are similar to what I found before using my definition of waves. However, the results at the country level become a little more significant, probably because of the country-level relationships between companies are stronger. As far as the characteristics are concerned, total assets are significantly positively related to the first wave returns for most of the countries. For China and India, a lot of variables show a significant relationship with the first wave returns, as I found before using our definition of waves.

Table 12. Robustness Checks. Country level variation in the relationship across waves-- Alternative definitions of waves

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	US	UK	Brazil	China	France	Germany	India	Italy
	4thwave alt	4thwave alt	4thwave alt	4thwave alt	4thwave alt	4thwave alt	4thwave alt	4thwave alt
1stwave_alt	-0.007* (0.004)	-0.004 (0.003)	-0.032** (0.013)	-0.058** (0.020)	-0.006* (0.003)	-0.031 (0.048)	0.034* (0.017)	0.081 (0.054)
2ndwave_alt	-0.018 (0.018)	0.005 (0.009)	0.035*** (0.009)	-0.093*** (0.010)	-0.052 (0.034)	0.037 (0.026)	0.018 (0.037)	-0.111 (0.096)
3rd wave_alt	-0.054** (0.019)	-0.002 (0.009)	0.121*** (0.032)	-0.035 (0.031)	-0.010 (0.010)	-0.093*** (0.019)	0.035 (0.044)	-0.215 (0.327)
Total assets	0.050*** (0.012)	0.020* (0.010)	0.024 (0.013)	0.006 (0.009)	-0.007 (0.007)	-0.007 (0.008)	-0.086*** (0.012)	-0.070 (0.104)
Debt	0.017* (0.009)	0.014 (0.034)	-0.002 (0.036)	-0.014 (0.013)	0.009 (0.051)	0.085 (0.063)	0.085* (0.045)	-0.034 (0.193)
Cash	-0.036 (0.025)	-0.001 (0.052)	0.053 (0.093)	-0.015 (0.049)	-0.102* (0.052)	-0.033 (0.108)	-0.478** (0.208)	-0.286 (0.161)
Capex	0.002 (0.234)	-0.098* (0.048)	0.113 (0.287)	-0.274*** (0.036)	-0.212 (0.208)	0.027 (0.082)	-0.595*** (0.109)	1.883 (2.300)
Brand	-0.105 (0.139)	-0.207* (0.098)	0.048 (0.388)	0.349 (0.334)	-0.183 (0.108)	0.495* (0.235)	-0.678** (0.226)	0.881 (0.501)
Compensation	0.000 (0.001)	-0.006 (0.005)	-0.374*** (0.087)	-0.363 (0.302)	-0.076*** (0.015)	-0.028 (0.017)	-0.259*** (0.053)	0.282* (0.137)
Ceo chair duality	0.000 (0.010)	-0.025 (0.018)	0.009 (0.018)	-0.028** (0.010)	-0.012 (0.011)	-0.003 (0.018)	-0.049 (0.036)	-0.001 (0.164)
log(age)	0.005 (0.021)	0.033* (0.018)	0.096 (0.054)	0.142*** (0.041)	0.087* (0.047)	0.031 (0.022)	-0.053 (0.051)	0.018 (0.085)
Beta	0.002 (0.004)	-0.012** (0.004)	-0.039** (0.013)	0.000 (0.003)	0.008 (0.014)	-0.042 (0.024)	0.012 (0.018)	0.094 (0.055)
Closely held shares	-0.060* (0.028)	-0.018 (0.021)	0.074 (0.047)	0.042*** (0.011)	-0.022 (0.023)	-0.003 (0.052)	-0.038 (0.034)	-0.034 (0.078)
constant	-0.377** (0.119)	-0.225** (0.094)	-0.641* (0.291)	-0.520** (0.193)	-0.271 (0.179)	-0.091 (0.091)	1.020*** (0.212)	0.098 (0.649)
Clustering	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry

Observations	2,157	853	192	3,379	422	141	2,652	28
R-squared	0.139	0.033	0.238	0.039	0.062	0.207	0.044	0.322

This table reports the country level variation in relationship between buy-and-hold return of the fourth wave and other waves—using an alternative definition of waves, following Polat et al. (2023) and Iftimie et al. (2021) to track the pandemic evolution. Following them, the first wave is 17 January 2020-22 May 2020, the second wave is 1 July 2020-15 October 2020, the third wave is 1 November 2020-31 March 2021, and the fourth wave is 1 December 2021-19 January 2022. The dependent variable is BHAR Fourth wave. All the control variables are pooled at the end of 2019 (before covid). All variables are defined in Appendix 4.2. The t-statistics are calculated based on clustered (industry) adjusted standard errors and reported in parentheses. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively.

4.6.3 Industry-level variation in the relationship across waves-- Alternative definitions of waves

To test industry-level variation, I use the buy-and-hold return during the first wave using alternative definitions for different industries as dependent variables and repeat our regressions. The results are reported in Table 11. The results show that the third wave and fourth wave returns are significant and negative for consumer discretionary, health care, energy and industrials. Telecom and basic materials show a positive relationship between the fourth and third waves. Technology shows a significant negative relationship between the first and fourth waves. Energy shows a significant negative relationship between the fourth and second waves. There is more evidence of learning hypotheses when I use the alternative definitions of waves.

Lockdowns, travel restrictions, and alterations in consumer behaviour are common outcomes of COVID-19 waves, and they can all be harmful to the economy. Businesses such as hotels, leisure, and entertainment that primarily depend on face-to-face contact can struggle during lockdowns and dips in consumer spending. Global supply networks may be disrupted by COVID-19 waves, which might result in a shortage of components, finished commodities, and raw resources. Industries with intricate supply networks or a reliance on imports are especially susceptible to interruptions. For instance, the COVID-19 epidemic caused delays in both chip production and international transportation, which finally resulted in a shortage of automotive chips. Furthermore, it is not as straightforward to solve the problem—opening more car chip manufacturing plants, for example. It takes years and billions of dollars to open a new factory.

Table 13. Robustness Check. Industry level variation in the relationship across waves-- Alternative definitions of waves

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Technology	Consumer Discretionary	Health Care	Energy	Industrials	Consumer Staples	Telecomm	Basic Materials	Real Estate	Other
	4thwave_alt	4thwave_alt	4thwave_alt	4thwave_alt	4thwave_alt	4thwave_alt	4thwave_alt	4thwave_alt	4thwave_alt	4thwave_alt
3rdwave_alt	-0.001 (0.006)	-0.036*** (0.012)	-0.032*** (0.009)	-0.002 (0.002)	-0.020* (0.012)	-0.012 (0.017)	0.072*** (0.025)	0.031** (0.015)	-0.014 (0.037)	0.002 (0.076)
2ndwave_alt	0.017 (0.025)	0.019 (0.020)	-0.004 (0.014)	-0.097*** (0.016)	-0.037** (0.016)	0.003 (0.029)	-0.055 (0.036)	-0.025* (0.014)	0.041 (0.050)	0.087 (0.099)
1stwave_alt	-0.129*** (0.027)	-0.011 (0.031)	0.006 (0.011)	-0.009 (0.008)	0.007 (0.020)	0.004 (0.050)	0.000 (0.046)	0.004 (0.028)	0.086 (0.064)	-0.235 (0.242)
Total assets	0.033*** (0.011)	-0.011 (0.010)	0.049*** (0.010)	0.021** (0.010)	0.002 (0.008)	-0.025 (0.019)	0.036** (0.017)	-0.004 (0.010)	0.017 (0.017)	0.054 (0.071)
Debt	-0.056 (0.038)	0.090*** (0.028)	-0.044 (0.037)	-0.011 (0.038)	0.091*** (0.026)	0.159** (0.065)	0.130*** (0.049)	0.111*** (0.030)	-0.008 (0.073)	-0.033 (0.163)
Cash	-0.171*** (0.061)	-0.208*** (0.063)	-0.028 (0.048)	-0.139* (0.081)	-0.222*** (0.056)	-0.299** (0.126)	-0.284*** (0.100)	-0.269*** (0.082)	-0.139 (0.116)	-0.693 (0.434)
Capex	-0.317 (0.228)	-0.488*** (0.183)	-0.026 (0.206)	0.026 (0.170)	-0.214*** (0.079)	-0.770*** (0.288)	-0.641 (0.390)	-0.582*** (0.157)	-0.921** (0.362)	-0.466 (0.776)
Brand	-0.541 (0.416)	-0.606** (0.247)	-0.282* (0.166)	-0.699** (0.302)	-0.923*** (0.323)	-0.233 (0.255)	-0.304 (0.764)	-0.799** (0.390)	-0.253 (0.583)	-13.698 (18.603)
Compensation	-0.009 (0.006)	-0.014* (0.007)	-0.014*** (0.004)	0.012* (0.007)	-0.011** (0.006)	-0.011 (0.016)	0.001 (0.012)	-0.003 (0.010)	-0.003 (0.012)	0.007 (0.056)
Ceo chair duality	-0.081*** (0.029)	-0.081*** (0.025)	-0.056** (0.024)	-0.038 (0.028)	-0.076*** (0.019)	-0.080* (0.044)	-0.106** (0.045)	-0.067** (0.032)	-0.100** (0.049)	-0.121 (0.545)
log(age)	0.100** (0.047)	0.021 (0.034)	0.094** (0.038)	-0.045 (0.038)	-0.001 (0.026)	-0.045 (0.058)	-0.012 (0.079)	-0.079* (0.044)	0.039 (0.073)	0.124 (0.336)
Beta	0.011 (0.008)	0.012 (0.008)	0.000 (0.007)	0.028** (0.013)	-0.012 (0.009)	-0.034* (0.020)	0.033 (0.021)	-0.026** (0.011)	0.020 (0.022)	-0.052 (0.076)
Closely held shares	0.177*** (0.035)	0.108*** (0.029)	0.060* (0.034)	-0.036 (0.041)	0.056** (0.022)	-0.001 (0.054)	0.135** (0.055)	0.098*** (0.033)	0.066 (0.058)	-0.238 (0.236)
constant	-0.556*** (0.194)	0.052 (0.145)	-0.638*** (0.152)	0.131 (0.150)	0.100 (0.114)	0.520** (0.255)	-0.149 (0.326)	0.466*** (0.177)	-0.154 (0.310)	-0.285 (1.287)
Clustering	No	No	No	No	No	No	No	No	No	No
Observations	1,095	2,019	1,179	400	2,375	655	303	1,371	338	89
R-squared	0.110	0.055	0.108	0.161	0.051	0.055	0.198	0.061	0.079	0.133

This table reports the industry level variation in the relationship between buy-and-hold returns of the fourth wave and other waves—using alternative definition of waves, following Polat et al. (2023) and Ifimie et al. (2021) to track the pandemic evolution. Following them, the first wave is 17 January 2020-22 May 2020, the second wave is 1 July 2020-15 October 2020, the third wave is 1 November 2020-31 March 2021, and the fourth wave is 1 December 2021-19 January 2022. The dependent variable is BHAR of the first wave. All the control variables are pooled at the end of 2019 (before covid). All variables are defined in Appendix 4. 2. The t-statistics are calculated based on robust standard errors and reported in parentheses. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively.

Cash is negative and significant for most of the industries, while total assets and debt show significance in a few industries only.

4.6.4 Stringency and returns across waves—alternative definition of waves.

In this section, I examine whether the stringency changes are related to the buy-and-hold returns for companies using an alternative definition of waves. The results are reported in Table 12. In the first column, the dependent variable is the buy-and-hold return during the first wave using the alternative definition and the main independent variable is the change in the stringency measure from the beginning to the end of the first wave. The results show that the change in the stringency measures is negative and significantly related to first wave returns. The higher the stringency measures the lower the buy-and-hold returns.

Table 14. Robustness Checks. Stringency and returns across waves—alternative definitions of waves.

	(1) 1stwave_alt	(2) 2ndwave_alt	(3) 3rdwave_alt	(4) 4thwave_alt
stringency_1st	-0.003*** (0.000)			
stringency_2nd		-0.002 (0.002)		
stringency_3rd			0.011*** (0.002)	
stringency_4th				0.004*** (0.000)
Total assets	-0.040** (0.017)	-0.023* (0.012)	-0.080** (0.030)	0.002 (0.011)
Debt	0.018 (0.021)	0.002 (0.025)	0.096 (0.062)	0.056** (0.021)
Cash	0.146** (0.054)	-0.070 (0.061)	-0.213* (0.114)	-0.128*** (0.019)
Capex	-0.095 (0.115)	0.068 (0.045)	0.645 (0.663)	-0.281*** (0.077)
Brand	-0.122 (0.163)	-0.121 (0.069)	-0.160 (0.245)	-0.308*** (0.092)
Compensation	0.005 (0.006)	0.008 (0.006)	0.050** (0.017)	-0.016*** (0.002)
Ceo chair duality	-0.021 (0.027)	-0.019 (0.018)	0.137* (0.071)	-0.052*** (0.007)
log(age)	-0.071*** (0.021)	-0.060** (0.023)	-0.176*** (0.049)	0.036 (0.020)

Beta	-0.008 (0.009)	-0.004 (0.006)	0.019* (0.009)	-0.003 (0.006)
Closely held shares	-0.018 (0.031)	-0.100*** (0.018)	-0.011 (0.066)	0.042** (0.014)
Constant	0.605*** (0.145)	0.569*** (0.090)	1.480*** (0.310)	-0.087 (0.140)
Clustering	Industry	Industry	Industry	Industry
Observations	9,824	9,884	9,973	10,104
R-squared	0.033	0.008	0.026	0.093

This table reports the relationship between buy-and-hold returns and changes in stringency across the waves covid—using alternative definition of waves, following Polat et al. (2023) and Ifitimie et al. (2021) to track the pandemic evolution. Following them, the first wave is 17 January 2020-22 May 2020, the second wave is 1 July 2020-15 October 2020, the third wave is 1 November 2020-31 March 2021, and the fourth wave is 1 December 2021-19 January 2022. The dependent variable is BHAR of the first wave, 2nd wave, 3rd wave and 4th wave. All the control variables are pooled at the end of 2019 (before covid). All variables are defined in Appendix 4. 2. The t-statistics are calculated based on clustered (industry) adjusted standard errors and reported in parentheses. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively.

In column 2, I use as the dependent variable the buy-and-hold return during the second wave using an alternative definition and the main independent variable is the change in the stringency measure from the beginning to the end of the second wave. The results show that the change in the stringency measures is negative and but not significantly related to second wave returns. In columns 3 and 4, the dependent variable is the buy-and-hold return during the third wave and fourth wave, using alternative definitions of waves, respectively, and the main independent variable is the change in the stringency measure from the beginning to the end of the third wave and fourth wave, respectively. The results show that the change in the stringency measures is positive and significantly related to third and fourth wave returns. The lower the changes in stringency (less strict) measures the higher the buy-and-hold returns. These results are consistent with what I found before using our definition of waves.

4.6.5 Relationship across waves—Sample Excluding China and India

Since China and India constitute the largest parts of the sample, I wanted to make sure they are not influencing our results. Hence, I rerun our analysis of the relationship between the fourth wave and other waves first excluding China, then excluding India and then excluding both countries from our sample. The results are presented in Table 13. Column 1 presents the relationship between the fourth and other waves excluding China. The results show no

significant correlation across the waves. Column 2 presents the relationship between the fourth and other waves excluding India. The results show that the fourth and first and second waves are significantly negatively related. However, the third wave is also negatively related but not significant. Column 3 presents the relationship between the fourth and other waves excluding China and India. The results show that fourth and first waves are significantly negatively related. All these results are supportive of the learning hypothesis.

Table 15. Robustness Check. Sample excluding China and India. The dependent variable is fourth wave.

	(1)	(2)	(3)
	Sample excluding China	Sample excluding India	Sample excluding China and India
	4thwave	4thwave	4thwave
3rdwave	0.008 (0.008)	-0.001 (0.002)	0.005 (0.006)
2ndwave	0.029 (0.016)	-0.016** (0.006)	-0.005 (0.005)
1stwave	0.018 (0.021)	-0.018** (0.006)	-0.020** (0.007)
Total assets	0.015 (0.008)	0.021** (0.009)	0.014*** (0.004)
Debt	0.057* (0.027)	-0.036** (0.014)	-0.014 (0.018)
Cash	-0.291*** (0.042)	-0.074** (0.023)	-0.082** (0.027)
Capex	-0.231** (0.081)	0.052 (0.076)	0.123 (0.104)
Brand	-0.586*** (0.116)	-0.111* (0.050)	-0.112 (0.079)
Compensation	-0.002 (0.004)	-0.001 (0.005)	-0.000 (0.004)
Ceo chair duality	-0.066*** (0.014)	-0.018 (0.011)	0.021 (0.012)
log(age)	0.002 (0.027)	0.015 (0.018)	-0.005 (0.017)
Beta	0.005 (0.004)	0.007** (0.002)	0.002 (0.004)
Closely held shares	0.095*** (0.020)	0.012 (0.008)	-0.032* (0.017)
Constant	0.023 (0.161)	-0.130 (0.104)	-0.035 (0.090)
Clustering	Industry	Industry	Industry
Observations	6,448	7,173	3,796
R-squared	0.048	0.018	0.020

This table reports the relationship among buy-and-hold returns of four waves of covid. The dependent variable in columns 1,2 and 3 is BHAR for the 4th wave excluding China, BHAR excluding India, and BHAR excluding China and India. All the control variables are pooled at the end of 2019 (before covid). All variables are defined in Appendix 4. 2. The t-statistics are calculated based on clustered (country and industry) standard errors and reported in parentheses. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively.

In sum, when I exclude China, India and China and India, the results change a little. As country level results are a slightly different, as I demonstrate earlier, the results excluding China and India make sense.

4.6.6 Industry variation in Relationship across waves—Sample Excluding China and India

To test industry-level variation, I use the buy-and-hold return during the fourth wave excluding China and India using different industries as dependent variables and repeat our regressions. The results are reported in Table 14. The results show that the fourth wave and all third wave returns are positive and significant for technology, consumer discretionary, industrials and basic materials. Fourth and second and first waves are negatively related for consumer staples. Without China and India, the results show more evidence of the business model hypotheses for the third and fourth waves.

Table 16. Robustness Check. Industry variation. Sample excluding China and India. The dependent variable is fourth wave.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Technology	Consumer Discretionary	Health Care	Energy	Industrials	Consumer Staples	Telecomm	Basic Materials	Real Estate	Other
VARIABLES	4thwave	4thwave	4thwave	4thwave	4thwave	4thwave	4thwave	4thwave	4thwave	4thwave
3rdwave	0.063** (0.027)	0.027** (0.012)	-0.004 (0.009)	-0.003 (0.004)	0.076*** (0.015)	-0.004 (0.028)	0.068 (0.059)	0.037* (0.021)	0.010 (0.054)	-0.211 (0.168)
2ndwave	-0.014 (0.013)	0.017 (0.016)	-0.014 (0.018)	0.018 (0.026)	-0.020 (0.020)	-0.080*** (0.027)	0.106 (0.073)	0.003 (0.021)	0.060 (0.059)	-0.042 (0.039)
1stwave	0.005 (0.042)	-0.018 (0.025)	-0.012 (0.010)	-0.009 (0.012)	-0.011 (0.023)	-0.053*** (0.015)	-0.027 (0.078)	-0.035 (0.024)	0.026 (0.077)	-0.622** (0.251)
Total assets	0.016 (0.022)	0.008 (0.010)	0.025** (0.012)	0.019 (0.019)	0.003 (0.010)	0.021 (0.014)	-0.015 (0.022)	0.009 (0.015)	0.021 (0.025)	-0.101 (0.062)
Debt	0.004 (0.087)	0.028 (0.032)	-0.004 (0.037)	-0.068 (0.061)	-0.086** (0.039)	-0.001 (0.050)	-0.074 (0.081)	-0.051 (0.049)	0.101 (0.079)	0.392 (0.372)
Cash	-0.098 (0.115)	0.030 (0.058)	-0.082* (0.045)	-0.007 (0.126)	-0.107* (0.065)	0.010 (0.095)	-0.176 (0.146)	-0.038 (0.094)	0.136 (0.117)	-0.214 (0.234)
Capex	0.573 (0.605)	1.086*** (0.211)	-0.365 (0.250)	0.333 (0.270)	0.078 (0.073)	0.144 (0.298)	0.563 (0.630)	-0.101 (0.222)	-1.117*** (0.423)	-1.162*** (0.356)
Brand	-0.707 (0.609)	0.063 (0.182)	0.057 (0.155)	-0.115 (0.425)	0.164 (0.281)	-0.004 (0.133)	-0.721 (0.766)	-0.623* (0.341)	-0.008 (0.430)	313.997** (125.546)
Compensation	0.020** (0.010)	-0.001 (0.005)	-0.004 (0.004)	-0.008 (0.010)	-0.009* (0.005)	-0.011 (0.008)	-0.002 (0.013)	0.010 (0.008)	-0.001 (0.009)	0.005 (0.034)
Ceo chair duality	0.074 (0.051)	0.022 (0.022)	0.029 (0.025)	0.073 (0.046)	-0.016 (0.019)	-0.010 (0.026)	0.017 (0.062)	0.021 (0.040)	0.064 (0.054)	0.022 (0.363)
log(age)	0.003 (0.075)	0.014 (0.028)	-0.032 (0.035)	0.070 (0.054)	-0.067*** (0.025)	0.004 (0.035)	-0.115 (0.095)	0.052 (0.051)	0.004 (0.067)	-0.297 (0.272)
Beta	-0.026 (0.019)	-0.008 (0.009)	0.004 (0.007)	-0.004 (0.019)	0.026** (0.012)	0.001 (0.015)	-0.010 (0.031)	0.019 (0.011)	-0.072*** (0.027)	0.009 (0.072)
Closely held shares	-0.108 (0.092)	-0.019 (0.036)	-0.053 (0.044)	0.061 (0.084)	-0.012 (0.035)	-0.070 (0.043)	-0.170 (0.106)	0.048 (0.058)	0.068 (0.071)	0.054 (0.173)
Constant	-0.050 (0.325)	-0.157 (0.123)	-0.054 (0.148)	-0.315 (0.229)	0.301*** (0.115)	-0.126 (0.161)	0.578 (0.404)	-0.212 (0.195)	-0.158 (0.306)	1.496 (1.007)
Clustering	No	No	No	No	No	No	No	No	No	No
Observations	490	790	719	263	808	207	110	271	114	24
R-squared	0.055	0.050	0.040	0.054	0.064	0.180	0.091	0.077	0.196	0.745

This table reports the industry level variation in the relationship between buy-and-hold returns of the fourth wave and other waves excluding China and India. The dependent variable is BHAR fourth wave for different industries. All the control variables are pooled at the end of 2019 (before covid). All variables are defined in Appendix 4.2. The t-statistics are calculated based on robust standard errors and reported in parentheses. ***, **, and * represent significance at the 1, 5 and 10 percent level, respectively.

In sum, though some of the results are slightly different compared to the full sample, the consumer discretionary and health care show a significantly negative relationship between the fourth and other waves. These results are similar to what I find for the full sample.

4.6.7 Stringency and Returns across the waves—excluding China and India

In this section, I examine whether the stringency changes are related to the buy-and-hold returns for companies using a restricted sample. The results are reported in Table 15. In the first column, the dependent variable is the buy-and-hold return during the first wave and the main independent variable is the change in the stringency measure from the beginning to the end of the first wave. The results do not show any significant relationship between stringency changes and returns.

In column 2, I use the buy-and-hold return during the second wave and the main independent variable is the change in the stringency measure from the beginning to the end of the second wave. The results show that the change in the stringency measures is negative and significantly related to second wave returns. The higher the stringency measures the lower the buy-and-hold returns for the second wave.

Table 17. Stringency and returns across waves (Excluding China and India)

	(1) 1stwave	(2) 2ndwave	(3) 3rdwave	(4) 4thwave
Δ Stringency_1st	0.000 (0.001)			
Δ Stringency_2nd		-0.009*** (0.002)		
Δ Stringency_3rd			-0.012*** (0.001)	
Δ Stringency_4th				0.001** (0.001)
Total assets	-0.067** (0.023)	-0.087*** (0.016)	0.009 (0.018)	0.018*** (0.005)
Debt	0.056 (0.071)	0.039 (0.131)	-0.028 (0.034)	-0.007 (0.015)
Cash	0.100	-0.201**	-0.134	-0.072**

	(0.067)	(0.086)	(0.140)	(0.023)
Capex	-0.251	1.130	-0.003	0.132
	(0.177)	(1.403)	(0.128)	(0.111)
Brand	0.055	0.072	-0.737**	-0.131
	(0.096)	(0.154)	(0.282)	(0.094)
Compensation	0.005	-0.019***	0.033*	-0.002
	(0.005)	(0.005)	(0.015)	(0.003)
Ceo chair duality	-0.036*	0.034	0.007	0.019
	(0.017)	(0.034)	(0.078)	(0.012)
log(age)	-0.018	-0.063	-0.052	0.006
	(0.029)	(0.072)	(0.040)	(0.018)
Beta	-0.005	-0.005	0.039**	0.002
	(0.016)	(0.012)	(0.014)	(0.004)
Closely held shares	-0.022	0.070	0.016	-0.017
	(0.074)	(0.051)	(0.118)	(0.018)
constant	0.400	0.895**	0.431*	-0.092
	(0.261)	(0.297)	(0.219)	(0.090)
Clustering	Industry	Industry	Industry	Industry
Observations	3,796	3,837	3,947	4,052
R-squared	0.018	0.030	0.017	0.022

This table reports the relationship between buy-and-hold return and changes in stringency across the covid waves. The dependent variable is BHAR first wave, 2nd wave, 3rd wave and 4th wave. All the control variables are pooled at the end of 2019 (before covid). All variables are defined in Appendix4. 2. The t-statistics is calculated based on clustered (industry) adjusted standard errors and reported in parentheses. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively.

In column 3, I use the buy-and-hold return during the third wave and the main independent variable is the change in the stringency measure from the beginning to the end of the third wave. The results show that the change in the stringency measures is negative and significantly related to second wave returns. The higher the stringency measures the lower the buy-and-hold returns for the second wave. In column 4, the dependent variable is the buy-and-hold return during the third wave and fourth wave, and the main independent variable is the change in the stringency measure from the beginning to the end of the third wave and fourth wave, respectively. The results show that the change in the stringency measures is positive and significantly related to the fourth wave returns. The lower the changes in stringency (less strict) measures the higher the buy-and-hold returns. These results are consistent with what I find in our full sample analysis.

