

The Quest for Multidimensional Financial Immunity to the COVID-19 Pandemic: Evidence from International Stock Markets

Abstract

What determines a country's financial immunity to a global pandemic? To answer this question, we investigate the behavior of 67 equity markets around the world during the COVID-19 outbreak in 2020. We consider a multidimensional data set that includes factors from finance, economics, demographics, technological development, healthcare, governance, culture, and law. Our study also accounts for government interventions, such as containment and closure policies, and economic stimuli. We apply machine learning techniques, panel regression, and factor analysis to ascertain sources of financial immunity to the coronavirus pandemic. Our findings demonstrate that stock markets in countries with low unemployment rates and populated with firms with conservative investment policies and low valuations relative to expected profits tend to be more immune to the healthcare crisis. We also find that firm government policy responses tend to support stock markets in times of the pandemic.

Keywords: COVID-19; Economy; Financial Immunity; Fundamentals; Government Interventions; Policy Responses; Healthcare; International Stock Markets; Institutions; National Culture; Governance; Novel Coronavirus

JEL Classification: G11; G15; G18; I18

1 Introduction

The unprecedented economic impact of the COVID-19 pandemic can hardly be compared with any event before; completely unexpected, it may be remembered as one of the most significant, widespread events affecting the global financial markets, economies, and all of humanity. Its rapid spread has also demonstrated the dark side of globalisation and how intense may be a global spillover effect between countries. The outbreak itself, as well as the ensuing spiral of containment and closure policies, led to an unprecedented economic and financial downturn not witnessed for decades since the Great Depression, which is believed to be very different from any previous downswings (Bernanke, 2020; Reinhart, 2020), and far worse than the Global Financial Crisis (Fund, 2020). A collapse in the prices of global equities by 20% only in the first quarter of 2020 is a barometer of such a downswing. It is worth noting that these losses from equity market investments were not evenly distributed across the globe. While some emerging market countries, such as Brazil, Argentina, and South Africa, recorded massive losses of 40% or more, other countries, such as China, Denmark or Switzerland, fared much better hardly exceeding 10% drawdown (Baker et al., 2020; Phan and Narayan, 2020; Ashraf, 2020b; Al-Awadhi et al., 2020; Ramelli and Wagner, 2020).

The unexpected health crisis has triggered a multifaceted response from scholars, and has engendered a new and fast growing realm of research, which aims to ascertain what shapes corporate immunity to the coronavirus crisis. The type of operating activity (Skinner and Sloan, 2002; Haroon and Rizvi, 2020; Mazur et al., 2020), financial situation (Ramelli and Wagner, 2020; Fahlenbrach et al., 2020; Ding et al., 2020a), international exposure (Heyden and Heyden, 2020), environmental and social factors (Albuquerque et al., 2020; Onali and Mascia, 2020), as well as ownership structure (Takahashi and Yamada, 2020) are only few of the potential drivers that manifest the complexity of corporate vulnerability. Even a wrong company's name can become a curse (Corbet et al., 2020a). While all of these studies focus on firm-level data, evidence on the country-level financial immunity to COVID-19 is next to empty. What drives the country's degree of financial immunity or vulnerability to the pandemic? What decides that one firm is vulnerable to the COVID-19 pandemic, while others remain unscathed? What determines that some stock markets cope better with the pandemic than others? The aim of this paper is to demystify the country-level financial immunity and vulnerability to the COVID-19 pandemic.

Our research design seizes a comprehensive list of potential drivers that comprises cross-country differences in corporate policies, economy, healthcare provision, governance, law origin, and national culture. Our study is also informed by the stringency of restrictions imposed by the government on the society in response to the pandemic, which ranged from no response (Sweden) to highly stringent restrictions (the UAE). To explore the country-level financial immunity to the coronavirus pandemic, we consider five major categories of factors: i) financial variables, ii) economic and population statistics, iii) quality of healthcare provision, iv) government interventions, and v) governance and culture. We first consider each of these categories on a stand-alone basis and then examine them in joint tests. By evaluating this multidimensional information set, we are the first to test how corporate policies, country's characteristics, and government interventions affect the returns on stock market investments in response to the coronavirus pandemic.

To explore the role of different variables on stock market returns, we examine data from 67 countries for the period of the first major wave of the COVID-19 pandemic: January to April 2020. We examine

the interactions between the growth of the coronavirus case count around the world and different variables outlined above to evaluate their qualitative contribution to stock market immunity to the pandemic. In the absence of an established methodological framework, we employ a frankly agnostic but rigorous research approach. We undertake a battery of state-of-the-art methods, which we structure in several stages. We begin with a set of panel-data regressions that examine individual interactions. Naturally, some of almost a hundred market features, country-specific characteristics, and policy responses that we consider may prove irrelevant or significant just by chance, due to intensive data mining. Also, many of them may potentially feature similar or overlapping information contents. To alleviate these problems, we take a novel approach and build on a rapidly growing literature on feature selection in asset pricing (Gu et al., 2020; Feng et al., 2020; Sun, 2018; Bryzgalova et al., 2019) and employ machine learning methods. In particular, we employ the elastic net (Zou and Hastie, 2005) which combines the benefits of the popular LASSO and ridge-regression techniques. We take advantage of the benefits of the elastic net to determine the economically meaningful set of determinants of stock market immunity to the COVID-19 pandemic, and to evaluate their role in random-effects panel-data regressions that account for multiple interactions.