4.7 Discussion of results and Conclusion

This chapter examines the relationship among the four Covid waves. I define the waves by the severity of confirmed deaths. I also find that the second, third and fourth waves are positively related. This is more supportive of business model hypotheses. Insights into how a firm may have been influenced by the COVID-19 epidemic and how it behaved during the first and second waves may be gained from looking at its business strategy. A company's revenue streams, cost structures, and client segmentation are all part of its business model, which covers how it develops, delivers, and makes a profit.

On the other hand, I find that returns across the third and second waves are negatively related. This is consistent with the learning hypotheses. Many businesses, particularly those in industries like healthcare, pharmaceuticals, and technology, saw huge increases in their stock values during the initial wave of the COVID-19 epidemic. Positive mood resulted from investors' optimism on prospective remedies, such as vaccines and therapies. While the wave persisted, lockdowns and lower consumer spending caused reductions in other industries including travel, hotel, and retail. When the entire economic impact of the pandemic became more apparent, there may have been a change in attitude or market performance, which affected a reversal in stock prices.

The third and fourth COVID-19 waves, in particular, may have seen a similar pattern of reversals in market mood and sector performance. Stocks may have initially suffered as the number of instances increased, especially in industries that are susceptible to lockdowns and limitations. However, other industries, such as travel, entertainment, and hospitality, may have enjoyed a resurgence, leading to positive reversals in their stock values as vaccinations became more widely accessible and the chances of ending the epidemic improved. The third and fourth waves are positively related providing support for the business model hypothesis.

The returns of companies during the waves of COVID-19 can, in fact, differ significantly between different countries due to a variety of observed and unobserved factors, such as variations in the waves' severity, government responses, healthcare systems, economic structures, and the makeup of industries within each country. Therefore, I look at how COVID-19 waves relate to different firms and vary by country. I find evidence that there are country-level variations in the correlations among returns. All things considered, a combination of stringent control measures, centralised response, public compliance, and a robust healthcare infrastructure likely contributed to the COVID-19 waves in China, containing outbreaks in multiple regions before they had a chance to spread widely. On the other hand, in India, a variety of factors, such as high population density, mobility, differing control measures and healthcare facilities, and variations in testing and reporting protocols, are to blame for the positively associated COVID-19 waves observed in India.

The composition of each country's industries may also be significant. Enterprises operating in sectors deemed essential during the pandemic, such as healthcare, technology, and e-commerce, might have fared better throughout both waves, whereas enterprises in non-essential areas faced more challenges. I find significant variations in returns across the waves. All things considered, consumer discretionary indicates a strong correlation between the fourth and subsequent waves. Consumer discretionary businesses, which comprise non-essential goods and services, are often impacted by changes in consumer behaviour. The several waves of the Covid-19 epidemic may have altered consumers' priorities and shopping behaviours. For example, during lockdowns and periods of heightened uncertainty, consumers who had saved a significant amount of money may have chosen to spend it on luxuries and healthcare-related goods and services. This could support consumer discretionary by demonstrating a favourable correlation between the fourth and subsequent waves. "Consumer discretionary" refers to a wide range of companies that produce goods and services that consumers commonly seek out

for entertainment, enjoyment, and leisure but which are not essential for day-to-day living. Amazon.com, Inc. is an example. Amazon is a multinational technology company that started out as an online bookseller but has now expanded to sell a range of goods, including clothing, gadgets, and home goods. It also offers services for digital streaming, cloud computing, and artificial intelligence.

In order to contain the virus during the first wave of the pandemic, a number of countries implemented strict and prolonged lockdowns. These economies suffered as a result of these activities, which led to a decline in consumer spending, business closures, and supply chain disruptions. In this part, I investigate the relationship between the stringency modifications and the companies' buy-and-hold returns. I find that higher stringency is related to negative returns in the first and second waves of Covid. When the stringency is lower in the third and fourth waves of covid it is positively related to the returns. Government-imposed COVID-19-related regulations that are too strict might significantly affect business and financial market returns during different pandemic waves. To stop the spread of the virus during the pandemic's initial wave, several nations imposed stringent and protracted lockdowns. These actions had a negative impact on the economy, resulting in decreased consumer spending, company closures, and supply chain disruptions. Businesses in industries that were severely impacted by lockdowns, such as travel, hospitality, and retail, frequently saw major drops in profits (Tudoran et al. 2024). In later waves, several governments changed their strategy to be less strict, trying to strike a compromise between worries about the public's health and the stability of the economy. Businesses in industries such as e-commerce, technology, and healthcare that adapted to the “new normal” may have been more resilient and generated more favourable returns during these waves.

Because the COVID-19 epidemic was worldwide in nature, its progression and intensity varied throughout nations. I check whether I was overlooking other prevalent trends for the markets

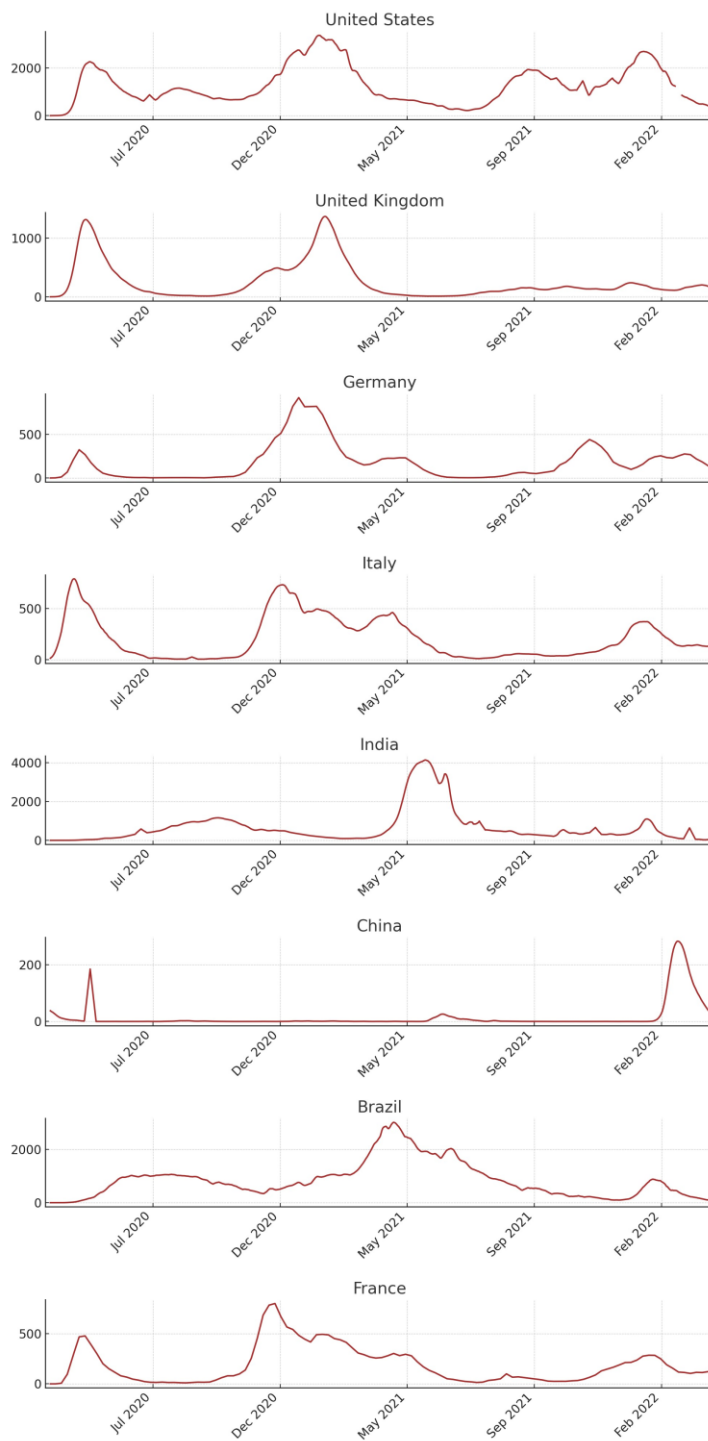
because I defined distinct waves based on the severity of Covid deaths. As an alternative definition, I monitor the pandemic evolution by following Ifitimie et al. (2021) and Polat et al. (2023). The periods that follow are as follows: 1 July 2020–15 October 2020 is the second wave, 1 November 2020–31 March 2021 is the third wave, and 1 December 2021–19 January 2022 is the fourth wave. While some of the results are similar when I use alternative definitions of waves, some results are different. While using common time to define the waves, the fourth wave is not significantly related to the other waves. Mostly common trends drive the returns across the same time periods. Investors frequently look for safe-haven assets during times of increased uncertainty, such as gold, government bonds, and specific currencies (such as the US dollar, Japanese yen, and Swiss franc). This flight to safety is indicative of a desire to protect capital in the face of economic and financial volatility. Financial markets saw unparalleled volatility as a result of the epidemic, with major stock indices seeing steep drops followed by quick recovery. When investor fear increased during the early stages of the pandemic, volatility indicators, such as the VIX (CBOE Volatility Index), rose as uncertainty skyrocketed. Economic indicators that affect market mood and patterns include GDP growth, inflation rates, interest rates, and employment statistics. A number of industries and asset classes were typically impacted by changes in macroeconomic conditions at the same time, which caused associated changes in returns. Market movements and herd behaviour can be influenced by investor sentiment and risk appetite. Investing in riskier assets and taking on more risk may be more common during optimistic times, which could cause associated changes in returns across many industries. On the other hand, investors may seek out safer assets during uncertain or risk-averse times, which could result in correlated changes in returns away from riskier assets (Neukirchen et al. 2022).

Sectors that depend on in-person activities were disproportionately affected by strict controls. These industries frequently saw major drops in returns. The harshness of the measures

and the ability of firms to react determined the extent of the impact on certain industries over successive rounds. While some industries went through phases of recovery, other industries, including technology and healthcare, continued to thrive and provide significant profits.

Figure 1. Daily new confirmed covid-19 deaths per million people
Daily new confirmed Covid-19 deaths

7-days rolling average. Due to varying protocols and challenges in the attribution of the cause of death, the number of confirmed deaths may not accurately represent the true number of deaths caused by COVID-19.

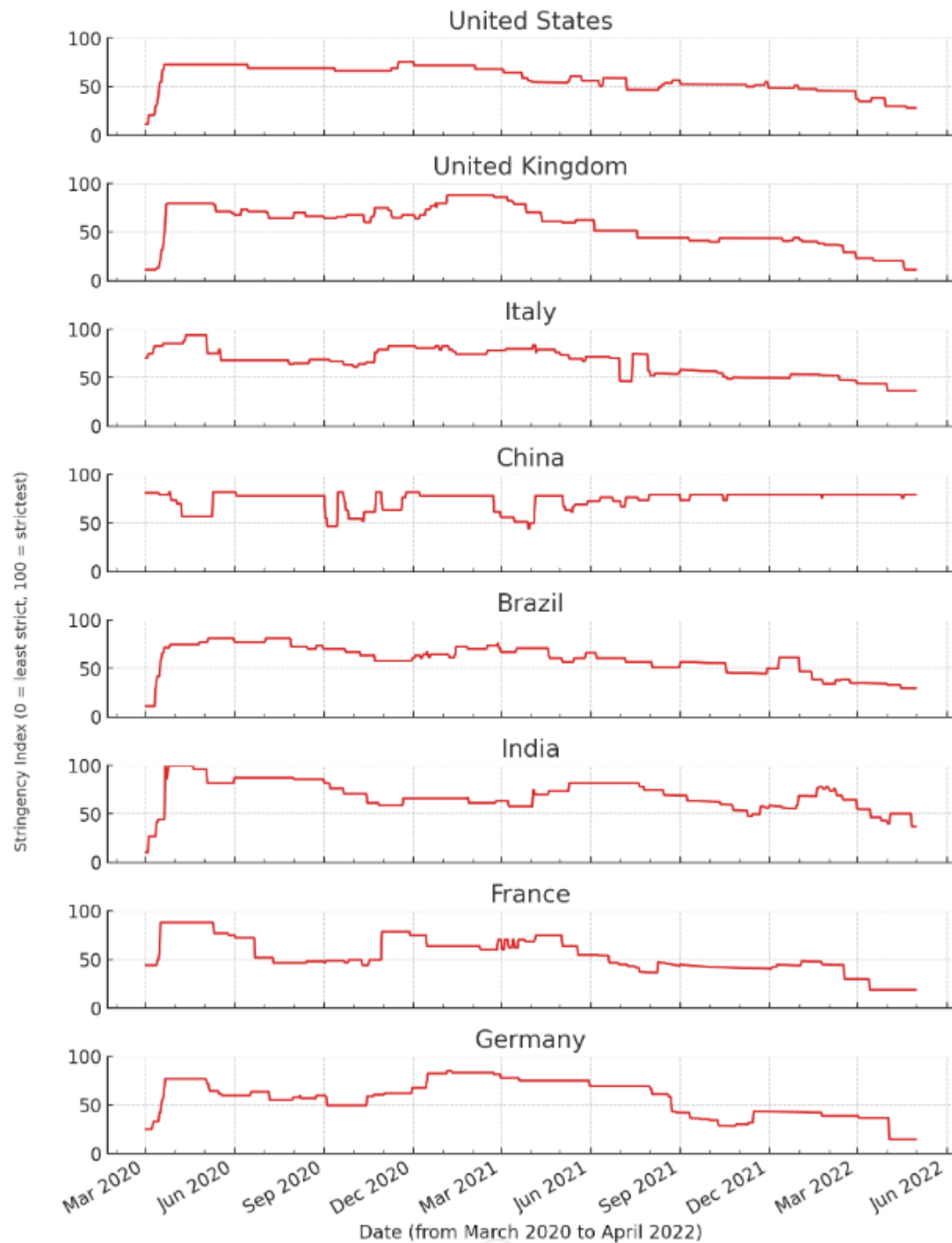


Source: WHO COVID-19 Dashboard

Figure 2. Covid-19 Stringency Index

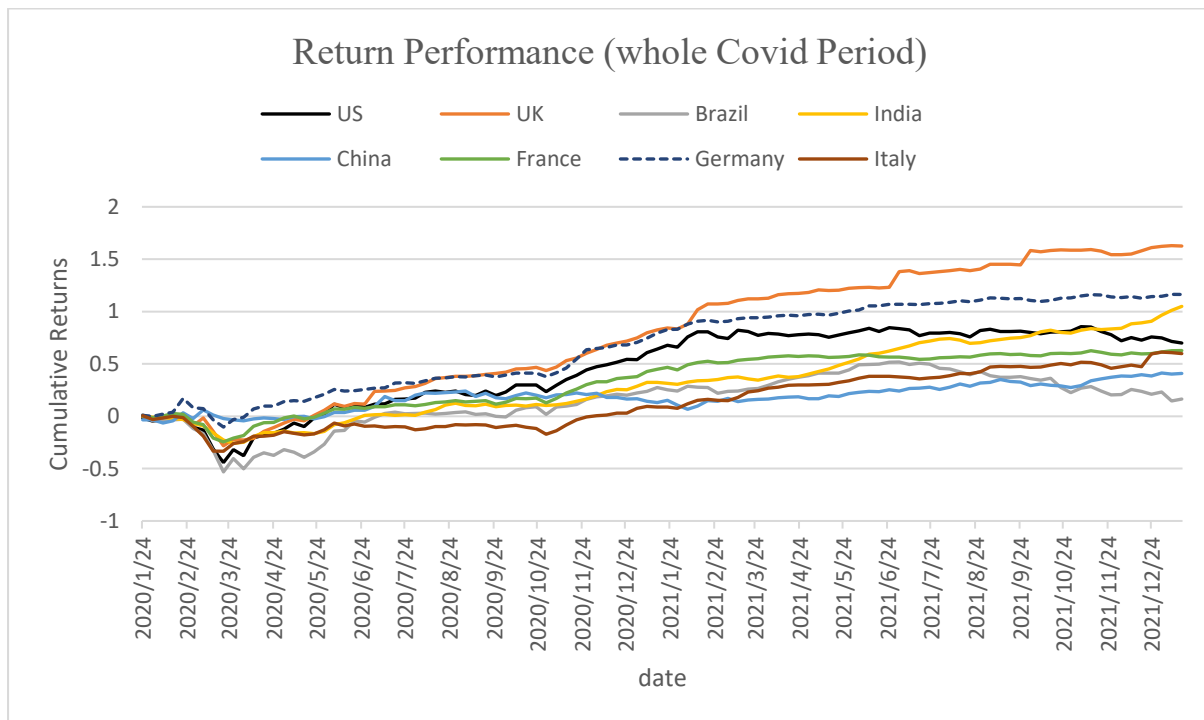
COVID-19: Stringency Index

The stringency index is a composite measure based on nine response indicators including school closures, workplace closures, and travel bans, rescaled to a value from 0 to 100 (100 = strictest).



Data source: Hale, T., Angrist, N., Goldszmidt, R. et al. A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). Nat Hum Behav 5, 529–538 (2021). <https://doi.org/10.1038/s41562-021-01079-8>.

Figure 3. Return Performance (Whole Covid Period)



Chapter 5

Are covid risk and political risk priced during
Covid-19? Evidence based on earnings conference
call-based measures

5.1.Introduction

One of the biggest worldwide disasters in recent memory, the Covid-19 epidemic has had a profound impact on financial markets, economies, and public health (Baker et al. 2020). The quick spread of the virus and the consequent adoption of social separation and lockdowns as containment measures caused supply networks to break down, economic activity to stop, and general uncertainty (Ding et al. 2021). Financial markets saw significant changes as a result of these difficulties, including greater volatility, abrupt swings in asset values, and a rise in investor risk aversion. In light of this, it is more important than ever to determine how to evaluate and account for Covid-19 risk while making investment decisions. Though the literature on Covid-19 is growing, to the best of my knowledge, none of the previous studies examine whether firm-level Covid risk and firm-level political risk were being priced in the financial markets during Covid.³ In other words, none of the previous studies examine them together. In this chapter, I fill this gap in the literature. I use the quarterly stock returns in the US market and relate it to firm-level covid risk and firm-level political risk.

The complex consequences of Covid-19 risk and political risk for public health, economies, financial markets, political stability, policy responses, and societal well-being make it imperative to investigate during periods of Covid-19. Policymakers, companies, investors, and individuals may all foresee difficulties, reduce vulnerabilities, and strengthen their resilience in the face of uncertainty and adversity brought on by the pandemic and its aftermath by having a better grasp of the drivers, dynamics, and repercussions of these risks.

³ Benton, Cobb, & Werner, T. (2022) examine the interaction between COVID-19 and political dimensions at the firm level. However, the focus and methodology of Benton and Cobb (2022) differ fundamentally from this chapter. Their study is rooted in strategic management and disclosure behaviour, analysing how firms' partisan positioning and political polarization shape voluntary COVID-related risk communication. By contrast, this chapter examines whether firm-level COVID risk and political risk are priced in financial markets, using text-based risk measures from earnings conference calls and linking them directly to stock returns within an asset-pricing framework.

Hence, in this chapter, I examine whether covid risk and political risk is related to the returns during Covid-19 pandemic.

The Covid-19 pandemic brought unprecedented levels of political risk, which significantly affected firms' operations, investment decisions, and financial stability. Analysing firm-level political risk during this period is critical because it helps us understand how political uncertainty, such as abrupt regulatory changes, stimulus policies, and trade disruptions, impacts businesses differently depending on their size, industry, and geographical location (Baker et al., 2020). For instance, firms operating in sectors reliant on cross-border supply chains, such as manufacturing, were disproportionately affected by shifting trade policies and border closures, leading to significant operational challenges (Baldwin and Tomiura, 2020). Additionally, the rapid introduction of government aid packages and taxation policies created uncertainty around financial planning, especially for smaller firms with limited resources to adapt. Understanding these dynamics provides insights into firms' risk mitigation strategies and the role of political stability in fostering economic resilience during crises.

From an academic perspective, firm-level analysis reveals heterogeneous effects that are often masked in macroeconomic studies. During the Covid-19 period, political risk varied widely across regions and industries, driven by inconsistent government responses, such as vaccine distribution policies and pandemic-related labour regulations (Gourinchas et al., 2020). Examining political risk at the firm level enables researchers to assess how specific characteristics, like size, capital structure, or industry type, influence a firm's vulnerability to political uncertainty. Furthermore, it highlights the importance of institutional quality and governance frameworks in mitigating the adverse effects of political risk (Handley and Limão, 2015). Such insights are essential for policymakers and investors seeking to design better risk management practices and support mechanisms for businesses during future crises.

This chapter makes use of the measures based on earnings conference calls to contribute to the literature. Hassan et al. (2023) build on earlier studies in this field by employing natural language processing (NLP) technologies to evaluate the text of quarterly earnings calls and detect the concerns expressed by both firm management and non-corporate participants over Covid-19. Unlike past studies (e.g., Loughran and McDonald, 2011) that only used textual analysis of regulatory filings, this methodology allows for a more dynamic and sophisticated understanding of how companies are responding to the pandemic's issues as they arise. Similarly, Hassan et al (2019) developed the firm-level political risk based on earnings conference calls.

Using the measures developed by Hassan et al (2023 and 2019), the findings demonstrate that, throughout the course of the Covid period, returns are positively correlated with all of the Covid risk metrics. This demonstrated the fundamental principle of finance: The higher the risk the higher the returns. A one standard deviation of covid exposure is associated with a 0.061 (6.1%) increase in returns. The economic magnitude of the impact of covid on the stock market is quite sizable. Covid was important in 2020 and 2021. Hence, I examine whether the performance was different in 2020 as compared to 2021. I examine whether the pricing of the covid risk is different in 2020. In order to do this, I use a dummy variable for 2020 (D 2020) and interact it with all the covid risk measures. The findings demonstrate that all the interaction terms are positive and significant showing that in 2020 return is positively correlated with all of the Covid risk metrics. Covid exposure was positively related in 2020, a 0.043 (4.3%) increase in returns in comparison to 2021. The financial impact of Covid-19 on the stock market was substantial in 2020. The dummy for 2020 (D2020) shows a significant negative coefficient in all the specifications except for Table 2, Column 5. For example, the coefficient for D2020 is -0.061, which shows that the return is 0.061 lower in 2020 compared to 2021. These results show the severity of the covid in 2020 as compared to 2021.

As Covid-19 was a health-related pandemic, during Covid-19, political risk may or may not be significant. Therefore, I examine whether political risk is factored into financial market prices in the context of Covid-19. I correlate the political risk at the firm level, as estimated by Hassan et al. (2019), with share price returns during the Covid-19 pandemic. The analysis reveals that political exposure and risk variables are positively associated with returns, with a one standard deviation increase in political exposure linked to a 0.006 increase in returns. Further investigation into the pricing of political risk in 2020 shows that the interaction variable $D2020 \# c.st_prisk$ is significant and positive (coefficient: 0.007, significant at the 10% level). However, these results also indicate that at the onset of the Covid-19 pandemic, political risk contributed to a negative relationship between political risk and returns. The shift in the relationship between political risk and returns from 2020 to 2021 reflects the transition from heightened uncertainty and risk aversion during the early pandemic to improved clarity and confidence in managing its economic and political consequences. In 2020, political risk exacerbated market volatility and investor pessimism, resulting in lower returns. By contrast, in 2021, better policies, economic recovery, and increased investor adaptability reduced uncertainty, leading to a more neutral or positive association between political risk and returns.

To check the robustness of my findings, I use Return on Assets as a dependent variable. Return on Assets (ROA) evaluates how effectively a business converts its assets into earnings, offering insights into operational efficiency and profitability. Unlike stock price return, ROA can be influenced by accounting and management choices, which may impact its reliability in certain contexts. ROA is used as the dependent variable because it is an accounting measure unaffected by market participant actions. The findings reveal that most COVID-related measures do not have a significant relationship with ROA, suggesting a limited impact on operational efficiency during the pandemic. Two of the political measures, it turns out, have a significant relationship with ROA. Negative sentiment and net sentiment is positively related

to ROA. Moreover, the economic impact is negligible. A 0.002 increase in ROA is linked to a one standard deviation rise in net sentiment.

Despite the fact that political risk and Covid risk are measured using separate keywords and, therefore, measure different concepts, I nevertheless included them in the same models to see if they were still significant. With the exception of covid net sentiment, all of the Covid risk metrics are significant and positive. At the 10% threshold, political risk and exposure are both positive and significant. Covid risk is more significant economically than political risk. This makes sense because it was during the Covid-19 pandemic, and political risk was far less significant at that time than Covid-19 risk was.

Political risk can be caused by various things such as trade, institutions, health, and tax policies (Hassan et al., 2019). Trade relations could be a part of political risk. Modifications to trade barriers, import/export regulations, and taxes can cause supply chain disruptions, raise expenses, and restrict a company's access to markets. Health can be a source of political risk. Strict health restrictions, for instance, might affect the food, pharmaceutical, and manufacturing sectors. Business operations may be impacted by lockdowns, travel restrictions, and shifts in consumer demand in response to health emergencies such as pandemics (such as Covid-19). A shift in public health policy may have an impact on customer behaviour, staff availability, and operating expenses. I look at how commerce, institutions, health, the environment, taxes, and security affect political risk. The majority have a positive relationship with returns. This indicates that returns will be higher the more political risk there is.

Covid risk and political risk might be endogenously determined. I address endogeneity using instrumental variable two-stage least squares (IV-2SLS). For the Covid risk, I used firm-level exposure to H1N1 as an instrument. For the political risk, I use the previous firm-level political risk as an instrument. The results obtained using 2SLS are consistent with the baseline results. I also use a dynamic Generalised Method of Moments model (GMM). The results hold.

Lastly, I use quantile regressions. Quantile regressions are used to examine how the relationship between independent variables and the dependent variable varies across different points of the outcome distribution, rather than focusing solely on the mean as in OLS regressions. This allows for a more comprehensive understanding of heterogeneous effects, especially in the presence of outliers or skewed distributions. Specifically, I estimate regressions for 25, 50, 75 and 100th quantiles and across the quantiles the covid risk and political risk are positively related to returns. Finally, I adjusted stock returns using the CAPM, Fama-French three-factor, and five-factor models, and the results remained robust.

My work is based on Hassan et al (2023) and Hassan et al (2019) but is very different from what they did in these two papers. Hassan et al (2023) created text-based measures to evaluate listed firms' primary concerns regarding the spread of Covid-19, SARS, and H1N1. Textually, they dissect how an outbreak affects a firm's supply and demand, as well as which firms benefit, and which suffer losses. This work differs in a number of ways. While Hassan et al (2023) examined earlier pandemics such as SARS and H1N1, I only concentrate on Covid-19 and offer a more thorough examination of it. Secondly, I investigate whether the Covid risk, which was derived from the earnings calls, is included in the pricing of all Covid waves. I expand on the research of Hassan et al (2023) by incorporating the entire Covid era and all of its waves, but neither SARS nor H1N1.

The question of whether firm-level political risk is priced in the cross-section of stock returns is investigated by Hassan et al (2019). By investigating whether firm-level political risk is priced during Covid, I expand on the work of Hassan et al (2019). For this reason, my research differs greatly from Hassan et al's (2019). There wasn't any Covid when Hassan et al. (2019) published their work. They did not investigate whether political risk is priced during Covid as a result. Hassan et al (2023) looked at Covid-19, SARS, and H1N1, not political risk at the corporate level.

Political risk was important during the Covid period. The Covid-19 pandemic introduced unprecedented political risks, significantly disrupting firms' operations, investment decisions, and financial stability. Firm-level analysis is essential to understand how political uncertainty, such as regulatory changes, trade disruptions, and stimulus policies, affected businesses differently based on size, industry, and location (Baker et al., 2020). Sectors like manufacturing, reliant on cross-border supply chains, faced severe operational challenges due to trade policy shifts and border closures (Baldwin and Tomiura, 2020). Hence, it is important to examine political risk during Covid period.

This chapter makes a novel contribution to the emerging literature on risk pricing during the COVID-19 pandemic by empirically demonstrating that both COVID-19 and firm-level political risks are priced in equity markets. Leveraging text-based measures developed from earnings conference calls (Hassan et al., 2019; 2023), it shows that firms with higher exposure to COVID-19 and political risks earned higher quarterly returns during 2020–2021, consistent with risk compensation theory. Notably, the pricing of Covid risk was more pronounced in 2020—when uncertainty was highest—suggesting time-varying sensitivity in investor responses. Political risk, while smaller in magnitude, also displayed a positive association with returns and became more salient as policy responses intensified. These findings are robust across econometric techniques, including 2SLS and GMM estimations, and are reinforced by cross-sectional heterogeneity tests. Moreover, by comparing results across return and ROA, the study highlights the divergence between market-based and accounting-based risk assessments, indicating that Covid-related risks influenced investor sentiment more than operational efficiency. Overall, the chapter advances understanding of how informational content embedded in corporate communication reflects investor perceptions during crises and suggests that earnings calls serve as timely, forward-looking sources for pricing emergent risks under conditions of extreme uncertainty.

If political risk is priced alongside Covid risk and creates predictable mispricing or risk premia, a profitable trading strategy is possible. Investors can exploit these by designing trading strategies that anticipate market overreactions to political events, such as lockdown policies, fiscal stimulus, or international tensions. By identifying assets or sectors disproportionately affected—such as healthcare, travel, or emerging markets—and using event-driven or volatility-based trading, it is possible to generate abnormal returns. However, success depends on accurate measurement, timing, and control of tail risks.

The rest of the chapter is organised as follows. Section 5.2 provides a literature review. Section 5.3 develops testable hypotheses. In Section 5.4, I describe the data and methodology for this chapter. Section 5.5 presents empirical results. Section 5.6 presents robustness and further analysis. Finally, Section 5.7 concludes.

5.2 Literature review

One of the most important global crises of the twenty-first century, the Covid-19 pandemic—caused by the new coronavirus SARS-CoV-2—has had a profound impact on governance systems, economies, cultures, and public health around the globe. The pandemic has sparked a massive and quickly growing amount of scholarly literature across a variety of fields, including epidemiology, public health, economics, sociology, psychology, and political science, since it first emerged in late 2019. The goal of this thorough literature review is to summarise the literature on the covid focusing on our objective to examine whether the covid risk and political risk are priced during covid. First, this chapter examines the characteristics of Covid, and then how it impacted the financial markets and economies. This chapter then looked at some of the literature on how earnings conference calls are being used as soft data, and then how covid risk and political risk measures are developed based on earnings conference calls.

5.2.1 Characteristics of Covid-19

Many studies have been conducted on the epidemiological features of Covid-19 since the beginning of the pandemic, including its clinical presentations, risk factors, and dynamics of transmission. Studies have demonstrated the virus's high contagiousness, with respiratory droplets and close contact being the main modes of human-to-human transmission (Bourouiba, 2020). Additionally, studies have linked a number of variables, such as older age, underlying medical disorders, and socioeconomic disparities, to an increased risk of severe illness and fatality from Covid-19 (Wu and McGoogan, 2020).

The way that different nations and areas responded to the pandemic in terms of public health reflects variations in healthcare systems, governmental regulations, and sociocultural elements. Studies have looked into how well non-pharmaceutical measures including mask wearers, lockdowns, social distancing, and vaccination programmes work to stop the virus's spread and lessen its effects on healthcare systems (Chu et al., 2020; Flaxman et al., 2020). Furthermore, research has shown how crucial it is to implement coordinated, evidence-based public health policies to lower Covid-19-related morbidity and mortality while minimising negative social and economic effects (Gostin and Wiley, 2020).

Barrot et al. (2024) investigate the potential causal relationship between state-mandated business closures, which were imposed in response to the Covid-19 epidemic, and health and economic results. They find that these limits impose significant costs on both companies and workers, with the former carrying about two-thirds of the cost, consistent with employers partially insuring their workers. This is based on plausible exogenous fluctuations in exposure to these restrictions. They further demonstrate that compulsory company closures significantly lower death rates, especially in locations with high concentrations of contact-intensive jobs. They go over the presumptions that business closures have a greater positive impact on health than they do on the economy.

5.2.2 Impact on economies

The Covid-19 epidemic caused previously unheard-of disturbances to the world's economies, including recessions, problems in the labour market, supply chain disruptions, and generalised economic uncertainty. Studies have revealed how the pandemic affected different areas of the economy differently; sectors such as travel and hospitality, retail, and entertainment all saw notably sharp declines (Nicola et al., 2020). Furthermore, research has shown that vulnerable groups, including low-income workers, women, minorities, and those employed in the unorganised sector, have been disproportionately affected financially by the epidemic (Alon et al., 2020; McKibbin and Fernando, 2020).

In an effort to lessen the negative effects on individuals, companies, and financial markets, the government responded to the economic repercussions from the epidemic with fiscal stimulus packages, monetary policy interventions, and social protection measures (Blanchard et al., 2020). Studies have looked at how well these policy measures worked to keep jobs, stabilise economies, and keep widespread poverty and inequality at bay (Auerbach and Gorodnichenko, 2020). Additionally, research has shown that concerted international measures are required to handle the pandemic's consequences on the world economy and avoid long-term economic damage (Baldwin and Tomiura, 2020).

Social structures, relationships, and behaviours were all significantly altered by the Covid-19 pandemic, which resulted in modifications to social norms, attitudes, and practices. Studies have looked into the psychological impacts of the pandemic, such as people experiencing higher levels of stress, anxiety, depression, and loneliness (Brooks et al., 2020). Additionally, research has examined the socio-cultural drivers of Covid-19-related behaviours, including the use of masks, hand washing, and vaccination uptake, emphasising the significance of elements including societal norms, perceived risk, and government trust (Bavel et al., 2020).

Pre-existing social vulnerabilities and inequalities, such as differences in access to social support networks, work opportunities, healthcare, and education, were also brought to light and made worse by the pandemic (Van Lancker and Parolin, 2020). Studies have indicated that the epidemic had a disproportionate effect on underprivileged and marginalised groups, such as individuals with impairments, immigrants, refugees, and members of racial and ethnic minorities (Yaya et al., 2020). Additionally, research has shown how crucial it is to address social determinants of health and underlying structural disparities in pandemic response initiatives (Marmot et al., 2020).

The public's trust in government, governance frameworks, and political institutions was all severely impacted by the Covid-19 pandemic. Studies have looked at how the government handled the pandemic, including how policies were made, how they were communicated, and how political leadership affected public health outcomes (Hale et al., 2020). Additionally, research has looked into how the epidemic has affected human rights, democracy, and civil liberties. Concerns about authoritarianism, monitoring, and the deterioration of democratic norms have all been raised (Hale et al., 2021).

In order to combat risks to global health and pandemics, the pandemic also brought attention to the significance of international collaboration, multilateralism, and global governance. Scholarly investigations have examined the functions of global institutions including the World Health Organisation (WHO), the United Nations (UN), and the World Bank in terms of organising responses to pandemics, promoting the exchange of knowledge, and mobilising resources for impacted nations (Kickbusch et al., 2020). Studies on the pandemic's effects on international governance frameworks have also called for changes to improve equity, resilience, and readiness in pandemic response (Ghebreyesus, 2021).

5.2.3 Impact on Financial markets

The Covid-19 crisis caused the Treasury market to endure extreme stress and illiquidity, which was a stark contrast to most previous crisis experiences and raised concerns that the US Treasuries' standing as a safe haven may be deteriorating. He, Nagel, and Song (2022) record significant changes in Treasury holdings during this time, as well as a brief build-up of Treasury and reverse repo positions on dealer balance sheets. An exceptional context for assessing the significance of a nation's fiscal capability in elucidating the relationship between economic growth shocks and sovereign default risk is the Covid-19 pandemic. Augustin et al. (2022) demonstrate a positive and significant sensitivity of sovereign default risk for governments with limited resources to the severity of the virus's transmission for a sample of thirty wealthy nations.

Companies in global financial markets were significantly impacted by the Covid-19 epidemic (Latif et al., 2021). The market uncertainty brought on by Covid-19 led to financial instability (Latif et al., 2021; Phan & Narayan, 2020). As such, markets experienced extreme volatility (Zhang et al., 2020). The financial industry suffered the biggest losses (Herwany et al., 2021). The tourism and hotel industries saw a sharp downturn. The industries of communication services, consumer goods, industrial goods, energy, and materials were all strongly correlated with the epidemic. While there was a weak to moderate relationship between the utilities sector and those two sectors, there was a moderate association between the real estate sector and consumer staples.

Uddin et al. (2021) report that 34 countries experienced volatility as a result of Covid-19 between July 1, 2020, and August 14, 2020. They investigate whether a nation's stock market volatility is related to its economic characteristics. By linking Covid-induced volatility to national determinants, they supplement the research of Baker et al. (2020) and Fernandes (2020). They find that national characteristics help mitigate the volatility caused by Covid-19. Ramelli and Wagner (2021) analyse the cross-sectional changes in different characteristics of

US firms during the Covid-19 pandemic. They discovered that companies with an international focus initially performed worse, especially those that were more involved in trading with China. Corporate debt and cash balances were among the key performance indicators. Ramelli and Wagner (2021) analyse just US data and use cash and leverage statistics to explain US equity performance. Using analyst conference calls, they also assess the impact of Covid-19. Huang et al. (2021) find that companies with greater brand values have superior equity returns, lower market risk, and lower business risk during the coronavirus pandemic than other firms based on data from US corporations.

Ding et al. (2021) evaluate the extent of the coronavirus's effect on stock prices using data from 6,700 companies in 61 countries. The weekly stock return of certain companies over the weeks t and $t-1$ is the dependent variable employed by Ding et al. (2021). They also make use of the rise in Covid instances that is confirmed each week. Companies with a stronger capital foundation, unused credit capacity, lower leverage, lower short-term leverage, and higher profitability outperformed their rivals in terms of how the stock market responded. Furthermore, they find that businesses performed better during the pandemic whose CSR performance was stronger prior to the outbreak. But companies with more well-established executives fare worse during the pandemic.

According to Darmouni and Sutherland (2024), capital reallocation patterns across enterprises were considerably impacted by production disruptions caused by pandemics. The reduction in investment was mitigated by a spike in used capital trading activity as companies bought used capital from far-off and different rivals. Barry et al. (2022) examine the direct and combined consequences of various organisational flexibility strategies on both short- and long-term real business plans using the Covid shock. They discover that: i) workplace flexibility—that is, the ability for workers to work remotely—is crucial in shaping employers' employment strategies during the health crisis; ii) investment flexibility—which is influenced by workplace

flexibility—enables employers to raise or lower capital expenditures in response to changing business conditions; and iii) financial flexibility strengthens both employment and investment, especially in situations where fixed costs are high.

5.2.4 Earnings Conference call-based risk

A recent stream of literature develops different measures based on tone and soft information available through annual reports or earnings calls (e.g., Loughran and McDonald, 2014). These soft information-based measures are used in financial research. In this section, I describe earnings conference call-based measures. Though my topic is covid risk, first I discuss the earnings call-based climate risk measure as an example and then move to covid risk (the next section discusses covid risk in detail). Financial analysts listen to management during earnings calls and ask questions regarding recent and upcoming developments that are important to the company (Hollander, Pronk, and Roelofsen, 2010). Earnings calls are important corporate events. These calls, which usually take place every quarter, give management a vital forum for direct communication with analysts and investors. Management talks on market circumstances, strategic plans, and the company's recent financial performance during these calls. In response, analysts have the chance to pose insightful queries that can yield more in-depth information about the business's operations, difficulties, and prospects. In addition to aiding in the clarification of reported financial data, this interactive format offers qualitative data that has a major impact on stock prices and investor mood.

These metrics reflect how much management and financial analysts are paying attention to climate change issues at any particular moment. The emphasis on climate change during earnings calls is indicative of how environmental concerns are becoming more and more important in business strategy and investor decision-making. Concerning climate change, questioning from analysts can cover anything from the company's investments in sustainable technologies and adaptation plans to its carbon footprint and regulatory compliance. The

answers from management provide information about how the business views and handles the opportunities and hazards related to climate change. This conversation can demonstrate the business's dedication to sustainability and its readiness to deal with the changing market and regulatory environments.

These metrics have the advantage of reflecting "soft" data that comes from manager and analyst information exchanges. Earnings call talks offer qualitative insights that can be just as relevant as hard data, if not more so, than quantitative indicators of success seen in financial statements. The tone in which management speaks, the focus on particular concerns, and the subtleties of the exchanges between analysts and management are all considered forms of soft information. When evaluating the firm's future prospects, these qualitative factors might provide insight into management's confidence, strategic priorities, and reaction to evolving trends.

I utilise recent work that uses quarterly earnings calls as a source to identify organisations' varied risks and opportunities in order to create the covid and political risk exposure metrics (Hassan et al., 2019, 2021, 2023, 2024). These studies have shown how useful it is to examine the substance of earnings calls in order to determine how exposed a company is to particular problems. Researchers can determine the firm's emphasis and level of concern on a given topic by analysing the percentage of an earnings call discourse that is related to that topic. This approach offers a timely and dynamic exposure metric that can be adjusted every quarter to account for the most recent advancements and changes in the strategic priorities of the company.

To sum up, earnings calls are significant events that provide a wealth of qualitative information from the discussions between management and financial specialists. By analysing the topics discussed in these discussions, particularly those pertaining to climate change, one may discover a lot about how exposed a corporation is to environmental risks and opportunities.

This technique offers a timely and nuanced insight of how firms are navigating the complex landscape of climate change by exploiting the soft information offered on these calls. Measures constructed from earnings calls are highly valuable as they capture real-time, forward-looking insights directly from corporate decision-makers, reflecting firms' actual concerns and risk perceptions. Unlike static textual sources, earnings calls allow for dynamic interaction between management and analysts, enabling richer sentiment and risk assessments. However, these measures may be subject to managerial bias or strategic tone management, which can influence the objectivity of the information conveyed.

5.2.5 Disasters, shocks and Covid Risk

Understanding how supply shocks spread throughout firms has advanced significantly in recent years, especially in the setting of natural disasters. The studies of Barrot and Sauvagnat (2016), Boehm et al (2019), and Carvalho et al. (2021) have made significant contributions to this field. These studies have tracked and measured the propagation of shocks through supply chains by utilising incredibly precise data on customer-supplier networks and accounting records. Their research has shed important light on the interdependence of contemporary supply chains and the potential for vulnerabilities to develop in the event of disruptions. Pagano et al (2023) demonstrate that asset markets assign a time-varying price to firms' disaster risk exposure using the Covid-19 pandemic as a test case. The variance in the stock returns throughout the cross-section revealed how differently the firms were exposed to the epidemic based on how vulnerable they were to social distancing. The realised and expected return differentials moved in opposing directions, first broadening and then shrinking, as predicted by theory.

Though these approaches are useful, those approaches have several important drawbacks. The main difficulty is that very specific data must be obtained. Researchers need detailed information on customer-supplier relationships and firm-level accounting data in order to effectively quantify how supply shocks propagate across enterprises. This information is

frequently hard to come by, necessitating close collaboration from businesses and perhaps being accessible only through proprietary databases. Furthermore, even in cases where this kind of data is available, it usually has significant time lags, which means that researchers may only examine occurrences long after they have taken place. The findings' practical usefulness for prompt decision-making and responsiveness is limited by this delay.

In order to overcome these drawbacks, Hassan et al. (2023) presented a novel and adaptable technique for calculating the businesses' varying exposure to significant shocks.⁴ Because it offers near real-time insights, this strategy is a substantial development over previous systems that rely on trailing data. Making quick, well-informed decisions is critical, especially when faced with unforeseen disruptions. This requires having access to real-time information. The versatility of Hassan et al.'s technique in assessing various consequences is one of its most notable qualities. Their approach is able to identify whether a company's main concerns are related to supply, demand, or other factors related to Covid. This degree of information paints a complete picture of the possible vulnerabilities and areas of concern and enables a more nuanced understanding of how organisations are affected by different kinds of shocks.

5.2.6 Firm-level political Risk

A significant body of research shows how risk and uncertainty about political system shocks impact asset prices, global capital flows, investment, job creation, and the business cycle. Scholars such as Belo, Gala, and Li (2013), Handley and Limão (2015), Gourio, Siemer, and Verdelhan (2015), Kelly, Koijen, Philipson, and Uhlig (2016), Pástor, and Veronesi (2013), Besley and Mueller (2017), Mueller, Tahbaz-Salehi, and Vedolin (2017) have all made

⁴ For details, please refer to my methodology section. Also see Hassan et al. (2023) for measure of the Covid risk, the bag of words and how they validate their measures.

substantial contributions to this field. Together, these studies demonstrate how political risk can affect economic factors and corporate operations in a significant way.

Belo et al. (2013) provide empirical evidence on the effects of political risk on asset prices using a huge dataset spanning many different countries and asset types. Gourio et al. (2015) investigate how political risk affects and disperses across international capital flows. Handley and Limao (2015) investigate the impact of political risk on foreign direct investment (FDI) flows using firm-level data from multinational corporations operating in emerging economies. Kelly et al. (2016) examine the connection between political risk and corporate investment decisions using data on capital expenditures and investment plans from enterprises.

Koijen et al. (2016) examine the relationship between political risk and the business cycle using a dynamic stochastic general equilibrium (DSGE) model with endogenous political shocks. Besley and Mueller (2017) examine the impact of political risk on government contracting and public-private partnerships (PPPs) using data from infrastructure projects and procurement contracts. Mueller et al. (2017) investigate how political risk affects asset allocation decisions and portfolio performance using data from international bond and equity markets.

This literature has depended on different approaches to capture the consequences of political risk because there isn't a direct way to measure it. Using country-level indices to find variations in sector- and aggregate-level political risk is a popular strategy (Giambona et al. 2017). By gathering information on national political events, policies, and stability indicators, these indices offer a comprehensive assessment of political risk. Furthermore, event studies are widely used to examine how certain political events—such as elections, declarations of policy, or geopolitical crises—affect economic results. These studies evaluate how political shocks affect financial markets and economic activity in the short and immediate term.

Examining how different sectors are exposed to changes in government procurement is another technique (Giambona et al. 2017). Researchers can determine the degree of political risk that various companies experience by examining how changes in contracts and rules influence some industries more than others. This method is especially helpful for comprehending the effects of regulatory changes and government spending on sectors of the economy that significantly depend on public contracts.

An important measure of aggregate economic policy uncertainty in the United States created by Baker et al (2016) has been the basis for numerous subsequent studies. By counting the number of newspaper stories that address economic policy uncertainty, this index calculates the degree of economic policy uncertainty. It offers a thorough and ongoing assessment of political risk, allowing for the analysis of its impacts over time and in various situations. In the literature, the Baker, Bloom, and Davis index is now a common tool for examining how political risk affects economic results.

In contrast to previous research, Hassan et al (2019) offer a flexible deconstruction into topic-specific components as well as the first firm-level measure of political risk, enabling a significant differentiation between aggregate, sector-level, and firm-level exposure. This innovative method allows for a more detailed examination of the ways in which political risk impacts individual enterprises as opposed to depending only on sector- or aggregate-level data. By breaking down political risk into distinct areas, such as trade policy, regulatory changes, or geopolitical conflicts, one may gain a deeper understanding of the complex ways that various political risk factors affect businesses. Because enterprises may identify and mitigate specific political risks that are most relevant to their operations, this firm-level metric also enables more precise risk management and strategic planning.

Though there exists a large literature on Covid, there are many unanswered questions in the literature. For instance, was Covid-19 risk priced in the market? Is political risk priced

in the financial markets during Covid-19? I develop hypotheses based on the gaps in the literature in the next section.

5.3. Hypothesis Development

Using both conventional macroeconomic analysis and epidemic modelling, researchers have adopted a multidisciplinary method to investigate the effects of policy measures during the Covid-19 pandemic. Proponents of the integration of epidemic models, which clarify the dynamics of illness transmission, with macroeconomic models, which quantify the wider economic impacts of policy interventions, include Atkeson (2020) and Eichenbaum, Rebelo, and Trabandt (2021). Through the integration of these techniques, scholars can acquire a thorough comprehension of the ways in which governmental interventions intended to curb the transmission of Covid-19 impact economic consequences.

Moreover, Ding et al. (2021) measure shifts in the economy's pandemic exposure using empirical data on Covid-19 cases. They evaluate the degree to which changes in infection rates affect different economic sectors using advanced statistical analysis, providing insight into the intricate relationship between public health outcomes and economic activity. This method offers insightful information about how the pandemic affects different industries and geographical areas, which helps policymakers decide how best to allocate resources and implement intervention measures.

A substantial amount of research has been conducted on certain policy responses to the Covid-19 pandemic, with an emphasis on policies such as lockdowns, social distancing laws, and fiscal stimulus plans. Barro, Ursúa, and Weng (2020) use epidemiological models to simulate various scenarios and evaluate the effects on public health outcomes as they examine how well social distancing measures work to stop the virus's transmission. Their results highlight the need of prompt and strict actions in reducing the spread of Covid-19 and preventing overcrowding in the healthcare system.

In a similar vein, research conducted by Alon et al. (2020), Arnon, Ricco, and Smetters (2020), Kaplan, Moll, and Violante (2020), and Moser and Yared (2020) examines the financial effects of lockdowns implemented in reaction to the pandemic. These assessments investigate the trade-offs between the goals of public health and economic activity, looking at how different levels of restriction impact important economic metrics including output, employment, and consumption. The goal of the study is to provide policymakers with evidence-based recommendations on how to strike a balance between health concerns and economic imperatives by estimating the costs and advantages of lockdown rules.

In addition, how governments across the globe offered monetary assistance to companies that had been negatively impacted by the pandemic has come under a great deal of criticism. Joaquim and Netto (2020) examine loan disbursement and employment trends data to assess the PPP's efficacy in protecting jobs and assisting small enterprises. Their research provides insights into the opportunities and difficulties involved with government intervention in the economy, contributing to ongoing discussions regarding the best way to plan and carry out fiscal stimulus measures during times of crisis.

Stephany et al. (2022) add a great deal to the body of literature by tracking the development of Covid-19-related subjects at the industry and aggregate levels through text analysis of 10-K filings. Their method provides insightful information about how businesses in many industries addressed the difficulties brought on by the pandemic. Their analysis, while offering a comprehensive summary of Covid-19 discourse trends in corporate filings, does not, however, go into detail on the identification of exogenous shocks or their particular effects on individual enterprises. Conversely, Davis, Hansen, and Seminario-Amez (2021) concentrate on the connection between firm-level returns during periods of severe market volatility and pre-pandemic risk disclosures in 10-K filings. To determine which text-based risk categories influence firm-level return reactions to the Covid-19 shock, they examine risk factors in 10-K

filings made before the pandemic. Their research clarifies the degree to which a company's pre-existing risk exposures affect its ability to withstand or be vulnerable to unanticipated shocks such as the Covid-19 pandemic.

By using natural language processing (NLP) tools to analyse the content of quarterly earnings calls and identify the worries raised by both company management and non-corporate participants around covid, Hassan et al (2023) expand on previous research in this area. In contrast to earlier research that exclusively relies on textual analysis of regulatory filings, their methodology enables a more complex and dynamic understanding of how businesses are addressing the pandemic's problems in real time. Furthermore, by looking at a wide panel of listed companies from all around the world, their research offers global perspectives that go beyond national borders and give a thorough understanding of how the pandemic has affected business performance and behaviour. Their method's capacity to capture the dynamic character of Covid-19-related speech as it develops over time is one of its main advantages. One may be able to monitor shifts in how companies view the pandemic and how it affects their operations, strategy, and outlook by examining quarterly earnings calls. With this real-time view, can spot new trends, evaluate the success of governmental measures, and predict what obstacles businesses may face in the wake of the pandemic.

Additionally, Hassan et al. (2023) add to the body of knowledge by analysing the indirect effects of the pandemic on business performance as well as the direct effects that are mediated by shifts in investor behaviour, market mood, and macroeconomic conditions. They are able to reveal minute differences in corporate managers' and other participants' views and attitudes towards the pandemic by using natural language processing (NLP) techniques to examine the language they use during earnings calls. This allows us to gain important insights into the underlying mechanisms guiding firm-level responses to the crisis.

Financial markets experienced unprecedented levels of uncertainty and volatility due to the Covid-19 pandemic. This volatility was caused by a number of variables, including changing public health measures, erratic infection rates, and unknown economic repercussions. Due to the increased risk of asset price changes, capital losses, and portfolio underperformance, it was imperative that investors consider Covid-19 risk when making investment decisions (Baker et al., 2020). Significant financial repercussions of the Covid-19 pandemic included supply chain disruptions, recessions, and alterations in consumer behaviour. These macroeconomic shocks had a substantial impact on the cash flows, profitability, and revenue streams of businesses, which in turn affected the stock prices and valuations of those companies. Investors might take into consideration the possible negative impact of the pandemic on company profits and financial performance by pricing Covid-19 risk (Bauer et al., 2020).

The impact of Covid-19 risk on share price returns can be either positive or negative, depending on the sector, firm-specific factors, and market perception. On the negative side, heightened Covid-19 risks often translate into economic uncertainty, reduced consumer spending, and disrupted supply chains (Ding et al., 2021). These factors can adversely affect firms in industries such as travel, hospitality, and manufacturing, leading to lower revenues and investor confidence. Firms with higher debt levels or weak financial structures are particularly vulnerable, as market participants may perceive them as less likely to weather the crisis, resulting in declining share prices (Ramelli & Wagner, 2020).

Conversely, the impact can be positive for firms that adapt to pandemic-driven opportunities or operate in sectors that benefit from the crisis. Technology companies, for instance, experienced significant share price gains during the pandemic as demand for remote work solutions, e-commerce, and digital entertainment surged (Baker et al., 2020). Similarly, pharmaceutical and healthcare firms saw positive returns due to their role in combating the virus through vaccine development or treatment innovation. Additionally, government

stimulus measures and monetary easing bolstered overall market sentiment, creating tailwinds for certain stocks despite pandemic risks (Albuquerque et al., 2020).

In summary, the Covid-19 risk affects share price returns asymmetrically, with outcomes varying based on industry dynamics, firm adaptability, and broader economic conditions. Investors can limit sector-specific vulnerabilities by adjusting their sectoral allocations and portfolio diversification methods based on the pricing of Covid-19 risk (Altig et al., 2020). The Covid-19 pandemic is an example of a tail risk event, meaning that while it is unlikely, it could have disastrous effects. By pricing Covid-19 risk, investors could take tail risk scenarios into consideration and implement risk management techniques including portfolio hedging, diversification, and downside protection. Hence, I hypothesise that:

H1a. Covid risk is positively related to the share price returns during the Covid-19 pandemic.

H1b. Covid risk is negatively related to the share price returns during the Covid-19 pandemic.

Asset prices, capital flows, investment decisions, and macroeconomic results are significantly influenced by political risk, which is defined as uncertainty around laws, regulations, and geopolitical events. An increasing corpus of research has shown how political risk significantly affects financial markets and the whole economy, emphasising how important it is for investors, firms, and politicians to comprehend and properly manage these risks. This chapter will cover the main conclusions and research approaches of a few chosen studies that investigate the connection between political risk and other economic factors.

Belo et al. (2013) and Mueller et al. (2017) both explore the relationship between political risk and financial markets, yet they differ in scope and emphasis, offering complementary insights into how political uncertainty affects asset prices and investment decisions. While Belo et al. focus on macro-level impacts across a broad range of nations and asset classes, Mueller et al. examine portfolio-level implications, emphasizing the role of

investor behaviour and asset allocation dynamics. Both studies underscore the significant impact of political risk on financial markets. Belo et al. (2013) highlight the broader macroeconomic consequences, finding that political risk correlates with higher volatility, elevated risk premiums, and lower stock market values. Similarly, Mueller et al. (2017) reveal that political uncertainty drives risk premiums upward, depresses asset values, and increases portfolio volatility. Both studies emphasize that political uncertainty reshapes investor preferences and decisions, demonstrating that heightened risk perceptions lead to demand for higher returns, which can hinder economic growth and market stability.

Additionally, the importance of political risk in shaping asset pricing is a shared theme. Belo et al. (2013) stress the need to integrate political risk into asset pricing models to account for its pervasive effects on market performance. Similarly, Mueller et al. (2017) contribute to the understanding of political risk management by examining its time-varying and geographically diverse effects, thereby enriching the broader literature on risk and returns. Together, these studies underscore the multifaceted nature of political risk and its importance for both macroeconomic stability and portfolio management. Belo et al. (2013) offer a foundation for understanding the broad economic consequences of political risk, while Mueller et al. extend this knowledge by illuminating the diverse and dynamic ways in which investors respond to such uncertainty. Bridging these perspectives would provide a richer, more comprehensive understanding of political risk, encompassing both market-level and investor-specific dynamics.

Gourio et al. (2015) and Handley and Limao (2015) both explore the adverse effects of political risk on capital flows but do so at different levels of analysis, offering complementary insights into the phenomenon. Gourio et al. (2015) focus on macro-level impacts, examining how political uncertainty drives global capital outflows from high-risk nations to safer havens. Their findings highlight systemic effects, such as currency devaluation, increased borrowing

costs, and the contagion of political risk across nations, which amplifies shocks in international financial markets. This study underscores the interconnectedness of global markets and the need for coordinated risk management and policy responses. In contrast, Handley and Limao (2015) adopt a micro-level perspective, investigating how political risk affects firm-specific foreign direct investment (FDI) decisions in emerging markets. They reveal that heightened political unpredictability deters FDI inflows, particularly in sectors like infrastructure and extractive industries that are more sensitive to regulatory and political instability. Their analysis highlights the role of institutional quality and political stability in attracting foreign capital and promoting economic growth.

Kelly et al. (2016), Koijen et al. (2016), and Besley and Mueller (2017) all examine the effects of political risk but focus on different dimensions and levels of economic activity, offering complementary insights. Kelly et al. (2016) explore the firm-level impact, showing how political unpredictability leads businesses to delay capital projects, reduce expenditures, and adopt conservative financial practices, with smaller and financially constrained firms being particularly vulnerable. Similarly, Besley and Mueller (2017) examine political risk's impact on investment but focus on the public sector, finding that infrastructure projects and public-private partnerships (PPPs) suffer from delays, cost overruns, and cancellations due to unclear regulatory frameworks. Both studies emphasize how political risk disrupts long-term investment, though Kelly et al. (2016) focus on corporate behaviour, while Besley and Mueller (2017) highlight the critical role of governance reforms in mitigating investment barriers in the public domain.

In contrast, Koijen et al. (2016) adopt a macroeconomic perspective, using a Dynamic Stochastic General Equilibrium (DSGE model) to show how political risk amplifies business cycle fluctuations, leading to higher volatility, reduced output growth, and increased unemployment. While Kelly et al. (2016) and Besley and Mueller (2017) emphasize the

disruptive effects of political uncertainty on investment decisions, Koijen et al. focus on the broader systemic challenges political risk poses to economic stability. Furthermore, Koijen et al. (2016) reveal the limited effectiveness of countercyclical policies in mitigating these shocks, underscoring the need for proactive risk management. Taken together, these studies provide a comprehensive understanding of political risk, from its firm-level and sectoral effects to its broader implications for the economy, while collectively emphasizing the importance of governance stability and effective policy responses to mitigate its adverse consequences.

To mitigate the economic and public health impacts of the Covid-19 crisis, governments introduced unprecedented levels of policy interventions. Businesses faced an environment marked by significant ambiguity regarding potential changes to regulations, tax laws, trade barriers, and government assistance programs. This heightened uncertainty likely led investors to demand higher risk premiums to compensate for their exposure to political risk, thereby influencing firms' profitability, growth prospects, and investment decisions (Baker et al., 2020). Governments responded to the Covid-19 pandemic by enacting emergency protocols and amending regulations in order to support impacted businesses, address public health issues, and stabilise the financial system. Businesses that operated in regulated industries including healthcare, pharmaceuticals, banking, and energy had to adjust to these regulatory changes. For instance, regulatory control and stricter capital requirements were imposed on financial institutions, while pharmaceutical businesses were subject to more scrutiny and regulation in the production and sale of drugs. Stock prices and valuations fluctuated as a result of the uncertainty around regulatory changes, which may also affect a firm's compliance costs, market access, and competitive positioning (Bhanot et al., 2021).

The Covid-19 pandemic showed weaknesses in international supply chains, causing interruptions that had an impact on businesses in a range of industries. Transportation limitations, labour shortages, border closures, and production bottlenecks are a few examples

of the variables that caused supply chain disruptions. Businesses that depend significantly on foreign commerce and sourcing may be more vulnerable to political risk as a result of supply chain interruptions. Furthermore, companies functioning in politically volatile areas or nations with inadequate governance frameworks can encounter supplementary difficulties in managing supply chain interruptions, prompting investors to reduce the value of their stocks to account for elevated risk levels (Altig et al., 2020).

Geopolitical tensions increased as a result of the Covid-19 epidemic, with nations vying for access to vital medical supplies, vaccines, and strategic resources. Companies operating in impacted areas or industries faced risks as a result of geopolitical tensions that can intensify into trade disputes, sanctions, and military engagements. Technology businesses faced limitations on their exports to specific nations, whilst energy corporations experienced interruptions in their supply of oil and gas as a result of geopolitical disputes. The price of firm-level political risk was impacted by investors reevaluating their risk exposures and modifying their investment portfolios in response to the unpredictability of geopolitical developments (Burger et al., 2021).

Governments implemented fiscal stimulus packages, industrial bailouts, and liquidity support programmes in response to the Covid-19 epidemic, in an effort to lessen the crisis's negative economic effects. Access to capital markets, liquidity positions, and the financial health of businesses were all impacted by these government support initiatives. For instance, limitations on share buybacks, dividend payments, and executive remuneration were applied to companies receiving government assistance, which had an impact on stock prices and valuations. Furthermore, the pricing of firm-level political risk was impacted by the sustainability of government support programmes as well as the possibility of policy reversals or austerity measures (Berg et al., 2020).

Political risk can significantly disrupt economic and business activities, particularly in environments marked by uncertainty. Heightened political instability—such as regulatory changes, trade restrictions, social unrest, or abrupt policy shifts—discourages foreign direct investment (FDI) and capital inflows. Investors and businesses may perceive these risks as threats to returns and operational stability, leading to reduced investment and economic stagnation. For instance, firms facing high political risk often delay capital projects, curtail expenditures, and adopt conservative financial practices to mitigate potential losses. This cautious behavior, in turn, hampers economic growth and innovation. Political uncertainty also contributes to higher risk premiums and borrowing costs, impacting both businesses and governments. Additionally, political risk spillovers can trigger broader economic disruptions, including capital flight, currency devaluation, and contagion effects in global financial markets.

While often viewed negatively, political risk can present opportunities for investors and businesses that effectively navigate and manage such uncertainties (Bremmer, 2005). Political transitions, for example, may create openings for industries poised to benefit from new policies or regulatory frameworks. Investors with robust risk management strategies may exploit mispriced assets in volatile markets, achieving higher returns as compensation for taking on greater risk. Political uncertainty also drives demand for financial products like credit default swaps or hedging instruments, fostering innovation in financial markets. Moreover, the presence of political risk often incentivizes governments and institutions to undertake reforms, improve governance, and stabilize regulatory environments to attract investment and economic activity. For businesses with the capacity to adapt to uncertain political climates, such environments may offer a competitive edge over less agile competitors.

Hence it is an empirical question to fully comprehend the dynamics of firm-level political risk and how it affects market outcomes and investment choices in a world that is becoming more complicated and unpredictable. Thus, I propose:

H2a: Firm-level political risk is positively related to share price returns during times of Covid-19.

H2b: Firm-level political risk is negatively related to share price returns during times of Covid-19.

5.4. Data and Methodology

5.4.1 Data

I use US stock returns data at the quarterly level. The reason for using quarterly stock returns is that the firm-level covid risk and firm-level political risk data are provided at the quarterly intervals. I use firm-level covid risk data from Hassan et al (2023) and I use firm-level political risk data from Hassan et al (2019). All other variables are obtained from the Compustat database. For the purpose of creating their metrics of firm-level exposure to epidemic diseases, Hasan et al (2023) utilise transcripts of quarterly earnings conference calls conducted by publicly traded companies. Hassan et al (2019) developed the measure of firm-level political risk based on transcripts of earnings conference calls. These measures are available for US firms. My sample includes 13,149 unique firms, and I use quarterly data from 2020-2021 during the covid period, 31,280 firm-quarter observations.

5.4.2 Methodology

To calculate the quarterly returns, I use the following formula⁵:

$$R_{i,t} = \frac{P_{i,q} - P_{i,q-1}}{P_{i,q-1}} \quad (1)$$

Where, $R_{i,t}$ is the quarterly return, $P_{i,q}$ is the price at quarter q, and $P_{i,q-1}$ is the price at the previous quarter.

⁵ For robustness checks, I calculate CAPM, Fama-French 3 factors and Fama-French 5 factor model adjusted returns and rerun regressions.

To test hypotheses 1, I run the following ordinary least square (OLS) model:

$$R_{i,t} = \alpha + \beta \text{FCrisk}_{i,t} + V_v + \theta_t + \theta_s + \varepsilon_{i,t} \quad (2)$$

I use quarterly return ($\text{Return}_{i,t}$) as in Hassan et al (2023); Firm-level covid risk ($\text{FCrisk}_{i,t}$) is decomposed into three risks as in Hassan et al (2023)— Covid-19 exposure, sentiment, or risk score.⁶ After compiling their list of disease words, Hassan et al (2023) create a time-varying measure of a firm's exposure to Covid-19, called Covid exposure, by calculating the frequency with which the synonyms for Covid-19 are used. Then, in order to account for variations in transcript length, they divide this figure by the total amount of words in the transcript. They also create metrics of sentiment and risk, called $\text{Sentiment}_{i,t}$ and $\text{Risk}_{i,t}$, respectively, based on this epidemic illness exposure measure (Hassan et al. 2023). In particular, $\text{Risk}_{i,t}$ limits the count to terms that are synonymous with risk or uncertainty: it counts only terms (or word combinations) associated with Covid disease that occur within ten words of each other before and after the synonym. $\text{Risk}_{i,t}$ could be interpreted as a measure of the risk firm i associates with the spread of covid at time t.

In order to show the relationship between positive (negative) Covid-19 news and returns, Hassan et al (2023) additionally divided Covid-19 sentiment i,t into a negative and positive sentiment variable. Sentiment counts the words associated with the disease in a manner similar to that of Risk. The first moment is captured by counting positive-minus negative-tone words surrounding the mention of the disease, as opposed to conditioning on terms related to risk (i.e., the second moment). As a result, this study also divides Sentiment into Negative Sentiment and Positive Sentiment in later analysis by just conditioning on terms that convey positive or negative sentiment, respectively.

Text-based measures were developed by Hassan et al (2023) to assess the main concerns of listed corporations related to the spread of Covid-19, SARS, and H1N1. They

⁶ The data is downloaded from [Firm-level risk \(firmlevelrisk.com\)](https://firmlevelrisk.com)

textually break down the impact of an outbreak on a firm's supply and demand, as well as which firms profit or lose from it. This work is different from the literature in several aspects. Hassan et al (2023) looked at previous pandemics like SARS, H1N1. I focus only on covid and provide a deeper analysis of Covid. Second, I examine whether the Covid risk developed based on the earnings calls is priced in all the waves of Covid. I extend Hassan et al's (2023) analysis including the full covid period and all the waves of Covid.

The vector $\mathbf{V}_v$ includes my standard set of control variables (at quarterly level), and includes firm size, cash ratio, debt ratio, fixed assets ratio and capital expenditure. Larger firms tend to have more diversified operations, better access to capital markets, and lower volatility, which can influence returns and risk exposure (Fama and French, 1992). High cash holdings indicate greater liquidity, which may buffer against external shocks such as COVID-19 or political risk (Ding et al., 2021). Leverage affects a firm's risk profile and financial constraints. More indebted firms may face higher risk premiums and greater sensitivity to shocks (Ding et al., 2021). The fixed asset ratio indicates the proportion of tangible, long-term assets. Asset-heavy firms may be less agile and more exposed to operational disruptions. I use firm fixed effects and cluster the standard errors by industry. I expect the β to be positive (negative) and significant if H1a (H1b) is supported.

To test hypotheses 2, this study runs the following ordinary least square (OLS) model:

$$Return_{i,t} = \alpha + \beta FPrisk_{i,t} + \mathbf{V}_v + \theta_t + \theta_s + \varepsilon_{i,t} \quad (3)$$

I use the quarterly return ($Return_{i,t}$) following Hasan et al (2023). I use the information of data date (quarter date) from Hasan et al. (2023) to identify the quarter to calculate the stock returns for that quarter I continue to use St_PRisk_{it} as a measure of the proportion of conversation devoted to risks associated with political issues, accounting for the fact that some text passages are related to politics, and Hassan et al (2019) calculate it using a weighted rather

than a straight sum of bigrams (a pair of consecutive written units such as letters, syllables, or words).

In order to analyse the relationship between favourable (unfavourable) political news and returns, this study follows Hassan et al (2019) and additionally divided firm-level political sentiment $_{i,t}$ into a negative and positive sentiment variable. By counting the usage of political bigrams but not non-political bigrams and conditioning on proximity to positive and negative words instead of synonyms of risk or uncertainty, Hassan et al (2019) measure variation in the mean of the firm's political shocks using the same process as in the creation of political risk.

The vector $\mathbf{V}_v$ includes our standard set of control variables as described above. Fixed effects are included at the quarter (θ_t) and two-digit SIC sector (θ_s) levels. In all regressions, firm-level clustering is used to obtain robust standard errors. I expect the β to be positive (negative) and significant if H1a (H1b) is supported.

Hassan et al (2019) examine whether firm-level political risk is priced in the cross-section of stock returns. I extend Hassan et al (2019) by examining whether firm-level political risk is priced during Covid. Hence my study is very different from Hassan et al (2019). When Hassan et al (2019) was published, there was no covid. Hence, they did not examine whether political risk is priced during Covid. In their subsequent paper, Hassan et al (2023) examined Covid-19, SARS, and H1N1, not firm-level political risk.

5.4.3 Variables

The main dependent variable in this chapter is quarterly returns for individual firms for 2020-21, hence eight quarterly stock returns. In robustness analysis, return on assets (ROA) is used as an alternative measure. The main independent variables are firm-level covid risk (Hassan et al 2023) and firm-level political risk (Hassan et al, 2019). I use a number of control variables following the previous literature, like size, cash, leverage, PPE, capex, intangibles. I also use a number of corporate finance activities like mergers, dividend payments, net debt issuance,

buyback. Finally, Covid risk and political risk are normalised to have a mean of 0 and a standard deviation of 1 to facilitate comparison with each other.

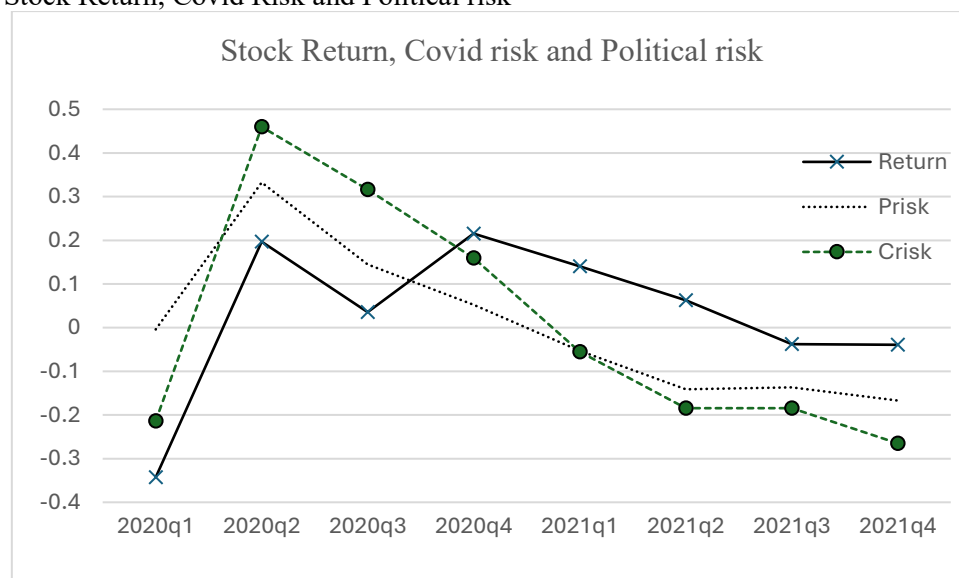
5.5. Empirical results

5.5.1 Descriptive analysis

Figure 1 plots the quarterly returns for eight quarters of 2020-21 (from the first quarter of 2020 to the last quarter of 2021). The results show that while the returns were the lowest in the first quarter of 2020, they gradually rebounded and became positive after the first quarter of 2020. The returns are negative again in the last two quarters of 2021.

The figure also shows that firm-level covid risk and firm-level political risk also move positively in line with the returns. This figure suggests a positive relationship between returns and firm-level covid risk and firm-level political risk.

Figure 1. Stock Return, Covid Risk and Political risk



The figure plots the quarterly returns for eight quarters of 2020-21 (the Y axis is returns, covid and political risk and x axis represents year-quarters). Covid risk (St_Crisk) and political risk (St_Prisk) are normalised to have a mean 0 and a standard deviation of 1.

Then I look at the descriptive statistics of all the variables. I report the number of observations, mean, median, standard deviation, 5th percentile and 95th percentile for all the variables. I find that the average (median) returns for both periods are positive. The average ROA is negative for 2020 but becomes positive in 2021. The initial effect of covid 19 is visible in the operating performance of the companies, measured through ROA. The Covid exposure and risk both are higher in 2020 as expected, but lower in 2021. This shows the severity of Covid at the beginning. The political risk is also higher in 2020 compared to 2021. Also, all the categories of political risk show a higher value in 2020 compared to 2021.

Table 1. Descriptive statistics

	2020 (N=15,452)			2021 (N=16,212)			Total (N=31,664)		
	mean	p50	sd	mean	p50	Sd	mean	p50	sd
Return	0.0276	0.0241	0.4125	0.0304	0.0024	0.2509	0.0290	0.0093	0.3395
CAPM adj returns	0.0227	0.0547	0.4542	0.0129	0.0161	0.2761	0.0177	0.0297	0.3738
FF3 adj returns	0.1055	0.0905	0.3521	0.0016	-0.0104	0.2534	0.0523	0.0396	0.3099
FF5 adj returns	0.1182	0.1053	0.3522	-0.0388	-0.0348	0.2674	0.0378	0.0241	0.3214
roa	-0.0049	0.0075	0.0740	0.0006	0.0098	0.0631	-0.0021	0.0086	0.0687
st_covid_exposure	0.2437	-0.0081	1.0964	-0.2322	-0.4961	0.8348	0.0000	-0.3077	1
st_covid_risk	0.1817	-0.4567	1.1756	-0.1731	-0.4567	0.7579	0.0000	-0.4567	1
st_covid_pos_sentiment	0.1330	-0.2320	1.0931	-0.1267	-0.6565	0.8840	0.0000	-0.3619	1
st_covid_neg_sentiment	0.2269	-0.1230	1.1524	-0.2162	-0.4844	0.7691	0.0000	-0.3417	1
st_covid_net_sentiment	-0.1502	0.2711	1.1564	0.1431	0.2711	0.7979	0.0000	0.2711	1
st_pexposure	0.1312	-0.1686	1.0691	-0.1251	-0.3721	0.9120	0.0000	-0.2860	1
st_prisk	0.1037	-0.2114	1.0566	-0.0989	-0.3556	0.9323	0.0000	-0.2896	1
st_psentiment	-0.2529	-0.3455	1.0244	0.2411	0.1943	0.9131	0.0000	-0.0246	1
st_npsentiment	-0.1656	-0.2881	0.9811	0.1578	0.1081	0.9924	0.0000	-0.0616	1
st_netsentiment	-0.2839	-0.2645	1.0167	0.2706	0.2659	0.9044	0.0000	0.0181	1
st_priskt_environment	0.0838	-0.1499	1.2133	-0.0799	-0.2539	0.7328	0.0000	-0.2105	1
st_priskt_trade	0.0841	-0.1349	1.2714	-0.0802	-0.2136	0.6320	0.0000	-0.1811	1
st_priskt_institutions	0.1021	-0.1755	1.1023	-0.0973	-0.3085	0.8807	0.0000	-0.2511	1
st_priskt_health	0.0841	-0.1628	1.1407	-0.0801	-0.2562	0.8365	0.0000	-0.2149	1
st_priskt_security	0.1249	-0.1663	1.1093	-0.1190	-0.3471	0.8668	0.0000	-0.2680	1
st_priskt_tax	0.1004	-0.1702	1.0648	-0.0957	-0.3086	0.9240	0.0000	-0.2480	1
st_priskt_technology	0.1075	-0.1849	1.0993	-0.1024	-0.3357	0.8831	0.0000	-0.2711	1
Lnassets	7.6036	7.6213	2.1938	7.6453	7.6201	2.1517	7.6250	7.6209	2.1724
cashratio	0.1999	0.1092	0.2279	0.2215	0.1209	0.2463	0.2110	0.1149	0.2377
ppe	0.2311	0.1306	0.2523	0.2101	0.1102	0.2414	0.2203	0.1202	0.2470
acquisitions	0.0078	0.0000	0.0380	0.0143	0.0000	0.0524	0.0112	0.0000	0.0460
intangibles	0.1743	0.0734	0.2127	0.1778	0.0747	0.2170	0.1761	0.0740	0.2149
capex	0.0163	0.0077	0.0251	0.0169	0.0068	0.0294	0.0166	0.0073	0.0274
div	0.0081	0.0000	0.0215	0.0084	0.0000	0.0301	0.0083	0.0000	0.0262
netdebt issuance	0.0141	0.0000	0.0877	0.0051	0.0000	0.0930	0.0095	0.0000	0.0906
buyback	0.0000	0.0000	0.0006	0.0000	0.0000	0.0005	0.0000	0.0000	0.0005

Table 1 reports the descriptive stats for 2020, 2021 and the full sample. All the variables are defined in Appendix 1.

All the control variables show slightly higher values in 2020 as compared to 2021. This is because of Covid it took some time to have an impact on the control variables.

5.5.2 Is Firm-level Covid risk priced during Covid?

Earnings calls are important occasions that offer a plethora of qualitative data from the conversations between financial experts and management. Through an analysis of the subjects covered in these talks, especially those related to covid risk, I can learn a great deal about a company's exposure to covid risk. By taking use of the soft information provided on these calls, this technique provides a timely and nuanced understanding of how businesses are managing the intricate world of covid risk.

In this section, I examine whether firm-level covid risk was priced during the Covid-19. I examine the whole of the Covid period, 2020-2021 and then test whether the effect is similar in 2020 as compared to 2021 using a dummy variable for 2020 (D2020). I define D2020 equals to 1 if the returns are in 2020 and 0 otherwise. The results for the whole of the Covid are reported in Table 2. I use firm fixed effects and cluster the standard errors by industry. The results show that all the Covid risk measures are positively related to returns during the whole of the covid period. This supports H1a. This demonstrated the fundamental principle of finance: The higher the risk the higher the returns. A one standard deviation of covid exposure is associated with a 0.061 increase in returns. The economic magnitude of COVID-19's impact on the stock market is considerable, as evidenced by the strong and significant relationship between most COVID-related risk measures and stock returns. However, the only exception is the COVID net sentiment variable, which shows a negative association with returns. This likely arises from the construction of the net sentiment measure itself, which is derived by subtracting negative sentiment from positive sentiment within earnings calls. During the pandemic, the overall tone in corporate communications was more pessimistic, resulting in a negative net

sentiment score. This explains its inverse relationship with market performance during the period.

All the control variables show impacts that are expected. For example, size is negative and significant as Lnassets is showing a negative coefficient across all models. This implies that large firms performed worse. Debt (longtermdebt) is negative and significant. Cash is positive and significant showing that firms holding higher cash perform better. Firms with higher capex perform better and firms with higher intangibles perform better. Also, Firms that have had acquisitions and buybacks perform better. Firms with net debt issuance perform worse.

Table 2. Return and Covid risk

	(1)	(2)	(3)	(4)	(5)
st_covid_exposure	0.061*** (0.005)				
D2020#c.st_covid_exposure	0.043*** (0.012)				
st_covid_risk		0.018*** (0.004)			
D2020#c.st_covid_risk		0.018*** (0.007)			
st_covid_neg_sentiment			0.041*** (0.005)		
D2020#c.st_covid_neg_sentiment			0.033*** (0.011)		
st_covid_pos_sentiment				0.036*** (0.003)	
D2020#c.st_covid_pos_sentiment				0.045*** (0.011)	
st_covid_net_sentiment					-0.005 (0.004)
D2020#c.st_covid_net_sentiment					-0.016** (0.006)
D2020	-0.061*** (0.022)	-0.032 (0.023)	-0.047** (0.023)	-0.037* (0.021)	-0.026 (0.024)
Lnassets	-0.154*** (0.053)	-0.158*** (0.054)	-0.157*** (0.055)	-0.153*** (0.054)	-0.155*** (0.055)
longtermdebt	-0.112* (0.056)	-0.102* (0.055)	-0.108* (0.059)	-0.107* (0.057)	-0.103* (0.057)
cashratio	0.671*** (0.111)	0.717*** (0.118)	0.699*** (0.114)	0.687*** (0.111)	0.725*** (0.119)
ppe	-0.003 (0.163)	-0.005 (0.170)	-0.003 (0.162)	0.009 (0.164)	-0.001 (0.166)
capex	0.916***	1.020***	0.966***	0.919***	1.036***

	(0.313)	(0.317)	(0.313)	(0.310)	(0.318)
goodwill	-0.201*	-0.206	-0.240*	-0.216*	-0.237*
	(0.120)	(0.125)	(0.122)	(0.125)	(0.125)
acquisitions	0.165**	0.173**	0.165*	0.159*	0.166**
	(0.078)	(0.081)	(0.084)	(0.082)	(0.082)
intangibles	0.480***	0.487***	0.512***	0.481***	0.513***
	(0.120)	(0.123)	(0.122)	(0.123)	(0.125)
div	0.056	0.101	0.095	0.050	0.111
	(0.155)	(0.173)	(0.166)	(0.157)	(0.175)
netdebtissuance	-0.087	-0.089	-0.086	-0.084	-0.092
	(0.063)	(0.065)	(0.065)	(0.063)	(0.065)
buyback	0.764**	1.467***	0.864***	0.917***	0.797**
	(0.345)	(0.332)	(0.323)	(0.321)	(0.323)
Constant	1.039***	1.040***	1.040***	1.015***	1.014**
	(0.377)	(0.382)	(0.389)	(0.378)	(0.386)
Firm FE	Y	Y	Y	Y	Y
Ind Clustering	Y	Y	Y	Y	Y
Observations	31,280	31,280	31,280	31,280	31,280
R-squared	0.058	0.024	0.043	0.045	0.019
Number of firms	4,630	4,630	4,630	4,630	4,630

This table reports the firm fixed effects regressions, where the dependent variable is quarterly returns for 2020-2021. All the Covid risk variables are standardised to have a mean 0 and standard deviation of 1. All variables are defined in Appendix 1. Robust clustered (industry) standard errors are in parentheses. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively.

Then I examine whether the pricing of the covid risk is different in 2020. In order to do this I use a dummy variable for 2020 (D 2020) and interact it with all the covid risk measures. I cluster the standard errors according to industry and employ firm fixed effects. The findings demonstrate that all the interaction terms are positive and significant showing that in 2020 return is positively correlated with all of the Covid risk metrics. This illustrated the basic tenet of finance: higher rewards correspond with more risk. Covid exposure was positively related in 2020 with a 0.043 increase in returns in comparison to 2021. The financial impact of Covid-19 on the stock market is substantial in 2020. Returns are only adversely correlated with Covid net sentiment (D2020#c.st_covid_net_sentiment). This is likely due to how the net sentiment measure is constructed—it reflects the difference between positive and negative sentiment expressed in earnings calls. Given that corporate communication during the pandemic was predominantly negative, the resulting net sentiment values were generally below zero. This negative tone helps account for the observed inverse relationship between net sentiment and

stock market performance during the period. The results of 2020 corroborate with the full sample analysis.

The dummy for 2020 (D2020) shows a significant negative coefficient in all the specifications except for column 5. For example, the coefficient for D2020 is -0.061 shows that the return is 0.061 lower in 2020 compared to 2021. These results show the severity of the covid in 2020 as compared to 2021.

5.5.3 Is political risk priced during covid?

Since political risk cannot be measured directly, the literature has relied on various methods to capture its effects. It is common practice to use country-level indices to identify fluctuations in political risk at the sector and aggregate levels. Unlike other studies, Hassan et al. (2019) provide the first firm-level measure of political risk and a flexible deconstruction into topic-specific components, allowing for a meaningful distinction between firm-level, sector-level, and aggregate exposure. Rather than relying solely on sector- or aggregate-level data, this novel approach enables a more thorough analysis of the ways that political risk affects individual firms.

In this section, this chapter examines whether firm-level political risk is priced during Covid-19. I use the quarterly returns as our main dependent variable. As the political risk variables were quite large, I use normalised variables with a mean of 0 and a standard deviation of 1. I find that political exposure and risk variables are positively related to the return. This supports H2a. The economic magnitude of the variables shows that a one standard deviation increase in political exposure is associated with 0.006 increase in returns. A one standard deviation increase in net political risk is associated with a 0.013 increase in returns. Negative sentiment is positively related to returns.

Table 3. Return and political risk

(1)	(2)	(3)	(4)	(5)
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st_pexposure	0.006*** (0.002)				
D2020#c. st_pexposure	0.007* (0.004)				
st_prisk		0.013*** (0.004)			
D2020#c. st_prisk		0.004 (0.004)			
st_psentiment			-0.007 (0.004)		
D2020#c.st_psentiment			-0.024*** (0.007)		
st_npsentiment				0.014** (0.006)	
D2020#c.st_npsentiment				-0.035*** (0.007)	
st_netsentiment					-0.009 (0.009)
D2020#c.st_netsentiment					-0.023*** (0.007)
D2020	-0.025 (0.024)	-0.025 (0.024)	-0.032 (0.026)	-0.023 (0.024)	-0.034 (0.029)
Lnassets	-0.154*** (0.054)	-0.155*** (0.054)	-0.158*** (0.055)	-0.151*** (0.055)	-0.159*** (0.056)
longtermdebt	-0.104* (0.056)	-0.104* (0.057)	-0.104* (0.057)	-0.097* (0.058)	-0.107* (0.059)
cashratio	0.724*** (0.119)	0.724*** (0.118)	0.726*** (0.119)	0.732*** (0.121)	0.731*** (0.122)
ppe	0.001 (0.168)	-0.000 (0.166)	-0.001 (0.165)	0.009 (0.165)	-0.011 (0.164)
capex	1.044*** (0.318)	1.043*** (0.322)	1.035*** (0.317)	1.040*** (0.315)	1.076*** (0.326)
goodwill	-0.228* (0.128)	-0.228* (0.127)	-0.240* (0.126)	-0.226* (0.125)	-0.238* (0.125)
acquisitions	0.168** (0.082)	0.172** (0.082)	0.176** (0.082)	0.165* (0.083)	0.183** (0.084)
intangibles	0.502*** (0.126)	0.502*** (0.125)	0.508*** (0.126)	0.505*** (0.125)	0.505*** (0.126)
div	0.106 (0.174)	0.104 (0.174)	0.102 (0.172)	0.094 (0.171)	0.109 (0.174)
netdebtissuance	-0.090 (0.065)	-0.090 (0.064)	-0.091 (0.064)	-0.093 (0.064)	-0.093 (0.065)
buyback	0.916*** (0.313)	0.854*** (0.319)	0.811** (0.340)	0.708** (0.342)	0.731* (0.379)
Constant	1.008** (0.383)	1.016** (0.384)	1.037*** (0.388)	0.969** (0.385)	1.050*** (0.394)
Firm FE	Y	Y	Y	Y	Y
Ind Clustering	Y	Y	Y	Y	Y
Observations	31,280	31,280	31,280	31,280	31,280
R-squared	0.018	0.019	0.021	0.020	0.020
Number of firms	4,630	4,630	4,630	4,630	4,630

This table reports the firm fixed effects regressions, where the dependent variable is quarterly returns for 2020-2021. All the political risk variables are standardised to have a mean 0 and standard deviation of 1. All variables are defined in Appendix 1. Robust clustered (industry) standard errors are in parentheses. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively.

Every control variable is exhibiting predicted effects. For instance, size is a negative and substantial indicator of poorer performance for large enterprises. Debt is a serious and detrimental thing. Cash is important and beneficial, indicating that businesses with more cash do better. Businesses with greater capital expenditures and intangible assets perform better. Businesses with buybacks and acquisitions also do better. Businesses that issue net debt do poorly. In sum, this chapter finds that firm-level political risk is quite important in the times of covid.

Then I examine whether the pricing of the political risk is different in 2020. I cluster the standard errors according to industry and employ firm fixed effects. The interaction variable $D2020 \# c.st_prisk$ is significant and positive (coefficient 0.007 and significant at 10% level). $D2020 \# c.st_psentiment$, $D2020 \# c.st_nsentiment$ and $D2020 \# c.st_psentiment$ are negative and significant. These results show that political risk at the beginning of the pandemic played a role that makes political risk and return negatively related. The difference in the relationship between political risk and returns in 2020 versus 2021 reflects a transition from extreme uncertainty and risk aversion to greater clarity and confidence in managing the pandemic's economic and political fallout. In 2020, political risk amplified market volatility and pessimism, dragging returns lower. By 2021, improved policies, economic recovery, and greater investor resilience led to a more neutral or positive response to political risk. Regarding the control variables, cash, capex, intangibles and div are all positively related to returns. Only net debt issuance is negatively related to returns.

5.5.4 Return, Covid and political risk

Recognising the fact that Covid risk and political risk are measured through different keywords, hence measuring different concepts, I put them in the same models to examine whether they still remain significant. All the Covid risk measures are positive and significant, except for covid net sentiment. Political exposure and political risk are significant and positive at the 10% level. In terms of economic magnitude, covid risk is a lot larger compared to political exposure. This does make sense as it was during Covid, hence, covid risk was much more important compared to political risk.

All control variables display the expected effects. Firm size is negatively and significantly associated with performance, indicating that larger enterprises tend to underperform relative to smaller ones. Leverage exerts a detrimental impact, while cash holdings prove beneficial, suggesting that firms with greater liquidity perform better. Higher levels of capital expenditures and intangible assets are positively related to performance, as are share repurchases and acquisitions. Conversely, firms engaging in net debt issuance exhibit weaker performance.

Table 4. Return, Covid and political risk

	(1)	(2)	(3)	(4)	(5)
st_covid_risk	0.028*** (0.003)				
st_prisk	0.003* (0.002)				
st_covid_exposure		0.080*** (0.005)			
st_pexposure		0.005* (0.003)			
st_covid_pos_sentiment			0.060*** (0.004)		
st_psentiment			-0.010*** (0.003)		
st_covid_neg_sentiment				0.060*** (0.004)	
st_npsentiment				0.010*** (0.004)	
st_covid_net_sentiment					-0.011*** (0.003)
st_netsentiment					-0.011** (0.005)
Lnassets	-0.127*** (0.044)	-0.101** (0.042)	-0.116*** (0.042)	-0.114** (0.044)	-0.128*** (0.044)
longtermdebt	-0.099* (0.057)	-0.107* (0.059)	-0.102* (0.057)	-0.102* (0.059)	-0.102* (0.059)
cashratio	0.685*** (0.107)	0.622*** (0.104)	0.652*** (0.102)	0.653*** (0.104)	0.696*** (0.108)

ppe	-0.083 (0.133)	-0.165 (0.127)	-0.106 (0.126)	-0.113 (0.126)	-0.079 (0.128)
capex	1.045*** (0.319)	1.020*** (0.323)	1.021*** (0.317)	1.015*** (0.319)	1.051*** (0.323)
goodwill	-0.199 (0.130)	-0.193 (0.130)	-0.212 (0.136)	-0.227* (0.126)	-0.225* (0.129)
acquisitions	0.193** (0.089)	0.224** (0.088)	0.207** (0.091)	0.203** (0.091)	0.191** (0.091)
intangibles	0.442*** (0.114)	0.405*** (0.114)	0.429*** (0.117)	0.446*** (0.112)	0.465*** (0.114)
div	0.122 (0.167)	0.117 (0.149)	0.098 (0.157)	0.135 (0.160)	0.126 (0.168)
netdebtissuance	-0.128 (0.077)	-0.160** (0.076)	-0.139* (0.075)	-0.140* (0.077)	-0.131* (0.077)
buyback	1.292*** (0.382)	0.809** (0.357)	0.897** (0.352)	0.788** (0.356)	0.979*** (0.349)
Constant	0.823** (0.316)	0.661** (0.311)	0.753** (0.307)	0.741** (0.320)	0.827** (0.318)
Firm FE	Y	Y	Y	Y	Y
Ind Clustering	Y	Y	Y	Y	Y
Observations	31,280	31,280	31,280	31,280	31,280
R-squared	0.021	0.048	0.039	0.037	0.018
Number of firms	4,630	4,630	4,630	4,630	4,630

This table reports the firm fixed effects regressions, where the dependent variable is quarterly returns for 2020-21. All the covid risk and political risk variables are standardised to have a mean 0 and standard deviation of 1. All variables are defined in Appendix 1. Robust clustered (industry) standard errors are in parentheses. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively.

5.5.5 Components of Political risk and Return

Political risk can be caused by various things such as trade, institutions, health, and tax policies.

Here are some ways that political risk may involve each of these components. First of all, trade relations could be a part of political risk. Modifications to trade barriers, import/export regulations, and taxes can cause supply chain disruptions, raise expenses, and restrict a company's access to markets. Commerce agreements (such as NAFTA and the EU) can change the competitive environment and have an effect on companies that depend on foreign commerce. Trade policy can be impacted by diplomatic ties between nations. Trade activities may be hampered by embargoes, sanctions, or poor diplomatic relations. Growing protectionist measures in certain nations might raise political risk by causing an unstable trading climate.

Health can be a source of political risk. Strict health restrictions, for instance, might affect the food, pharmaceutical, and manufacturing sectors. Business operations may be impacted by

lockdowns, travel restrictions, and shifts in consumer demand in response to health emergencies such as pandemics (like Covid-19). A shift in public health policy may have an impact on customer behaviour, staff availability, and operating expenses. Public health initiatives and government vaccination requirements may have a direct effect on employee health and business operations. Hence in this section, I examine the components of political risk.

Hassan et al (2019) identify the following types of political risk. Trade Risk – Mentions of trade policies, tariffs, export/import restrictions in a risk-related context; Institutional Risk – Discussions around political institutions, governance stability, legal frameworks; Health Risk – Political issues related to public health policy, healthcare reform, or pandemic management; Environmental Risk – Risks stemming from environmental regulation, climate policy, or sustainability mandates; Tax Risk – Uncertainty about tax policy changes, corporate tax reform, or tax enforcement; Security Risk – Political concerns related to terrorism, war, cybersecurity, or national security policy, Technology Policy Risk – Risks linked to regulation of tech sectors, data privacy, or innovation policy.

I examine the impact of various components of political risk on stock returns, specifically focusing on trade, institutions, health, environment, tax, and security. These categories capture the different dimensions through which political uncertainty can affect firm-level outcomes. The empirical results reveal that all of these components are positively associated with stock returns, indicating that higher exposure to certain political risks corresponds to higher expected returns. This finding is consistent with the fundamental risk-return trade-off in finance, suggesting that investors demand compensation for bearing elevated political uncertainty.

For instance, the health component of political risk shows a statistically significant positive coefficient of 0.007. This implies that a one standard deviation increase in health-

related political risk is associated with an average return increase of 0.007. This may reflect investor expectations that firms exposed to policy debates or regulatory shifts in the healthcare domain are also those positioned to benefit from government spending or changing market needs during health crises such as COVID-19. The positive relationship observed across these risk dimensions highlights the market's tendency to price in political uncertainties and assign risk premia accordingly. These findings provide nuanced insights into how specific types of political risk shape investor behaviour during periods of heightened uncertainty.

Table 5. Components of Political risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
st_priskt_environment	0.005* (0.002)						
st_priskt_trade		-0.006** (0.003)					
st_priskt_institutions			0.010*** (0.002)				
st_priskt_health				0.007*** (0.002)			
st_priskt_security					0.008*** (0.002)		
st_priskt_tax						0.009*** (0.002)	
st_priskt_technology							0.008*** (0.002)
Lnassets	-0.134*** (0.044)	-0.135*** (0.043)	-0.133*** (0.044)	-0.133*** (0.044)	-0.133*** (0.044)	-0.133*** (0.044)	-0.133*** (0.044)
longtermdebt	-0.100* (0.057)	-0.099* (0.057)	-0.100* (0.057)	-0.100* (0.057)	-0.100* (0.057)	-0.100* (0.057)	-0.101* (0.057)
cashratio	0.702*** (0.108)	0.704*** (0.108)	0.699*** (0.108)	0.699*** (0.108)	0.700*** (0.108)	0.700*** (0.108)	0.699*** (0.108)
ppe	-0.053 (0.132)	-0.046 (0.131)	-0.058 (0.132)	-0.055 (0.131)	-0.057 (0.132)	-0.056 (0.132)	-0.056 (0.131)
capex	1.041*** (0.320)	1.034*** (0.320)	1.044*** (0.319)	1.041*** (0.320)	1.043*** (0.319)	1.040*** (0.320)	1.045*** (0.319)
goodwill	-0.221* (0.128)	-0.225* (0.129)	-0.220* (0.130)	-0.222* (0.128)	-0.218* (0.130)	-0.219* (0.129)	-0.219* (0.130)
acquisitions	0.180** (0.089)	0.176* (0.089)	0.180** (0.089)	0.180** (0.089)	0.182** (0.089)	0.181** (0.089)	0.181** (0.089)
intangibles	0.471***	0.477***	0.468***	0.468***	0.466***	0.468***	0.467***

	(0.115)	(0.114)	(0.115)	(0.114)	(0.115)	(0.115)	(0.115)
div	0.117	0.114	0.117	0.116	0.120	0.118	0.118
	(0.169)	(0.169)	(0.169)	(0.169)	(0.170)	(0.169)	(0.169)
netdebtissuance	-0.119	-0.117	-0.119	-0.119	-0.120	-0.119	-0.119
	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)
buyback	0.813**	0.793**	1.084***	0.878**	0.904**	0.862**	0.839**
	(0.350)	(0.348)	(0.385)	(0.352)	(0.360)	(0.353)	(0.349)
Constant	0.861***	0.869***	0.857***	0.858***	0.855***	0.855***	0.858***
	(0.316)	(0.315)	(0.315)	(0.316)	(0.316)	(0.316)	(0.316)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Ind Clustering	Y	Y	Y	Y	Y	Y	Y
Observations	31,280	31,280	31,280	31,280	31,280	31,280	31,280
R-squared	0.017	0.017	0.017	0.017	0.017	0.017	0.017
Number of firmsy	4,630	4,630	4,630	4,630	4,630	4,630	4,630

This table reports the firm fixed effects regressions, where the dependent variable is quarterly returns for 2020-21. All the components of political risk variables are standardised to have a mean 0 and standard deviation of 1. All variables are defined in Appendix 1. Robust clustered (industry) standard errors are in parentheses. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively.

5.5.6 Cross sectional heterogeneity

Some of the firm characteristics are related to the riskiness of the firms. For example, the Fama-French three-factor model, which expands the Capital Asset Pricing Model (CAPM) by including size and value elements in addition to the market risk factor, includes the Small Minus Big (SMB) factor as one of its risk factors. This is a thorough description of the SMB factor's function in the model. The difference in returns between small-cap equities and large-cap companies is represented by the SMB factor. It is designed to take advantage of the size premium—the propensity for smaller businesses to outperform larger ones in the long run. Likewise, Investment is suggested as a factor in the asset pricing model. Hence, in this section, I examine the cross-sectional heterogeneity of covid risk by dividing my sample into large/small, high/low leverage, high/low capex, high/low PPE and High/low intangibles. I use the median values to define the large/high versus small/low.

The results are reported in Table 6. Across all specifications, *st_covid_risk* consistently shows a positive and statistically significant relationship with stock returns, regardless of firm characteristics. This finding supports the argument that investors required a risk premium for firms more exposed to COVID-related risks. Interestingly, the coefficient is slightly higher for firms with high PPE (0.033) and large size (0.032), suggesting that more capital-intensive or larger firms with significant exposure to COVID concerns experienced a stronger return compensation, possibly due to perceived resilience or strategic importance during the pandemic. In contrast, political risk (*st_prisk*) shows a weaker and more heterogeneous relationship with returns. It is positive and significant primarily in firms with low PPE, low Capex, and low leverage, indicating that political risk is priced in more agile or less capital-constrained firms. For example, firms with low PPE and low leverage may be more sensitive to shifts in policy or political environments and, therefore, exhibit a stronger pricing effect of political uncertainty.

The coefficient for st_prisk is negative or insignificant in high-capex and high-leverage firms, potentially due to these firms' reduced ability to adapt swiftly to political disruptions.

Table 6. Cross sectional heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Size		Cash		Leverage		PPE		Intangibles		Capex	
	large	Small	High	low	High	low	High	low	High	low	High	low
st_covid_risk	0.032*** (0.004)	0.025*** (0.005)	0.031*** (0.004)	0.026*** (0.005)	0.029*** (0.005)	0.026*** (0.003)	0.023*** (0.005)	0.030*** (0.003)	0.033*** (0.004)	0.023*** (0.004)	0.024*** (0.005)	0.029*** (0.004)
st_prisk	0.008*** (0.002)	-0.001 (0.004)	0.005 (0.003)	0.003 (0.003)	0.002 (0.003)	0.005* (0.003)	0.002 (0.003)	0.005** (0.002)	0.002 (0.003)	0.004 (0.003)	0.001 (0.002)	0.005* (0.002)
Lnassets	-0.047 (0.099)	-0.152*** (0.042)	-0.147*** (0.044)	-0.086 (0.130)	-0.185** (0.085)	-0.081* (0.041)	-0.328*** (0.098)	-0.075 (0.049)	-0.144*** (0.024)	-0.103 (0.064)	-0.304*** (0.056)	-0.013 (0.037)
longtermdebt	-0.111 (0.147)	-0.100* (0.050)	-0.089* (0.047)	-0.205 (0.166)	-0.128* (0.073)	-0.157 (0.162)	-0.097 (0.076)	-0.177*** (0.066)	-0.173* (0.088)	-0.115 (0.077)	-0.012 (0.081)	-0.083 (0.057)
cashratio	0.773*** (0.228)	0.728*** (0.108)	0.633*** (0.082)	1.329*** (0.479)	0.853*** (0.231)	0.660*** (0.103)	1.193*** (0.210)	0.536*** (0.115)	0.852*** (0.098)	0.728*** (0.153)	0.953*** (0.182)	0.540*** (0.133)
ppe	-0.204 (0.244)	0.011 (0.156)	-0.222 (0.197)	0.137 (0.248)	-0.025 (0.277)	0.080 (0.226)	0.049 (0.244)	-0.140 (0.272)	-0.241 (0.171)	0.171 (0.192)	0.212 (0.248)	-0.622*** (0.191)
capex	1.900*** (0.442)	0.452 (0.354)	0.537 (0.373)	1.451*** (0.373)	1.616*** (0.288)	0.203 (0.309)	1.414*** (0.328)	0.332 (1.115)	1.347*** (0.263)	0.932** (0.382)	1.119*** (0.393)	4.946** (1.912)
goodwill	-0.426 (0.268)	-0.037 (0.150)	0.116 (0.209)	-0.408* (0.240)	-0.342** (0.166)	0.024 (0.187)	-0.480* (0.270)	-0.064 (0.171)	-0.080 (0.132)	0.733 (0.672)	-0.365 (0.284)	-0.180 (0.181)
acquisitions	0.371*** (0.122)	0.054 (0.125)	-0.124 (0.100)	0.610*** (0.179)	0.463*** (0.110)	-0.061 (0.101)	0.711*** (0.206)	0.053 (0.089)	0.325*** (0.064)	-0.561 (0.554)	0.257* (0.134)	0.003 (0.125)
intangibles	0.551** (0.238)	0.431*** (0.141)	0.293* (0.148)	0.375 (0.298)	0.493** (0.225)	0.304* (0.165)	1.014*** (0.269)	0.191 (0.119)	0.468*** (0.133)	-0.901 (0.807)	0.778*** (0.237)	0.362** (0.151)
div	0.378 (0.521)	0.021 (0.113)	-0.054 (0.113)	0.237 (0.407)	0.311 (0.302)	-0.022 (0.126)	-0.189 (0.214)	0.363 (0.308)	-0.027 (0.133)	0.387 (0.281)	-0.314 (0.233)	0.440 (0.324)
netdebtissuance	-0.306*** (0.113)	-0.043 (0.065)	0.042 (0.066)	-0.512*** (0.098)	-0.201** (0.091)	0.010 (0.100)	-0.321*** (0.056)	-0.009 (0.096)	-0.146 (0.093)	-0.138 (0.116)	-0.031 (0.072)	-0.214* (0.117)
buyback	0.451 (0.732)	0.866** (0.410)	-4.956*** (0.439)	1.822** (0.755)	0.232 (0.541)	3.544*** (0.986)	-0.001 (0.562)	5.356*** (0.821)	4.275*** (0.442)	0.001 (0.585)	1.824*** (0.498)	-2.965*** (0.771)
Constant	0.368 (0.938)	0.656*** (0.238)	0.829*** (0.309)	0.640 (1.015)	1.368** (0.577)	0.382 (0.320)	2.226*** (0.646)	0.461 (0.387)	0.936*** (0.197)	0.585 (0.463)	2.005*** (0.335)	0.008 (0.307)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Ind Clustering	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	15,639	15,641	16,321	14,959	15,251	16,029	15,056	16,224	15,872	15,408	15,103	16,177

R-squared	0.028	0.022	0.027	0.025	0.024	0.021	0.035	0.020	0.029	0.018	0.036	0.020
Number of gvkey	2,288	2,613	3,182	2,731	2,568	2,901	2,401	2,724	2,516	2,497	3,108	3,585

This table reports the firm fixed effects regressions, where the dependent variable is quarterly returns for 2020-21. All the regressions are based on higher/lower than median values to partition samples. All the covid risk and political risk variables are standardised to have a mean 0 and standard deviation of 1. All variables are defined in Appendix 1. Robust clustered (industry) standard errors are in parentheses. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively.

5.5.7 Heterogeneity in corporate finance activities

Corporate finance activity can have an impact on the firm-level risk and returns. A company's risk profile can be dramatically changed by a merger, which can impact risks related to operations, finances, markets, regulations, strategy, and reputation. Scholarly investigations shed light on these modifications' mechanisms. Moeller, Schlingemann, and Stulz (2004) found that acquiring firms often experience increased financial risk due to higher leverage. Hence, I partition my sample according to corporate finance activities and repeat the regressions.

The results are reported in Table 7. Across all columns, *st_covid_risk* remains positive and statistically significant in most subsamples, reinforcing the finding that investors priced COVID-related risks and demanded compensation in the form of higher returns. Notably, the effect is stronger among firms issuing debt (*Column 3: 0.038* compared to those that did not (*Column 4: 0.026*), suggesting that the market viewed debt-issuing firms as exposed but potentially better positioned to deploy capital in uncertain times. However, the coefficient for buyback firms (*Column 5*) is negative and insignificant (-0.033), which may reflect investor skepticism about the prudence of capital return policies during a crisis, contrasting with the significantly positive effect among non-buyback firms (*Column 6: 0.028*).

Political risk effects are more heterogeneous. For firms conducting acquisitions (*Column 1*), *st_prisk* is positive and weakly significant (0.007), suggesting that acquirers may face political uncertainty but are still viewed as strategically proactive. However, for non-acquirers, political risk is insignificant. Among dividend payers (*Column 7*), *st_prisk* is positive and highly significant (0.009^{***}), possibly indicating that politically exposed but financially healthy firms reassured investors through stable payouts. In contrast, the relationship is negligible for non-dividend firms (*Column 8*).

Table 7. Heterogeneity and Corporate finance activity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Acq=1	Acq=0	Debtissue=1	Debtissue=0	Buyback=1	Buyback=0	Div=1	Div=0
st_covid_risk	0.025*** (0.005)	0.029*** (0.004)	0.038*** (0.005)	0.026*** (0.005)	-0.033 (0.017)	0.028*** (0.003)	0.030*** (0.004)	0.028*** (0.005)
st_prisk	0.007* (0.004)	0.002 (0.003)	0.005 (0.004)	0.006 (0.005)	-0.015 (0.012)	0.003* (0.002)	0.009*** (0.002)	0.001 (0.004)
Lnassets	-0.192*** (0.041)	-0.134** (0.058)	-0.216*** (0.080)	0.022 (0.041)	-0.437** (0.088)	-0.126*** (0.044)	0.076 (0.075)	-0.172*** (0.050)
longtermdebt	-0.302*** (0.111)	-0.058 (0.052)	-0.098 (0.065)	0.090 (0.094)	-0.839* (0.252)	-0.100* (0.057)	-0.178 (0.133)	-0.091 (0.058)
cashratio	0.871*** (0.118)	0.731*** (0.142)	0.740*** (0.235)	0.565*** (0.149)	-1.400*** (0.058)	0.685*** (0.108)	0.692*** (0.208)	0.700*** (0.115)
ppe	0.001 (0.273)	-0.200 (0.162)	-0.436 (0.287)	-0.561** (0.216)	0.639 (0.412)	-0.087 (0.134)	0.105 (0.218)	-0.130 (0.181)
capex	0.948*** (0.243)	1.188*** (0.378)	2.604*** (0.544)	-0.408 (0.371)	1.155 (1.153)	1.031*** (0.325)	1.507*** (0.333)	0.762 (0.497)
goodwill	0.258 (0.212)	-0.316 (0.196)	-0.151 (0.276)	-0.056 (0.173)	-2.871** (0.319)	-0.196 (0.130)	-0.161 (0.115)	-0.148 (0.219)
acquisitions	0.411*** (0.102)		0.586*** (0.158)	-0.324 (0.278)	-0.301 (0.258)	0.203** (0.090)	0.282** (0.133)	0.109 (0.100)
intangibles	0.325** (0.147)	0.632*** (0.172)	0.411 (0.280)	0.111 (0.176)	1.262* (0.304)	0.438*** (0.114)	0.419*** (0.151)	0.443*** (0.153)
div	0.430** (0.190)	0.109 (0.231)	1.174** (0.559)	0.132 (0.110)	4.543* (1.335)	0.115 (0.165)	0.390 (0.249)	
netdebtissuanc e	-0.072 (0.159)	-0.170* (0.091)	-0.325** (0.124)		0.991*** (0.098)	-0.129* (0.077)	-0.428*** (0.083)	-0.017 (0.066)
buyback	-4.143*** (0.686)	6.441*** (0.552)	4.212*** (0.500)	0.301 (0.810)	-3.275* (1.028)		3.182*** (0.509)	-1.315 (0.817)
Constant	1.380*** (0.348)	0.826** (0.400)	1.689*** (0.576)	-0.296 (0.268)	3.876* (0.980)	0.815** (0.318)	-0.770 (0.647)	0.944*** (0.301)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y

Ind clustering	Y	Y	Y	Y	Y	Y	Y	Y
Observations	7,487	23,129	10,910	6,567	261	31,019	14,719	16,559
R-squared	0.040	0.021	0.037	0.031	0.099	0.022	0.030	0.025
Number of gvkey	1,927	4,137	3,092	1,567	48	4,609	2,261	2,913

This table reports the firm fixed effects regressions, where the dependent variable is quarterly returns for 2020-21. All the regressions are based on whether the firms has a particular corporate finance activity to partition samples. All the covid risk and political risk variables are standardised to have a mean 0 and standard deviation of 1. All variables are defined in Appendix 1. Robust clustered (industry) standard errors are in parentheses. ***, ** and * represent significance at the 1,5 and 10 percent level, respectively.

5.6. Robustness and Further analysis

In this section, I conduct a series of robustness checks by changing the dependent variable, by addressing endogeneity, by estimating quantile regression and by adjusting the returns using the CAPM, Fama and French 3-factor and Fama and French 5-factor models.

5.6.1 ROA and Covid risk

Return metrics are useful for gathering information, but ROA provides a more comprehensive picture by taking asset utilisation efficiency into account. It is especially helpful for comparing enterprises of various sizes and industries, analysing management effectiveness, and analysing capital-intensive ventures. ROA offers a comprehensive measure of operational efficiency and profitability by concentrating on how well a business converts its assets into earnings. Return on Assets (ROA) provides an alternative—and sometimes better—measure compared to stock return because it evaluates a firm's ability to generate profit relative to its total assets, not just equity or market value. This makes ROA particularly useful for comparing operational efficiency across firms with different capital structures. While return measures can be distorted by market sentiment, ROA reflects core profitability from a firm's asset base. It's especially informative when assessing asset-intensive industries, as it highlights how effectively management uses resources to generate earnings. In this section, I change the dependent variable to return on assets (ROA). The reason for using ROA is that it is an accounting variable and hence is not affected by the market participants.

ROA is often considered better than ROE (Return on Equity) in certain contexts because it provides a clearer picture of a firm's overall operational efficiency, independent of its financial leverage. ROA measures profitability relative to total assets, whereas ROE is affected by the firm's debt level. A company can artificially boost ROE through high leverage, even if its core

operations are weak. ROA avoids this distortion. ROA allows better comparison between firms with different capital structures (i.e., different debt-to-equity ratios), making it more reliable when comparing operational efficiency across industries. ROA assesses how well a firm uses all its assets—not just shareholders' equity—to generate profit. This provides a more comprehensive measure of management performance.

I find that none of the measures for covid risk are significant in the regressions. This means most of the response was a market response. Most of the control variables are showing impacts that are expected. For example, size is positive and significant showing that large firms performed better. Debt is negative and significant. Firms with higher capex, intangibles and acquisitions perform worse. Firms also had dividends and buybacks perform better.

Table 8. ROA and Covid Risk

	(1)	(2)	(3)	(4)	(5)
st_covid_exposure	-0.000 (0.001)				
D2020#c.st_covid_exposure	0.002 (0.002)				
st_covid_risk		-0.000 (0.001)			
D2020#c.st_covid_risk		0.000 (0.001)			
st_covid_neg_sentiment			0.000 (0.001)		
D2020#c.st_covid_neg_sentiment			0.001 (0.001)		
st_covid_pos_sentiment				0.000 (0.001)	
D2020#c.st_covid_pos_sentiment				0.001 (0.001)	
st_covid_net_sentiment					0.000 (0.000)
D2020#c.st_covid_net_sentiment					-0.000 (0.000)
D2020	-0.002 (0.003)	-0.001 (0.003)	-0.002 (0.003)	-0.002 (0.003)	-0.001 (0.003)
Lnassets	0.049*** (0.014)	0.049*** (0.014)	0.049*** (0.014)	0.049*** (0.014)	0.049*** (0.014)
longtermdebt	-0.044** (0.018)	-0.044** (0.018)	-0.044** (0.018)	-0.044** (0.018)	-0.044** (0.018)
cashratio	0.010 (0.023)	0.011 (0.023)	0.010 (0.023)	0.010 (0.023)	0.011 (0.023)
ppe	-0.044	-0.045	-0.045	-0.044	-0.045

	(0.035)	(0.034)	(0.034)	(0.034)	(0.034)
capex	0.028	0.033	0.031	0.030	0.033
	(0.060)	(0.062)	(0.061)	(0.061)	(0.063)
goodwill	0.007	0.006	0.006	0.006	0.006
	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)
acquisitions	-0.044***	-0.043***	-0.043***	-0.043***	-0.043***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
intangibles	-0.031	-0.030	-0.030	-0.031	-0.030
	(0.021)	(0.021)	(0.021)	(0.021)	(0.022)
div	0.046***	0.047***	0.047***	0.046***	0.047***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
netdebtissuance	-0.011	-0.011	-0.011	-0.011	-0.011
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
buyback	0.197**	0.208**	0.202**	0.206**	0.203**
	(0.082)	(0.083)	(0.082)	(0.082)	(0.081)
Constant	-0.353***	-0.353***	-0.353***	-0.353***	-0.353***
	(0.096)	(0.096)	(0.096)	(0.096)	(0.095)
Firm FE	Y	Y	Y	Y	Y
Ind Clustering	Y	Y	Y	Y	Y
Observations	31,280	31,280	31,280	31,280	31,280
R-squared	0.081	0.080	0.080	0.080	0.080
Number of gvkey	4,630	4,630	4,630	4,630	4,630

This table reports the firm fixed effects regressions, where the dependent variable is quarterly ROA for 2020-2021. All the Covid risk variables are standardised to have a mean 0 and standard deviation of 1. All variables are defined in Appendix 1. Robust clustered (industry) standard errors are in parentheses. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively.

None of the interaction variables between covid risk and D2020 variables show any significance, implying that covid risk was not affecting ROA differently in 2020 as compared to 2021. Also, D2020 does not show any significance, implying that ROA is not different in 2020 as compared to 2021.

5.6.2 ROA and Political risk

I switch the dependent variable to return on assets (ROA) in this part. Because ROA is an accounting variable and is therefore unaffected by market participants, it is used. Two of the political measures, it turns out, have a significant relationship with ROA. Negative sentiment and net sentiment are positively related to ROA. Moreover, the economic impact is negligible. A 0.002 increase in ROA is linked to a one standard deviation rise in net sentiment.

The majority of the control variables are exhibiting predicted effects. For instance, size is a positive and substantial indicator of larger organisations' superior performance. Debt is a

serious and detrimental thing. Businesses with larger acquisitions, intangibles, and capital expenditures do worse. Businesses also offered dividends and buybacks did better.

Table 9. ROA and political risk

	(1)	(2)	(3)	(4)	(5)
st_pexposure	-0.000 (0.000)				
D2020#c. st_pexposure	-0.000 (0.000)				
st_prisk		0.001 (0.001)			
D2020#c. st_prisk		-0.003 (0.002)			
st_psentiment			0.001 (0.000)		
D2020#c.st_psentiment			-0.001*** (0.000)		
st_npsentiment				0.002*** (0.001)	
D2020#c.st_npsentiment				-0.002 (0.002)	
st_netsentiment					0.003*** (0.000)
D2020#c.st_netsentiment					-0.001 (0.001)
D2020	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.000 (0.003)
Lnassets	0.049*** (0.014)	0.050*** (0.014)	0.049*** (0.014)	0.050*** (0.014)	0.050*** (0.014)
longtermdebt	-0.044** (0.018)	-0.044** (0.018)	-0.044** (0.018)	-0.043** (0.018)	-0.043** (0.018)
cashratio	0.011 (0.023)	0.010 (0.023)	0.011 (0.023)	0.010 (0.023)	0.010 (0.023)
ppe	-0.045 (0.034)	-0.046 (0.033)	-0.045 (0.034)	-0.044 (0.034)	-0.043 (0.034)
capex	0.032 (0.063)	0.034 (0.064)	0.033 (0.063)	0.032 (0.063)	0.031 (0.063)
goodwill	0.005 (0.017)	0.006 (0.017)	0.005 (0.017)	0.006 (0.016)	0.006 (0.017)
acquisitions	-0.043*** (0.013)	-0.043*** (0.013)	-0.043*** (0.013)	-0.043*** (0.013)	-0.044*** (0.014)
intangibles	-0.030 (0.022)	-0.030 (0.022)	-0.030 (0.022)	-0.031 (0.022)	-0.031 (0.022)
div	0.047*** (0.013)	0.048*** (0.013)	0.047*** (0.013)	0.047*** (0.013)	0.047*** (0.013)
netdebtissuance	-0.011 (0.015)	-0.012 (0.015)	-0.011 (0.015)	-0.011 (0.015)	-0.010 (0.015)
buyback	0.201** (0.085)	0.180** (0.080)	0.189** (0.082)	0.184** (0.081)	0.158* (0.083)
Constant	-0.354***	-0.355***	-0.352***	-0.356***	-0.356***

	(0.095)	(0.095)	(0.095)	(0.095)	(0.096)
Firm FE	Y	Y	Y	Y	Y
Ind Clustering	Y	Y	Y	Y	Y
Observations	31,280	31,280	31,280	31,280	31,280
R-squared	0.080	0.081	0.080	0.080	0.081
Number of gvkey	4,630	4,630	4,630	4,630	4,630

This table reports the firm fixed effects regressions, where the dependent variable is quarterly ROA for 2020-2021. All the political risk variables are standardised to have a mean 0 and standard deviation of 1. All variables are defined in Appendix 1. Robust clustered (industry) standard errors are in parentheses. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively.

One of the interaction variables, D2020#c.st_psentiment is negative and significant. The Dummy D2020 is not significant in any of the specifications showing that political risk was not different in 2020 as compared to 2021.

5.6.3 Addressing Endogeneity

5.6.3.1 Addressing Endogeneity: Two stage least squares (2SLS)

It might be possible that the measure of covid risk is endogenous. Hence, I have applied an instrumental variable regression to address the endogeneity problem. The Instrument I chose is the firm-level risk measure of H1N1 (Hassan et al, 2023). The risk of H1N1 is correlated with the endogenous variable (COVID Risk). The risk of H1N1 is likely to be correlated with Covid-19 risk because countries, sectors, or firms that were exposed to H1N1 in the past may share structural or systemic characteristics that also make them vulnerable to COVID-19. For example: health system vulnerabilities, pandemic preparedness or response policies, geographic proximity to high-risk regions or trade dependencies. This correlation provides the relevance condition for using H1N1 risk as an instrument for Covid-19 risk.

The instrument is not directly related to the dependent variable (returns). The risk of H1N1 is plausibly exogenous to current returns because H1N1 occurred years before the Covid-19 pandemic and its direct economic impacts are no longer present. H1N1 occurred much earlier (2009–2010) and thus predates COVID-19, making it unlikely that the instrument is endogenously determined by the current returns or other contemporaneous economic variables. The temporal separation helps satisfy the exogeneity condition for IVs. Hence, I use firm-level

measure of H1N1 as an instrumental variable for the return and covid risk regression (Column 1).

Using previous political risk as an instrumental variable (IV) in a regression of returns on political risk can be justified under the framework of instrumental variables if it satisfies the two critical conditions: relevance and exogeneity. Here's why previous political risk might serve as a valid instrument. Political risk often has a time-dependent component, meaning that past political risk is likely to be correlated with current political risk. Thus, previous political risk is a strong predictor of current political risk, satisfying the relevance criterion. Past political risk (e.g., from years prior) should not directly affect current returns. Instead, its effect on returns operates through its impact on current political risk, satisfying the exclusion restriction. By focusing on lagged political risk, the IV framework mitigates concerns about simultaneity or reverse causality. Hence, I use the previous average firm-level political risk as an instrumental variable.

Table 10 shows the results from instrumental variable two stage least squares regressions. Column 1 shows the results that Covid exposure is positive and significant. In column 2, Political exposure is positively related to returns. To address the potential endogeneity of `st_covid_exposure`, I use `H1N1_Exposure` as an instrumental variable and conduct a series of standard tests to assess instrument validity and relevance. The results, reported in Table 10, strongly support the use of the instrument. First, the F-statistic of the excluded instrument in the first-stage regression is 124.81, well above the Stock-Yogo critical value of 16.38 for a single endogenous regressor at the 10% maximal IV size threshold. This confirms that `H1N1_Exposure` is a strong instrument and that weak instrument concerns are unlikely.

The underidentification test using the Anderson canonical correlation LM statistic yields a Chi-squared value of 124.37 ($p < 0.001$), rejecting the null hypothesis of underidentification. This indicates that the model is properly identified. The Cragg-Donald Wald F-statistic and the

Sanderson-Windmeijer robust F-statistic both return values of 124.81, further affirming the strength of the instrument under both homoskedastic and heteroskedastic settings. Finally, the Anderson-Rubin and Stock-Wright weak-instrument robust tests report a Chi-squared value of 8.13 ($p = 0.0044$), confirming that the endogenous regressor is jointly significant in the structural equation and that the instrument satisfies the orthogonality condition. Together, these tests provide strong evidence that H1N1_Exposure is a valid and powerful instrument for st_covid_exposure.

To mitigate endogeneity concerns surrounding the political risk exposure variable (st_prisk), I use st_priskt_historical as an instrumental variable. The instrument validity and strength are assessed through a range of first-stage and diagnostic tests, the results of which are reported in Table 10. The F-statistic of the excluded instrument in the first-stage regression is exceptionally high at 19,202 ($p < 0.001$), far exceeding the commonly accepted threshold of 10, and the Stock-Yogo critical value of 16.38 for one endogenous regressor at the 10% maximal IV size. This confirms that st_priskt_historical is a strong instrument for political risk exposure. The Anderson LM underidentification test produces a Chi-squared statistic of 11,901 ($p < 0.001$), decisively rejecting the null hypothesis of underidentification. This indicates that the excluded instrument contributes sufficiently to explaining variation in the endogenous regressor and that the model is identified. Both the Cragg-Donald Wald F-statistic and the Sanderson-Windmeijer F-statistic are consistent with the high first-stage F-statistic, further confirming the instrument's strength under homoskedasticity and robust conditions, respectively. Additionally, the Anderson-Rubin and Stock-Wright weak-instrument robust tests yield a Chi-squared statistic of 10.30 ($p = 0.0013$), providing further support for the relevance and orthogonality of the instrument. These results indicate that the instrument not only strongly predicts political risk exposure but also satisfies the exclusion restriction required for valid inference. Taken together,

these diagnostics demonstrate that st_priskt_historical is a reliable and valid instrument for addressing endogeneity in political risk exposure estimation.

Table 10. Addressing Endogeneity: 2SLS results

Panel A	(1)	(2)
	Return	Return
st_covid_exposure	0.088*** (0.031)	
st_pexposure		0.010*** (0.003)
Lnassets	0.002 (0.002)	-0.002** (0.001)
Longtermdebt	-0.023*** (0.009)	-0.014* (0.009)
Cashratio	0.009 (0.011)	0.018* (0.010)
Ppe	-0.028*** (0.010)	-0.026** (0.010)
Capex	0.548*** (0.083)	0.535*** (0.083)
Goodwill	0.044 (0.029)	0.022 (0.028)
Acquisitions	0.169*** (0.058)	0.067 (0.045)
Intangibles	-0.046* (0.026)	0.007 (0.019)
Div	0.147* (0.081)	0.054 (0.074)
Netdebtissuance	-0.082*** (0.023)	-0.066*** (0.022)
Buyback	1.563 (3.583)	0.493 (3.568)
Constant	0.016 (0.013)	0.039*** (0.010)
Observations	31,280	31,280
R-squared	0.003	0.002
Strong instrument		
F-test of excluded instrument: F(1, 31,267) =	124.81	19,202
Instrument Validity Tests		
Underidentification (Anderson LM)	Chi ² (1) = 124.37	Chi ² (1) = 11,901
Weak identification (Cragg-Donald F)	F = 124.81	F = 19,202
Sanderson-Windmeijer F	F = 124.81	F = 19,202
Stock-Yogo 10% threshold	16.38	16.38
Weak-Instrument Robust Inference		

Anderson-Rubin Chi ² test	Chi ² (1) = 8.13	Chi ² (1) = 10.30
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Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

5.6.3.2 General Method of Moments estimation

Generalized Method of Moments (GMM) addresses endogeneity in econometric models by using instruments—variables that are correlated with the endogenous explanatory variables but uncorrelated with the error term. GMM relies on instrumental variables (IVs), which satisfy 1. relevance— instruments are correlated with the endogenous variable and 2. Exogeneity— instruments are uncorrelated with the error term. In panel data models, GMM often uses lagged values of endogenous variables as instruments.

GMM is estimated in a two-Step process. The first stage is instrument construction. GMM uses instruments to construct predicted values of the endogenous variables, isolating the variation unrelated to the error term. In the second stage is parameter estimation. Using the predicted values, GMM estimates the model parameters while satisfying the moment conditions.

Table 11. Dynamic General method of moments results

	(1)	(2)
	Return	Return
L.return	0.162*** (0.059)	-0.069*** (0.018)
st_covid_exposure	0.152*** (0.025)	
st_pexposure		0.047*** (0.008)
Lnassets	-0.166*** (0.037)	-0.204*** (0.050)
Longtermdebt	0.414* (0.213)	0.686*** (0.251)
cashratio	0.159 (0.206)	1.024*** (0.282)
ppe	0.532*** (0.123)	0.825*** (0.164)
capex	-1.682*** (0.366)	-1.893*** (0.279)
goodwill	0.672 (0.719)	-0.359 (0.588)

acquisitions	-0.266 (0.442)	-0.261 (0.213)
intangibles	-0.385 (0.500)	0.458 (0.486)
div	1.751*** (0.489)	1.172** (0.498)
netdebtissuance	2.165*** (0.456)	-0.379** (0.149)
buyback	78.815 (75.557)	-3.753 (11.374)
Constant	1.071*** (0.307)	1.050** (0.465)
AR(1) Z	-11.35 (0.00)	-14.63 (0.00)
AR (2)	1.35 (0.178)	-1.44 (0.150)
Sargan test of overid. restrictions: chi2	211.98 (0.00)	2513.41 (0.00)
Hansen test of overid. restrictions: chi2	223.17 (0.00)	1118.58 (0.00)
Difference (IV = exogenous): chi2(1)	0.67 (0.412)	3.04 (0.081)
Observations	26,167	26,167
Number of Companies	4,279	4,279

For column 1, where I model the covid risk, the results show that covid risk is positively related to returns. The diagnostic tests show the model performs adequately. The Arellano-Bond Test for Autocorrelation assesses whether the residuals of the first-differenced equation exhibit serial correlation. The AR(1) is $z = -11.35$, $p = 0.000$. A significant result ($p < 0.05$) is expected in AR(1), as differencing introduces first-order serial correlation in the residuals. This is normal and not a cause for concern. The AR(2) is $z = 1.35$, $p = 0.178$. A non-significant result ($p > 0.05$) suggests the absence of second-order serial correlation. This is a crucial condition for the validity of GMM instruments, as lagged dependent variables are often used as instruments. The AR(1) and AR(2) results confirm that the residuals meet the requirements for valid GMM estimation. No second-order serial correlation (AR(2)) implies the instruments are likely valid. The significant result raises concerns about instrument validity. However, because the Sargan test is not robust, more weight should be given to the Hansen test. The significant Hansen test result suggests either: Endogeneity of instruments, or Overfitting due to an excessive number

of instruments. Difference test (null = exogeneity): $\chi^2(1) = 0.67$, $p = 0.412$. A non-significant result ($p > 0.05$) indicates that the H1N1_Exposure instrument is exogenous and valid.

In column 2, I estimate the GMM model for the relationship between returns and political risk. The results show that the return and political risk are positively related. The results for the AR (1) and AR (2) tests show that there is evidence of autocorrelation at the first order but there is no evidence of autocorrelation at the second order. Difference test (null = exogeneity): $\chi^2(1) = 3.04$, $p = 0.081$. A marginally significant result ($p > 0.081$) indicates that the previous political_exposure instrument is valid.

5.6.4 Quantile Regressions

OLS focuses solely on the conditional mean of the dependent variable given the independent variables. This approach assumes that the effects of predictors are constant across the distribution of the dependent variable. Quantile regression estimates the relationship at different points (quantiles) of the conditional distribution (e.g., median, 25th percentile, 75th percentile). This allows for a more comprehensive analysis, capturing how the effects of predictors vary across the distribution. OLS assumes that the residuals are normally distributed and homoscedastic (constant variance across all values of the independent variables). Quantile regression does not require normality or homoscedasticity of errors. It works well with heteroskedastic data (where the variance of errors changes across levels of independent variables) because it models conditional quantiles directly.

The results of the quantile regression analysis, estimated across the 25th, 50th (median), 75th, and 100th percentiles, reveal varying effects of explanatory variables on the dependent variable across the distribution. The coefficients indicate how the impact of each variable differs depending on the quantile of the outcome variable being analysed. The impact of st_covid_exposure is consistently positive and statistically significant across all quantiles, with

coefficients increasing from 0.026 at the 25th quantile to 0.093 at the 100th quantile. This suggests that firms more exposed to Covid-19 experience higher increases in the dependent variable, with the effect magnifying for firms in the uppermost quantiles.

Table 12. Quantile regression: Return and Covid risk

Quantile	(1) 25	(2) 50	(3) 75	(4) 100
st_covid_exposure	0.026*** (0.002)	0.018*** (0.001)	0.030*** (0.002)	0.093*** (0.014)
Lnassets	0.016*** (0.001)	-0.001* (0.001)	-0.019*** (0.001)	0.044*** (0.007)
longtermdebt	-0.031*** (0.009)	0.028*** (0.005)	0.056*** (0.009)	-0.589*** (0.062)
cashratio	-0.068*** (0.011)	-0.032*** (0.006)	-0.023** (0.011)	0.068 (0.076)
ppe	-0.046*** (0.011)	-0.016*** (0.006)	0.054*** (0.011)	-0.738*** (0.075)
capex	0.504*** (0.091)	0.027 (0.046)	-0.191** (0.092)	2.428*** (0.604)
goodwill	-0.007 (0.031)	0.071*** (0.016)	0.084*** (0.031)	0.336* (0.204)
acquisitions	0.058 (0.050)	0.040 (0.025)	0.020 (0.050)	0.409 (0.330)
intangibles	0.001 (0.021)	-0.042*** (0.011)	-0.089*** (0.021)	0.198 (0.141)
div	0.417*** (0.081)	0.071* (0.041)	-0.409*** (0.082)	0.678 (0.538)
netdebtissuance	-0.098*** (0.025)	-0.007 (0.012)	0.038 (0.025)	-0.092 (0.163)
buyback	0.383 (3.924)	-0.644 (1.994)	-6.391 (3.959)	29.192 (26.032)
Constant	-0.202*** (0.011)	0.032*** (0.006)	0.319*** (0.011)	-1.096*** (0.075)
Observations	31,280	31,280	31,280	31,280
Pseudo R2	0.0257	0.0070	0.0195	0.1359

This table reports the quantile regressions, where the dependent variable is quarterly returns for 2020-21. All the covid risk and political risk variables are standardised to have a mean 0 and standard deviation of 1. All variables are defined in Appendix 1. Standard errors are in parentheses. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively.

The analysis reveals that the effects of variables such as st_covid_exposure, Lnassets, and longtermdebt vary significantly across the distribution of the dependent variable. These findings underscore the importance of considering heterogeneity in economic relationships, as

mean regression methods (e.g., OLS) may fail to capture these dynamics. Quantile regression provides a more detailed picture, particularly valuable in contexts with diverse impacts across the spectrum of outcomes. In sum, these results highlight that where covid risk is the highest, it affects the return in a higher magnitude.

Table 13 shows that the effect of st_nprisk is positive and significant at the 25th (0.004), 50th (0.006), and 75th (0.011) quantiles but becomes insignificant at the 100th quantile (0.012). This indicates that political risk has a stronger impact on lower and middle quantiles of the dependent variable, with diminishing influence at the uppermost quantile. The quantile regression results highlight the heterogeneous effects of predictors across the conditional distribution of the dependent variable.

Table 13. Quantile regression: Return and political risk

Quantile	(1) 25	(2) 50	(3) 75	(4) 100
st_nprisk	0.004** (0.002)	0.006*** (0.001)	0.011*** (0.002)	0.012 (0.015)
Lnassets	0.016*** (0.001)	-0.002*** (0.001)	-0.021*** (0.001)	0.044*** (0.008)
longtermdebt	-0.034*** (0.009)	0.033*** (0.005)	0.056*** (0.009)	-0.573*** (0.064)
cashratio	-0.064*** (0.011)	-0.029*** (0.006)	-0.009 (0.011)	0.123 (0.079)
ppe	-0.036*** (0.011)	-0.016*** (0.006)	0.054*** (0.011)	-0.731*** (0.078)
capex	0.463*** (0.091)	0.007 (0.047)	-0.175* (0.091)	2.394*** (0.627)
goodwill	-0.033 (0.031)	0.081*** (0.016)	0.069** (0.031)	0.279 (0.211)
acquisitions	0.006 (0.050)	0.016 (0.026)	-0.017 (0.049)	0.338 (0.342)
intangibles	0.038* (0.021)	-0.033*** (0.011)	-0.056*** (0.021)	0.283* (0.146)
div	0.362*** (0.081)	0.076* (0.042)	-0.438*** (0.081)	0.650 (0.558)
netdebtissuance	-0.084*** (0.024)	0.003 (0.013)	0.044* (0.024)	-0.054 (0.169)

buyback	0.814 (3.913)	-0.617 (2.035)	-5.890 (3.910)	31.899 (27.010)
Constant	-0.202*** (0.011)	0.031*** (0.006)	0.325*** (0.011)	-1.146*** (0.078)
Observations	31,280	31,280	31,280	31,280
Pseudo R2	0.0198	0.0042	0.0151	0.1161

This table reports the quantile regressions, where the dependent variable is quarterly returns for 2020-21. All the covid risk and political risk variables are standardised to have a mean 0 and standard deviation of 1. All variables are defined in Appendix 1. Standard errors are in parentheses. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively.

5.6.5 CAPM, Fama-French 3 factors and Fama-French 5 factors Adjusted Returns

Using CAPM, Fama and French 3-factor, and Fama and French 5-factor adjusted returns in finance research provides a more robust assessment of risk-adjusted performance than raw returns alone. The Capital Asset Pricing Model (CAPM) adjusts for market risk by isolating abnormal returns (alpha) unexplained by market movements, allowing researchers to evaluate performance net of systematic risk. The Fama-French 3-factor model improves upon CAPM by incorporating size (SMB) and value (HML) factors, capturing persistent cross-sectional return patterns observed in small-cap and high book-to-market stocks. The 5-factor extension further adds profitability (RMW) and investment (CMA) factors, offering a more comprehensive explanation of asset returns. Hence in this section, I use CAPM, Fama-French 3 factors and Fama-French five factors adjusted returns.

I collect the Fama-French factor data from Kenneth French's Website.⁷ Then I convert the data using month end data for 3, 6, 9 and 12 months as quarterly factors. Finally, I subtract those factors from the returns calculated in the earlier part of this chapter. I use these returns as the dependent variable in the regressions reported in Table 14.

⁷ [Kenneth R. French - Data Library](#)

Table 14. Adjusted returns

VARIABLES	(1) return	(2) FF3adjret	(3) FF5adjret	(4) lnreturns	(5) return	(6) FF3adjret	(7) FF5adjret	(8) lnreturns
st_covid_exposure	0.087*** (0.006)	0.034*** (0.005)	0.043*** (0.005)	0.102*** (0.007)				
st_prisk					0.008*** (0.002)	0.006*** (0.002)	0.008*** (0.002)	0.013*** (0.003)
Lnassets	-0.149*** (0.048)	-0.234*** (0.039)	-0.273*** (0.041)	-0.037 (0.043)	-0.183*** (0.049)	-0.247*** (0.039)	-0.290*** (0.041)	-0.078* (0.043)
longtermdebt	0.028 (0.105)	-0.123** (0.048)	-0.131** (0.050)	-0.101 (0.067)	0.034 (0.103)	-0.121** (0.048)	-0.128** (0.050)	-0.094 (0.065)
cashratio	0.556*** (0.110)	0.562*** (0.083)	0.607*** (0.084)	0.683*** (0.109)	0.639*** (0.115)	0.594*** (0.085)	0.647*** (0.086)	0.790*** (0.113)
ppe	-0.214* (0.122)	0.252** (0.099)	0.308*** (0.104)	-0.380* (0.202)	-0.099 (0.129)	0.296*** (0.103)	0.363*** (0.110)	-0.242 (0.209)
capex	1.273*** (0.231)	-0.617 (0.402)	-0.562 (0.397)	1.127*** (0.291)	1.304*** (0.233)	-0.602 (0.397)	-0.542 (0.391)	1.183*** (0.310)
goodwill	-0.161 (0.101)	-0.374*** (0.105)	-0.412*** (0.108)	-0.117 (0.130)	-0.186* (0.100)	-0.382*** (0.104)	-0.422*** (0.107)	-0.157 (0.136)
acquisitions	0.203** (0.096)	-0.050 (0.063)	-0.068 (0.065)	0.273** (0.114)	0.159 (0.097)	-0.066 (0.065)	-0.089 (0.067)	0.224* (0.112)
intangibles	0.397*** (0.122)	0.624*** (0.095)	0.681*** (0.098)	0.409*** (0.134)	0.460*** (0.120)	0.647*** (0.096)	0.709*** (0.100)	0.506*** (0.141)
div	0.021 (0.180)	-0.507*** (0.089)	-0.506*** (0.092)	0.345 (0.240)	0.025 (0.201)	-0.505*** (0.091)	-0.502*** (0.097)	0.367 (0.275)
netdebtissuance	-0.170** (0.081)	0.058 (0.060)	0.100 (0.063)	-0.252** (0.110)	-0.126 (0.081)	0.075 (0.061)	0.122* (0.065)	-0.199* (0.111)
buyback	3.170*** (0.301)	-1.791*** (0.337)	-2.291*** (0.343)	-2.507*** (0.349)	3.248*** (0.299)	-1.736*** (0.336)	-2.206*** (0.342)	-2.770*** (0.326)

Constant	0.999*** (0.361)	1.638*** (0.285)	1.897*** (0.297)	0.146 (0.357)	1.205*** (0.370)	1.716*** (0.287)	1.995*** (0.299)	0.392 (0.356)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Ind Clustering	Y	Y	Y	Y	Y	Y	Y	Y
Observations	31,280	31,280	31,280	27,510	31,280	31,280	31,280	27,510
R-squared	0.046	0.038	0.048	0.048	0.016	0.032	0.038	0.014
Number of firms	4,630	4,630	4,630	4,070	4,630	4,630	4,630	4,070

This table reports regression results, where the dependent variable is CAPM, Fama-French 3 factors, Fama-French 5 factors adjusted returns and ln returns for 2020-21. All the covid risk and political risk variables are standardised to have a mean 0 and standard deviation of 1. All variables are defined in Appendix 1. Standard errors are in parentheses. ***, ** and * represent significance at the 1, 5 and 10 percent level, respectively.

In Models (1)–(4), `st_covid_exposure` is positive and statistically significant across all specifications (CAPM, FF3, FF5, `lnreturns`). Firms with greater exposure to COVID-risk experienced higher risk-adjusted returns, possibly due to investor overreaction followed by correction or adaptive business models that performed well during the pandemic. In Models (5)–(8), `st_pexposure` also shows small but significant positive coefficients, suggesting that firms that have more political risk saw better risk-adjusted returns. The economic magnitude is smaller than for COVID exposure but still statistically robust. The results are qualitatively similar to my baseline estimates.

In sum, in this section, I performed a battery of robustness checks. First, changing the returns to an accounting-based measure—ROA. The results show that ROA is not in general related to Covid and Political risk. This is because as ROA is an accounting measure that was not affected by the Covid and Political risk. Then I address the endogeneity issue by estimated two stage least squares (2SLS) method, using General method of Moments (GMM) and the results hold. I also performed quantile regressions to see that my results are not affected by the least square method. Finally, I adjust the returns using CAPM, Fama-French 3 factors and Fama-French 5 factors model and the results hold.

5.7. Conclusion

Covid had an unprecedented impact on our lives, society and economy. Covid caused major changes in the financial markets, such as increased volatility, sharp fluctuations in asset values, and an increase in investor risk aversion. Because of this, learning how to assess and take Covid-19 risk into account while making investment decisions is more crucial than ever. To the best of my knowledge, despite the fact that the body of research on Covid-19 is expanding, none of the earlier studies have looked at whether firm-level political and Covid risk were being

valued in the financial markets during Covid. This chapter closes this gap in the literature in this chapter. I compare firm-level political risk and firm-level Covid risk using the US companies' quarterly data.

The results show that returns have a positive correlation with all of the Covid risk metrics over the duration of the Covid period. This demonstrated the fundamental principle of finance: greater rewards are correlated with increased risk. Due to the uncertainties surrounding the pandemic, stock markets experienced extreme volatility at the start of Covid-19. The stock markets recovered as I moved on to the next wave of Covid-19. This begs the question of whether Covid-risk was priced at the start of the pandemic and not at any other point during the outbreak. In this chapter, I answer this question. The findings demonstrate a positive correlation between returns and each of the Covid risk variables in 2020.

Political risk may or may not be substantial during Covid-19 because it was a health-related pandemic. In light of Covid-19, I therefore investigate whether political risk is taken into account when determining financial market returns. I use Hassan et al. (2019) to assess the political risk at the firm-level and compare it to share price returns during the Covid-19 epidemic. I find that risk factors and political exposure have a positive correlation with return. I then look into whether political risk is valued differently in 2020. The findings indicate that in 2020, when the Covid era began, political risk and exposure had a positive correlation with returns. The computed coefficients indicated a significant economic magnitude. I then examine the political risk and return projection for 2021. The research indicates that most political risk indices are considerable and favourable. The economic significance is around six times smaller than it was in 2020.

Although return metrics are useful for measuring performance, ROA provides a more comprehensive view because it takes asset utilisation efficiency into account. It is especially helpful for comparing companies of various sizes and industries, assessing managerial

effectiveness, and assessing capital-intensive initiatives. By concentrating on how well a business converts its assets into earnings, relative operating efficiency, or ROA, offers a thorough indicator of both profitability and operational efficiency. As a substitute metric, I utilise return on assets (ROA) as the dependent variable. ROA is used since it is an accounting variable and is therefore independent of market actors. It turns out that most Covid measures don't really affect ROA. The standardised Covid-19 positive sentiment shows the only significant and positive relationship.

I added political risk and Covid risk to the same models to check if they were still significant even if they are measured using different keywords and so measure different concepts. Every Covid risk statistic, with the exception of covid net sentiment, is noteworthy and positively related. Political risk and exposure are favourable and substantial at the 10% mark. Economically speaking, Covid risk is even more important than political risk. That makes sense since it happened during the Covid-19 epidemic, when political risk was much smaller than Covid-19 risk.

I conducted a comprehensive set of robustness checks. To address potential endogeneity concerns, I employed a two-stage least squares (2SLS) approach using the Generalized Method of Moments (GMM), and the core findings remained consistent. I further applied quantile regression analysis to ensure that the results were not driven by the estimation method used in ordinary least squares. Lastly, I adjusted returns using the CAPM, Fama-French three-factor, and five-factor models, and the main conclusions continued to hold.

A number of factors, including commerce, institutions, health, and tax laws, can contribute to political risk. One aspect of political risk might be trade connections. Changes to taxes, import/export laws, and trade obstacles can increase costs, disrupt supply chains, and limit a company's access to markets. Politics may be at risk from health issues. For example, strict health regulations may have an impact on the food, pharmaceutical, and industrial

industries. Lockdowns, travel restrictions, and changes in customer demand in reaction to health catastrophes like pandemics (like Covid-19) may have an effect on business operations. Changes in public health policy could affect personnel availability, customer behaviour, and operating costs. I find that there is a positive relationship between political risk and trade, institutions, health, the environment, taxes, and security.

The Covid-19 epidemic caused supply chains to break, customer behaviour to change, and regulatory environments to shift, posing hitherto unheard-of hurdles to enterprises globally. In this setting, investors, companies, and politicians now need to take firm-level political risk—which is defined as uncertainty around laws, regulations, and geopolitical events—into serious account. This study contributes to the debate on whether the variables affecting firm-level political risk pricing in the context of the Covid-19 pandemic, looking at the potential and actual reasons why such risk is priced effectively or inefficiently in financial markets. Political risk may or may not have been important during the Covid-19. Hence, I test whether political risk is priced in the financial market during Covid-19. I use firm-level political risk measured by Hasan et al (2019) and relate it to share price returns during times of Covid. This chapter contributes on the dynamics of firm-level political risk and how it affects investment choices and market outcomes.

The assessment made by investors as a whole on the possible effects of the pandemic on company fundamentals, market dynamics, and macroeconomic circumstances is reflected in the price of Covid-19 risk in the stock market. Due to the dynamic and unpredictable character of the pandemic, pricing Covid-19 risk is intrinsically difficult; yet it is necessary for accurately representing underlying economic fundamentals, evaluating risk-return trade-offs, and fostering market efficiency. Furthermore, the pricing of Covid-19 risk has consequences for enterprises, investors, and policymakers in equal measure, underscoring the significance of comprehending and mitigating the risks linked to the pandemic in financial markets and the

wider economy. In this chapter, I use firm-level covid risk based on earnings conference calls developed by Hassan et al (2023) and relate it to the returns during covid period.

It is crucial to do research during Covid-19 outbreaks due to the intricate effects of political and Covid-19 risk on public health, economy, financial markets, political stability, policy responses, and social well-being. By better understanding the drivers, dynamics, and effects of these risks, policymakers, businesses, investors, and individuals can all anticipate challenges, lessen their vulnerabilities, and increase their resilience in the face of uncertainty and adversity brought on by the pandemic and its aftermath. Therefore, this chapter investigates whether political risk and covid risk are associated with returns during the Covid-19 epidemic and provides evidence that indeed both risks are priced in the market.

Chapter 6

6. Conclusion

6.1 Summary of Results

The COVID-19 pandemic brought about an unprecedented global crisis, testing the resilience of firms and financial markets alike. This thesis has examined three key dimensions of corporate response and market pricing during the pandemic: (1) the predictive power of pre-pandemic firm characteristics on performance; (2) the temporal correlation of firm returns across COVID-19 waves, testing whether firms learn or remain locked into their business models; and (3) the pricing of firm-specific COVID and political risks using conference call-based textual analysis. Collectively, the findings contribute to the growing literature on firm resilience and crisis-era financial behaviour.

Empirical Chapter 3 investigates whether firm-level characteristics observed before the COVID-19 outbreak help explain the variation in stock market performance during the pandemic's first wave. While previous research has explored this question, much of the existing work focuses predominantly on U.S. firms. Given the variation in institutional arrangements, cultural contexts, and financial systems across countries, results from U.S.-centric studies cannot be readily generalized. For instance, Bates et al. (2009) explain why U.S. firms hold more cash, noting that average American businesses tend to maintain sufficient liquidity to meet all debt obligations. Such behaviours, shaped by riskier cash flows and agency conflicts, may differ significantly across countries.

To address this gap, I utilize a cross-country dataset to examine firm characteristics at the end of 2019 and their predictive power for company performance during the pandemic. I find that variables such as firm size, cash holdings, capital expenditure, executive compensation, stock beta, and ownership concentration significantly influence firm outcomes

during the health crisis. Surprisingly, smaller firms tended to outperform larger firms, contradicting the common belief that scale provides resilience. Our results highlight the critical role of liquidity—"cash is king"—as firms with greater cash reserves weathered the crisis more effectively. Conversely, capital expenditures undertaken before COVID-19 appear to have produced diminishing returns during the pandemic. Firms with higher-paid executives and more concentrated ownership structures fared better, suggesting that incentives and governance structures contributed positively to resilience. High-beta firms, as expected, underperformed during the turbulent period.

In addition to firm-level variables, I also assess the influence of country-level factors. Government-imposed stringency measures negatively affected corporate performance, as did pandemic severity measured through COVID-19 deaths and cases per million. Stronger institutional quality, however, is associated with better firm performance, suggesting that effective governance may cushion systemic shocks.

To validate our findings, I use alternative performance metrics—ROA, ROE, and Tobin's q —in addition to buy-and-hold returns (BHR). Unlike stock returns, accounting measures are less susceptible to investor sentiment and market volatility. The consistency of results across these metrics strengthens the reliability of our conclusions. Further robustness checks, including fixed effects regressions, alternative standard error clustering, and quantile regressions, confirm the stability of our findings.

My results yield important policy implications. Investors and policymakers should recognize that firm-level fundamentals can significantly impact resilience during crisis periods. By identifying traits associated with strong stock performance during the pandemic, investors can make more informed decisions in turbulent environments. For instance, prioritizing firms with healthy liquidity, disciplined capital expenditure, and effective executive incentives could yield better returns. These insights align with existing literature linking corporate success to

financial health and incentive alignment (Fresard, 2010; Giroud and Mueller, 2017; Murphy, 2013; Rau, 2015).

From a managerial perspective, the findings underscore the importance of strategic liquidity management and performance-based compensation. My results challenge the notion that entrenched leadership always erodes value, as firms with closely held shares—often associated with concentrated control—performed better, contrary to prior critiques (Gompers et al., 2003; Bebchuk et al., 2009). Additionally, the underperformance of firms with large capital expenditures during the crisis suggests the need for greater caution in investment planning under uncertain conditions. Industry-specific patterns also emerge. Sectors like consumer staples, basic materials, and real estate demonstrated stronger performance during the crisis. These findings help investors and managers identify areas of comparative resilience and guide future portfolio or operational adjustments.

Nevertheless, the role of firm size raises critical questions. Contrary to conventional wisdom, my data suggest that larger firms did not enjoy greater protection during the COVID-19 shock. Further research is needed to unpack why smaller firms outperformed, and whether agility, niche focus, or operational flexibility played a role. Liquidity, while protective, comes at a cost. The opportunity cost of idle cash must be weighed carefully, particularly in periods of low returns or inflation. This trade-off warrants further exploration, especially in relation to firm-specific strategies and macroeconomic contexts.

On the policy front, my findings suggest that stringent government restrictions, though potentially necessary for public health, adversely affect firm performance. Future research should explore optimal policy design that balances public safety with economic continuity. Additionally, institutional strength emerges as a buffer against crisis impacts, reinforcing the importance of governance in national resilience strategies. In sum, this chapter contributes to the growing literature on firm resilience during crises by providing robust cross-country

evidence on the predictive power of firm characteristics and policy environments. The insights offer valuable guidance for investors, policymakers, and business leaders preparing for future systemic shocks.

Empirical Chapter 4 explores the relationship between firm-level returns across successive waves of COVID-19, offering a novel test of the "business model" versus the "learning" hypothesis. This chapter investigates the relationships between stock returns across the second, third, and fourth waves of the COVID-19 pandemic. Defining pandemic waves based on the severity of confirmed deaths, our analysis offers mixed evidence in support of both the business model and learning hypotheses. I find a positive association between returns in the third and fourth waves, and between the second and fourth waves—consistent with the business model hypothesis. Firms' business models, including revenue structures, cost dynamics, and customer segmentation, appear to influence how they weather repeated health shocks. Firms that adapted early particularly in healthcare, technology, and consumer services—demonstrated continued resilience.

In contrast, the negative return correlation between the second and third waves supports the learning hypothesis, which posits that investors and firms learn and adapt based on past experience. The initial overreaction in some sectors was corrected in later waves as information about the pandemic's impact became clearer. Sector rotation and revaluation are evident in industries such as travel, retail, and pharmaceuticals, which faced volatility across waves.

My country-level analysis reveals significant heterogeneity in return correlations across waves. In China, stringent and well-coordinated containment strategies, along with public compliance and robust healthcare infrastructure, contributed to negatively correlated waves, suggesting effective outbreak suppression. In contrast, India exhibited positively correlated returns across waves, likely due to differing control measures, healthcare limitations, and high population density. Additionally, industrial composition shaped wave-specific outcomes—

countries dominated by essential sectors such as healthcare and e-commerce experienced different performance trajectories than those reliant on discretionary sectors. Consumer discretionary sectors demonstrated particularly strong correlations between the fourth and earlier waves, highlighting shifts in consumer spending behaviour under changing pandemic conditions. Firms offering digital goods, remote services, and essential non-durables (e.g., Amazon.com) saw continued demand despite lockdowns.

I also explore the impact of government policy stringency. In early waves, high stringency (e.g., extended lockdowns and movement restrictions) was negatively associated with firm performance. As governments adjusted policies in later waves to strike a balance between public health and economic activity, the relationship turned positive. My findings confirm that overly strict measures can damage business activity, particularly in in-person sectors such as travel, hospitality, and retail, while moderate restrictions during later waves allowed some sectors to rebound.

To ensure robustness, I use alternative wave definitions based on Iftimie et al. (2021) and Polat et al. (2023). Although core findings remain stable, some differences emerge depending on wave delineation. When using synchronized calendar periods across countries, common macroeconomic shocks (e.g., inflation, GDP fluctuations) and investor sentiment (e.g., risk aversion, flight to safety) dominate the return patterns, overshadowing firm- or country-level specifics. These broader market dynamics often influence sector-wide and cross-industry correlations, underscoring the role of herd behaviour and macroeconomic uncertainty in times of crisis.

While some industries recovered, others continued to thrive throughout the pandemic. For example, technology and healthcare consistently outperformed, while travel and hospitality experienced cyclical losses and gains tied to lockdown severity and vaccination progress.

Notably, the ability of firms to pivot—e.g., through digitization or product diversification—also shaped return performance.

In summary, my analysis reveals that the relationship among COVID-19 waves is multifaceted, driven by a mixture of firm-level business models, country-specific responses, sectoral dynamics, and macro-level investor sentiment. These findings provide a nuanced understanding of return persistence and reversal across waves and highlight the value of firm and policy adaptability during crises.

Empirical Chapter 5 addresses a previously underexplored area: whether firm-level COVID and political risks are priced by financial markets during the pandemic. The COVID-19 pandemic had an unprecedented impact on global health, societies, and economies. Among its many consequences, it triggered substantial disruptions in financial markets, marked by heightened volatility, sharp fluctuations in asset valuations, and increased investor risk aversion. Understanding how to evaluate and incorporate COVID-19 risk in financial decision-making has therefore become increasingly essential. Despite a growing literature on COVID-19 and its economic consequences, limited attention has been paid to whether firm-level COVID-19 and political risks were priced in the financial markets during the pandemic. This chapter fills that gap by examining whether these two forms of risk were reflected in equity valuations.

Using quarterly U.S. firm-level data, I compare the influence of firm-specific COVID-19 risk—measured using textual analysis of earnings conference calls (Hassan et al., 2023)—with firm-level political risk (Hassan et al., 2019). The findings show a robust and positive association between stock returns and various COVID-19 risk metrics during 2020, the first year of the pandemic. These results are consistent with fundamental financial theory: higher risk tends to be compensated with higher returns. The early phase of the pandemic witnessed extreme market volatility and uncertainty, leading investors to demand greater compensation

for exposure to pandemic-related risks. As markets adjusted and the initial shock subsided, the pricing of COVID-19 risk diminished.

In contrast, political risk—often seen as less relevant during a health crisis—also showed significant correlations with stock returns, particularly during the initial phase of the pandemic. In 2020, both political risk and exposure were positively associated with returns, suggesting that investors were pricing in broader uncertainties beyond health-related concerns. However, the economic significance of political risk in 2021 was substantially lower—nearly six times smaller—indicating that its impact diminished as the pandemic evolved and policy responses stabilized.

To validate these findings, I substitute market-based return measures with accounting-based performance indicators, specifically Return on Assets (ROA), to control for firm-specific operational efficiency. The results show that most COVID-19 risk variables do not significantly impact ROA, except for COVID-19 positive sentiment, which is positively associated. This implies that while market participants respond strongly to COVID-19 risk in terms of returns, these risks do not necessarily translate into measurable declines in firm-level operational performance.

Furthermore, I examine the joint effects of COVID-19 and political risks by including both in the same regression model. The results reveal that COVID-19 risk variables remain significantly and positively associated with returns, while political risk and exposure maintain significance at the 10% level. The relative economic magnitude indicates that COVID-19 risk was more influential than political risk—an intuitive result given the exceptional nature of the pandemic.

A deeper investigation into the composition of political risk reveals that it encompasses several dimensions—including trade, institutions, health, environment, taxation, and security—each of which may influence firm value during times of crisis. For instance, changes

in trade policy, public health regulations, and taxation during the pandemic all contributed to heightened uncertainty. The analysis confirms positive correlations between these political subcomponents and firm-level risk pricing, underscoring the multifaceted nature of political uncertainty during a global crisis.

The broader implications of these findings are substantial. The pandemic disrupted supply chains, altered consumer behaviour, and forced businesses and governments to adapt rapidly to shifting regulatory environments. In this context, firm-level political risk, traditionally viewed through the lens of regulatory and geopolitical uncertainty, took on new dimensions. Investors had to weigh not only health-related shocks but also how political responses—such as lockdown mandates, fiscal stimulus packages, and healthcare policies—would affect firms differently across sectors.

This chapter contributes to our understanding of how firm-level risks—both health-related and political—are integrated into market pricing during systemic crises. The evidence supports the conclusion that both COVID-19 risk and political risk were meaningfully priced during the early phases of the pandemic. These results have important implications for investment strategy, risk management, and policy formulation. Firms with greater transparency and adaptability to these risks may offer investors better protection against future shocks.

6.2 Contributions

This thesis makes several contributions to the academic literature. By using cross-country data, Chapter 1 expands the literature beyond U.S.-centric findings and highlights institutional heterogeneity in firm behaviour. Chapter 2 introduces a novel approach to studying firm adaptation over time, distinguishing between persistent vulnerability and dynamic learning. Chapter 3 leverages conference call transcripts to construct firm-level risk measures, offering a real-time, firm-specific lens for understanding asset pricing during crises. Together,

these contributions deepen our understanding of how firm fundamentals, learning processes, and information disclosure interact during systemic shocks.

6.3 limitations

While this thesis provides novel insights, several limitations warrant discussion. In Chapter 1, despite efforts to harmonize firm-level data across countries, differences in accounting standards, reporting quality, and institutional contexts may introduce noise or bias. Chapter 2 relies on broad definitions of pandemic "waves," which may vary in intensity and timing across countries and sectors. A more refined, localized delineation of waves would improve precision. Chapter 3 focuses on firms with publicly available earnings calls, which tend to be larger and more visible companies. As a result, findings may not generalize to smaller firms or private entities. While the analyses employ lagged variables and robustness checks, the potential for endogeneity—especially in the pricing of perceived risk—remains a concern. The pricing analysis in Chapter 3 focuses solely on U.S. equities. Expanding the scope to international markets could reveal different pricing mechanisms based on local investor behaviour.

6.4 Future research directions

This thesis opens several avenues for future research. Future studies could delve deeper into sectoral heterogeneity, examining how industry-specific traits influenced resilience, learning, and risk pricing. Linking firm outcomes to specific government responses—such as fiscal stimulus, lockdown policies, or vaccination campaigns—could provide insight into the effectiveness of policy in shaping firm behaviour. Further research could incorporate other real-time risk indicators, such as media sentiment, social media signals, or supply chain disruptions, to complement textual measures from earnings calls. While this thesis focuses on crisis-era performance, long-term consequences such as innovation, employment, and investment patterns warrant investigation. Extending the pricing analysis to bond markets, credit default

swaps, or derivatives could test whether risk is priced consistently across asset classes. More sophisticated natural language processing and machine learning techniques could improve the extraction of nuanced sentiment and topic modelling from unstructured data. Finally, exploring how managerial decisions, investor sentiment, and governance structures evolve in response to crisis learning could enhance our understanding of organizational behaviour in turbulent times.

The COVID-19 pandemic tested the resilience of firms in extraordinary ways, reshaping the landscape of risk and return. This thesis provides evidence that firm fundamentals, adaptability, and perceived risks all played crucial roles in shaping performance during the crisis. By integrating cross-country financial data, return dynamics, and innovative text-based risk measures, the research offers a multidimensional view of how firms and markets respond to systemic shocks.

The findings underscore the importance of preparedness, transparency, and adaptability in navigating uncertainty. As global markets face future crises—whether from pandemics, geopolitical tensions, or climate change—the insights from this thesis remain highly relevant, providing both theoretical and practical guidance for investors, policymakers, and firms alike.

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Appendix 3A: Variable definitions

Variable	Definition	Source	Reference
$BHR_{c,i,1st\ wave}$	Buy and hold return from weekly data for January 17, 2020 to May 22, 2020	Refinitiv	Ding et al (2021)
$BHR_{c,i,2nd\ wave}$	Buy and hold return from weekly data for October 9, 2020 to June 18, 2021	Refinitiv	Huang et al (2021)
ROA	Net income divided by total assets.	Refinitiv	Ding et al (2021)
ROE	Net Income divided by total equity	Refinitiv	Ding et al (2021)
Tobin's Q	Tobin's Q is calculated as market value of equities plus book value of liabilities divided by book value of equities plus book value of liabilities	Refinitiv	Huang et al (2021)
Firm size	Natural logarithm of the book value of total assets.	Refinitiv	Ding et al (2021)
Leverage	Ratio of total debt divided by total assets.	Refinitiv	Ding et al (2021)
Cash	Total amount of cash and short-term investments divided by total assets.	Refinitiv	Ding et al (2021)
ESG	Environmental, social and governance score	Refinitiv	Ding et al (2021)
Age	Age of firms	Refinitiv	Richardson, (2006)
Brand Capital	Total advertising expense divided by total assets	Refinitiv	Huang et al (2021)
Board size	Total number of board members.	Refinitiv	Ding et al (2021)
Board compensation	Total compensation paid to the board members of a company divided by size.	Refinitiv	Ding et al (2021)
Beta	Systematic risk of firms	Refinitiv	Huang et al (2021)
Ownership concentration	Percentage of shares closely held	Refinitiv	Richardson, (2006)
Co2	Carbon emission in tons. I use natural log of it.	Refinitiv	Bolton and Kacperczyk (2021)
Closely held shares	Closely held shares divided by total common shares outstanding	Refinitiv	Richardson, (2006)
Capex	Total Capital expenditure (CAPEX) and divided by lagged total asset (AT).	Refinitiv	Richardson, (2006)
Stringency Index	Sum of eight indicators of government containment and closure policies: closings of schools and universities, workplaces, cancelling of public events, limits on private gatherings, closing of public transport, orders to shelter-in-place, restrictions on internal movement between cities or regions, and restrictions on international travel. I take the median value for the stringency index for our sample period (17/1/2020-22/05/2020)	Oxford COVID-19 Government Response Tracker	Ding et al (2021)
Total deaths per million	Total deaths per million as per 22/05/2020	Oxford COVID-19 Government	Sharma et al (2021)

		Response Tracker	
New cases per million	New cases per million as per 22/05/2020	Oxford COVID-19 Government Response Tracker	Sharma et al (2021)
Governance	Governance is the average of the six indicators are Voice and Accountability, Political Stability and Absence of Violence/Terrorism, Government Effectiveness, Regulatory Quality, Rule of Law and Control of Corruption.	Kaufmann et al., (2010) updated 2020	Kaufmann et al., (2010) updated 2020

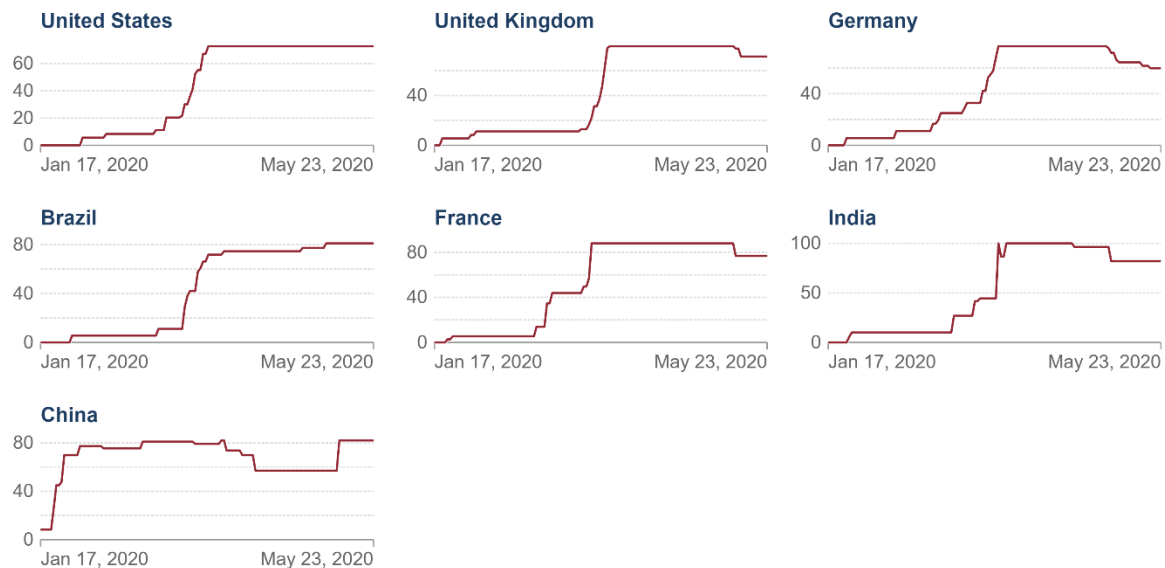
Appendix 3B. Stringency index during first wave of Covid

COVID-19: Stringency Index

The stringency index is a composite measure based on nine response indicators including school closures, workplace closures, and travel bans, rescaled to a value from 0 to 100 (100 = strictest).



■ Non-vaccinated ■ Vaccinated ■ Weighted average of vaccinated and non-vaccinated



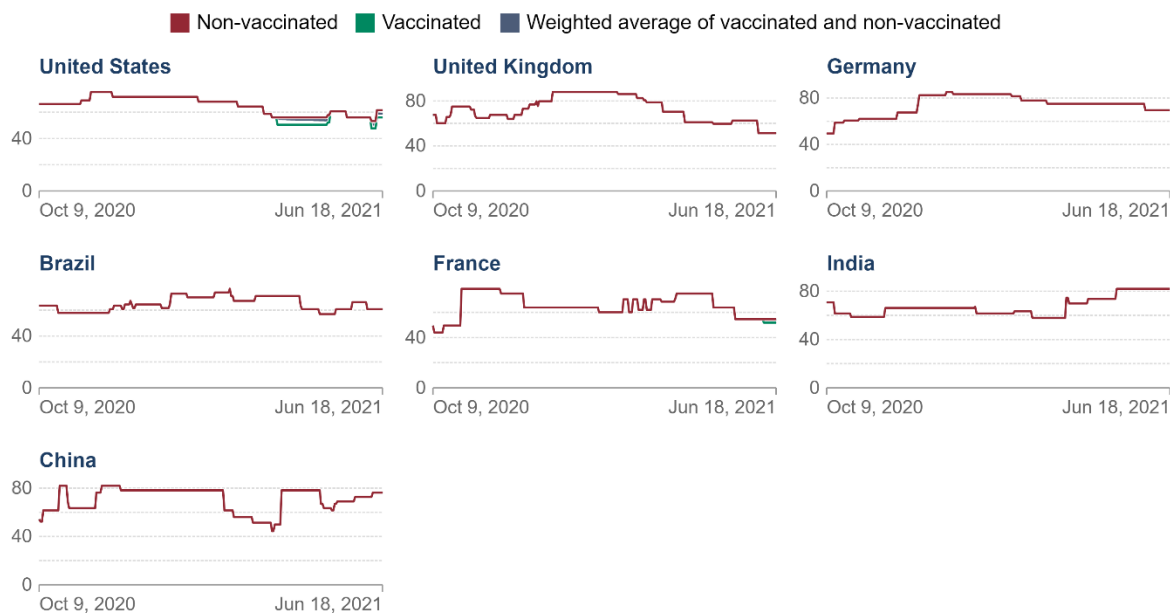
Source: Hale, T., Angrist, N., Goldszmidt, R. et al. A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). Nat Hum Behav 5, 529–538 (2021). <https://doi.org/10.1038/s41562-021-01079-8>
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Appendix C. Stringency index during second wave of Covid

COVID-19: Stringency Index

Our World
in Data

The stringency index is a composite measure based on nine response indicators including school closures, workplace closures, and travel bans, rescaled to a value from 0 to 100 (100 = strictest).



Source: Hale, T., Angrist, N., Goldszmidt, R. et al. A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). Nat Hum Behav 5, 529–538 (2021). <https://doi.org/10.1038/s41562-021-01079-8>
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Appendix 4.1. Definitions of Covid waves in different countries according to confirmed deaths

The beginning is when covid cases started to rise for at least three weeks (and then reaches at a peak) and the end is when covid cases declined until the deaths flatten out. I do not rely on confirmed cases as initially at the beginning of pandemic the testing of covid was not widespread.

	Beginning	End
	US	
1 st	09/03/2020	22/09/2020
2 nd	31/10/2020	06/06/2021
3 rd	20/07/2021	07/11/2021
4 th	06/12/2021	16/04/2022
	UK	
1 st	09/03/2020	17/06/2020
2 nd	02/10/2020	29/03/2021
3 rd	17/06/2021	24/11/2021
4 th	28/12/2021	30/04/2022
	Germany	
1 st	09/03/2020	06/05/2020
2 nd	21/10/2020	25/05/2021
3 rd	14/08/2021	04/01/2022
4 th	27/01/2022	21/04/2022
	France	
1 st	09/03/2020	06/07/2020
2 nd	17/09/2020	14/06/2021
3 rd	16/07/2021	04/11/2021
4 th	21/11/2021	04/04/2022
	Italy	
1 st	09/03/2020	17/06/2020
2 nd	13/10/2020	18/02/2021
3 rd	01/03/2021	11/06/2021
4 th	23/10/2021	23/03/2022
	India	
1 st	09/03/2020	07/01/2021
2 nd	22/03/2021	29/08/2021
3 rd	12/10/2021	01/01/2022
4 th	16/01/2021	24/04/2022
	Brazil	
1 st	09/03/2020	10/10/2020
2 nd	16/11/2020	18/02/2021
3 rd	01/03/2021	21/09/2021
4 th	07/01/2022	27/04/2022
	China	
1 st	09/03/2020	01/05/2020
2 nd	12/11/2020	24/02/2021
3 rd	14/05/2021	10/07/2021
4 th	30/01/2022	21/04/2022

Appendix 4.2. Definition of variables

Variable	Definition	Source	Reference
1stwave	Buy-and-hold return for first wave of Covid, please see appendix 1.	WHO Covid-19 dashboard	Who Covid-19 dashboard
2ndwave	Buy-and-hold return for second wave of Covid, please see appendix 1.	WHO Covid-19 dashboard	Who Covid-19 dashboard
3rdwave	Buy-and-hold return for third wave of Covid, please see appendix 1.	WHO Covid-19 dashboard	Who Covid-19 dashboard
4thwave	Buy-and-hold return for fourth wave of Covid, please see appendix 1.	WHO Covid-19 dashboard	Who Covid-19 dashboard
Covidwhole	Buy-and-hold return for whole of Covid, please see appendix 1.	WHOCovid-19 dashboard	Huang et al (2021)
Firm size	Natural logarithm of the book value of total assets.	Refinitiv	Ding et al (2021)
Leverage	Ratio of total debt divided by total assets.	Refinitiv	Ding et al (2021)
Cash	Total amount of cash and short-term investments divided by total assets.	Refinitiv	Ding et al (2021)
Age	Age of firms	Refinitiv	Richardson, (2006)
Brand Capital	Total advertising expense divided by total assets	Refinitiv	Huang et al (2021)
Board compensation	Total compensation paid to the board members of a company divided by size.	Refinitiv	Ding et al (2021)
Beta	Systematic risk of firms	Refinitiv	Huang et al (2021)
Ownership concentration	Percentage of shares closely held	Refinitiv	Richardson, (2006)
Closely held shares	Closely held shares divided by total common shares outstanding	Refinitiv	Richardson, (2006)
Capex	Total Capital expenditure (CAPEX) and divided by lagged total asset (AT).	Refinitiv	Richardson, (2006)
Δ stringency_1 st	Change in Sum of eight indicators of government containment and closure policies: closings of schools and universities, workplaces, cancelling of public events, limits on private gatherings, closing of public transport, orders to shelter-in-place, restrictions on internal movement between cities or regions, and restrictions on international travel. I take the change for the stringency index for our sample period of first wave	Oxford COVID-19 Government Response Tracker	Hale et al. (2021)
Δ stringency_2 nd	I take the change for the stringency index for our sample period of second wave	Oxford COVID-19 Government Response Tracker	Hale et al. (2021)
Δ stringency_3 rd	I take the change for the stringency index for our sample period of third wave	Oxford COVID-19 Government Response Tracker	Hale et al. (2021)

Δ stringency_4 th	I take the change for the stringency index for our sample period of fourth wave	Oxford COVID-19 Government Response Tracker	Hale et al. (2021)
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Appendix 5.1. Variable definitions

Variable Name	Definition	Source
Return	The price difference between two quarters for a company	Compustat
Lnreturns	$\ln(P_t/P_{t-1})$	Compustat
CAPM adj returns	Raw returns minus CAPM factor returns	Kenneth R. French - Data Library
FF3 adj returns	Raw returns minus FF 3 factor returns	Kenneth R. French - Data Library
FF5 adj returns	Raw returns minus FF 5 factor returns	Kenneth R. French - Data Library
ROA	Earnings Before Interest and Taxes divided by total assets	Compustat
st_covid_exposure	The frequency with which the synonyms for Covid-19 are used in earnings calls divided by the total number of words	Hassan et al (2023)
st_covid_neg_sentiment	The frequency with which Covid-19 are used negatively in earnings calls divided by the total number of words	Hassan et al (2023)
st_covid_pos_sentiment	The frequency with which Covid-19 are used positively in earnings calls divided by the total number of words	Hassan et al (2023)
st_covid_net_sentiment	Difference between negative and positive sentiment	Hassan et al (2023)
st_covid_risk	Covid Risk could be interpreted as a measure of the risk firm i associates with the spread of covid at time t	Hassan et al (2023)
st_prisk	The proportion of conversation devoted to risks associated with political issues in the earnings calls	Hassan et al (2019)
st_pexposure	The frequency with which the synonyms for political risk are used in earnings calls divided by the total number of words	Hassan et al (2019)
st_psentiment	The frequency with which political words are used negatively in earnings calls divided by the total number of words	Hassan et al (2019)
st_npsentiment	The frequency with which political words are used positively in earnings calls divided by the total number of words	Hassan et al (2019)
st_netsentiment	The difference between negative and positive sentiment	Hassan et al (2019)
st_prisk_trade	The proportion of conversation devoted to trade related risks associated with political issues in the earnings calls	Hassan et al (2019)
st_prisk_environment	The proportion of conversation devoted to environment related risks associated with political issues in the earnings calls	Hassan et al (2019)
st_prisk_institutions	The proportion of conversation devoted to institutions related risks associated with political issues in the earnings calls	Hassan et al (2019)

st_priskt_health	The proportion of conversation devoted to health related risks associated with political issues in the earnings calls	Hassan et al (2019)
st_priskt_security	The proportion of conversation devoted to security related risks associated with political issues in the earnings calls	Hassan et al (2019)
st_priskt_technology	The proportion of conversation devoted to technology related risks associated with political issues in the earnings calls	Hassan et al (2019)
st_priskt_tax	The proportion of conversation devoted to tax related risks associated with political issues in the earnings calls	Hassan et al (2019)
LnTA	Natural logarithm of total assets	Compustat
Lev	Debt divided by total assets	Compustat
ppe	Property, Plant and Equipment divided by total assets	Compustat
acq	If the firm had an Merger is 1, otherwise 0	Compustat
intang	Intangible assets scaled by total assets	Compustat
capex	Capital expenditure divided by total assets	Compustat
div	If the firm paid a dividend=1, otherwise 0	Compustat
NDI	If the firm issues debt=1, otherwise 0	Compustat
Buyback	If the firm conducted a buyback=1, otherwise 0	Compustat
Cash	Cash divided by total assets	Compustat

Appendix 5.2. Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Return	1											
(2) ROA	0.096*	1										
(3) st_covid_exposure	0.128*	-0.025*	1									
(4) st_covid_neg_sent	0.105*	-0.019*	0.744*	1								
(5) st_covid_pos_sent	0.121*	-0.011*	0.728*	0.535*	1							
(6) st_covid_net_sent	-0.020*	0.012*	-0.247*	-0.705*	0.222*	1						
(7) st_covid_risk	0.057*	0.006	0.416*	0.369*	0.279*	-0.192*	1					
(8) st_prisk	0.008	-0.011*	0.117*	0.127*	0.063*	-0.093*	0.196*	1				
(9) st_nprisk	0.022*	0.039*	0.073*	0.106*	0.031*	-0.096*	0.156*	0.225*	1			
(10) st_psentiment	-0.021*	-0.020*	-0.187*	-0.242*	-0.052*	0.235*	-0.112*	-0.122*	-0.132*	1		
(11) st_npsentiment	0.019*	0.190*	-0.152*	-0.178*	-0.041*	0.171*	-0.080*	-0.097*	-0.069*	0.346*	1	
(12) st_sentiment	0.008	0.052*	-0.231*	-0.312*	-0.029*	0.335*	-0.142*	-0.190*	-0.169*	0.669*	0.543*	1
(13) st_sentiment	0.008	0.052*	-0.231*	-0.312*	-0.029*	0.335*	-0.142*	-0.190*	-0.169*	0.669*	0.543*	1.000*
(14) Lnassets	-0.018*	0.340*	-0.099*	-0.082*	-0.081*	0.026*	-0.058*	0.074*	0.039*	-0.017*	0.164*	-0.001
(15) longtermdebt	-0.017*	0.063*	0.016*	0.001	0.022*	0.017*	-0.010*	-0.034*	0.015*	0.011*	0.076*	0.029*
(16) cashratio	0.017*	-0.391*	0.042*	-0.003	0.032*	0.030*	0.004	-0.009	-0.092*	0.084*	-0.182*	0.043*
(17) ppe	-0.006	0.093*	-0.030*	-0.003	-0.023*	-0.015*	-0.023*	-0.049*	0.004	-0.031*	0.087*	-0.036*
(18) capex	0.028*	0.059*	-0.021*	-0.017*	-0.016*	0.006	-0.026*	-0.056*	-0.022*	-0.007	0.065*	0.022*
(19) goodwill	0.009	0.142*	0.042*	-0.018*	0.039*	0.053*	-0.002	-0.056*	-0.059*	0.100*	0.150*	0.176*
(20) acquisitions	0.008	0.042*	-0.026*	-0.040*	-0.013*	0.035*	-0.026*	-0.037*	-0.032*	0.055*	0.043*	0.092*
(21) intangibles	0.008	0.129*	0.065*	0	0.063*	0.053*	0.009*	-0.059*	-0.063*	0.099*	0.136*	0.175*
(22) div	0.003	0.133*	-0.036*	-0.031*	-0.023*	0.016*	-0.007	-0.013*	0.017*	-0.016*	0.042*	-0.002
(23) netdebtissuance	-0.014*	-0.016*	0.006	-0.003	0	0.004	-0.003	-0.005	-0.009*	0.002	-0.028*	0.001
(24) buyback	0	0.014*	-0.010*	-0.010*	-0.007	0.006	-0.011*	0.004	-0.002	-0.010*	0.004	-0.010*

	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
(1) Return												
(2) ROA												
(3) st_covid_exposure												
(4) st_covid_neg_sent												
(5) st_covid_pos_sent												
(6) st_covid_net_sent												
(7) st_covid_risk												
(8) st_prisk												
(9) st_nprisk												
(10) st_psentiment												
(11) st_npsentiment												
(12) st_sentiment												
(13) st_sentiment	1											
(14) Lnassets	-0.001	1										
(15) longtermdebt	0.029*	0.133*	1									
(16) cashratio	0.043*	-0.444*	-0.261*	1								
(17) ppe	-0.036*	0.077*	0.243*	-0.300*	1							
(18) capex	0.022*	0.007	0.072*	-0.117*	0.525*	1						
(19) goodwill	0.176*	0.106*	0.109*	-0.219*	-0.181*	-0.085*	1					
(20) acquisitions	0.092*	-0.009	0.031*	-0.068*	-0.060*	-0.005	0.272*	1				
(21) intangibles	0.175*	0.071*	0.147*	-0.246*	-0.207*	-0.105*	0.876*	0.295*	1			
(22) div	-0.002	0.053*	0.073*	-0.095*	0.037*	0.053*	0.003	0.003	0.002	1		
(23) netdebtissuance	0.001	0.021*	0.141*	0.069*	-0.030*	0.034*	0.011*	0.238*	0.015*	0.011*	1	
(24) buyback	-0.010*	0.018*	0.012*	-0.020*	0.050*	0.026*	-0.018*	-0.001	-0.019*	0.017*	0.001	1

*Represents significant at 5% or better level.