We supplement our findings with several major robustness checks. To begin with, we explore the role of market reactions to changes in the number of COVID-19-related deaths rather than cases. Next, we apply two-stage least squares panel-data regressions. We treat the growth rate of COVID-19 cases as an endogenous variable. In our case, endogeneity might arise because changes in unobserved drivers of financial immunity can also concurrently trigger a change in the number of confirmed cases. Consequently, we select three instruments that satisfy the exogeneity conditions. First, we include the first lag of the covid-19 cases' growth, which indicates that the today's value is determined by its past values. Second, we include population density of each country as a risk factor responsible for the transmission of the coronavirus and third, the air pollution; factors that are highly significant in the COVID-19 literature (Benvenuto et al., 2020; Sajadi et al., 2020). Lastly, we utilize factor analysis to ascertain the most important variables that influence financial vulnerability to the pandemic. The factor analysis allows us to efficiently cope with the multicollinearity problems in our data set.

Overall, our analysis selects several drivers of the stock market immunity or vulnerability to the COVID-19 pandemic, which prove to be repeatedly important across the majority of our tests. First, our results underscore an important role of investment intensity measured by asset growth. The equity markets, which trade stocks of companies with conservative as opposed to aggressive investment policies cope better with the pandemic. Indeed, large investments and associated cash-flows may depend strongly upon external and internal financing, and the ability to raise funds tends to be more challenging during a pandemic. Second, we find that markets with low valuations relative to their expected profit tend to perform better. In other words, firms with high forward earnings-to-price (FEP) ratios tend to be more immune than firms with high FEP ratios.

Turning to the economic variables, we record the essential role of unemployment. Countries with high unemployment levels are less financially immune to health disasters. Notably, unemployment can be thought of as a simple acid test of the economic conditions. It can pinpoint ailing economies that find it challenging to implement vigorous actions to quickly deal with the COVID-19 pandemic.

Finally, we find that stringent policy responses exert positive, rather than negative, influence on financial immunity. The countries that imposed restrictive measures, such as the closing of public transport or restrictions on internal movement, and implemented economic stimuli, including debt relief and income support, were able to cope better with the negative consequences of the pandemic. In this regard, the key takeaway is that the dramatic market downturns are a direct consequence of the pandemic itself rather than associated government interventions, which tend to support stock market prices rather than impact upon them adversely.

While the academic literature on the coronavirus pandemic is fast-growing, our article contributes to knowledge in at least four ways. First, as far as we are concerned, this study is the first to study the relationships between multidimensional country- and market-specific characteristics and the degree of country's financial immunity to the coronavirus pandemic. The previous studies were largely limited to firm-level evidence (e.g.: [Ramelli and Wagner, 2020](#); [Fahlenbrach et al., 2020](#); [Ding et al., 2020b](#); [Davison, 2020](#); [Demir and Danisman, 2020](#); [Glossner et al., 2020](#); [Onali and Mascia, 2020](#); [Albuquerque et al., 2020](#); [Amore et al., 2020](#); [Pagano et al., 2020](#)). To the best of our knowledge, there are only several studies considering the market-level immunity. These include [Ashraf \(2020c\)](#) and [Fernandez-Perez et al. \(2020\)](#), who examine the role of national cultures, [Iyke \(2020b\)](#) exploring the importance of foreign exchange rates, [Erdem \(2020\)](#) scrutinizing different political regimes, or [Phan and Narayan \(2020\)](#) and [Narayan et al. \(2020\)](#) who check the effect government policies.

Second, our study is one of the first to examine the stock market effects of public restrictions imposed by governments as part of their attempts to contain the spread of the epidemic. Principally, earlier articles concentrated mainly on aspects different than pure stock returns, such as volatility ([Zaremba et al., 2020](#)) or herding behavior ([Kizys et al., 2020](#)). The several notable exceptions, that provided an early overview of stock market reactions, include [Ashraf \(2020b\)](#), [Phan and Narayan \(2020\)](#), and [Narayan et al. \(2020\)](#). Nevertheless, our study differs remarkably in terms of the breadth of the factors examined. Moreover, we propose the use of a variety of novel statistical tools that have not been used in other similar studies in such a manner.

Third, our findings are important and necessary for decision makers who consider the response to the current coronavirus crisis as well as the preparation to such crises in the future. What enhances and what weakens financial immunity to the coronavirus pandemic can be of interest to a wide range of market participants including individual and institutional investors who seek for a better risk diversification and investment allocation management. The results may be essential for investors' portfolios management during black swans such as the coronavirus pandemic.¹ Policymakers can find this research insightful from an economic perspective. For instance, our research helps policy makers to evaluate the consequences of their decisions on global financial markets. It also informs policy makers how to manage the pandemic crisis, and advise on the required pre-steps to be better prepared to respond to such black swan events in a timely manner. Preparing the economy to crises can be instrumental in a long-run macroeconomic stability.

¹Note-worthily, although the COVID-19 outbreak is frequently referred to as "black swan" in both practitioners' and academic literature (e.g., [Yarovaya et al., 2020](#); [Wind et al., 2020](#); [Cavanagh et al., 2020](#)), Nassim Taleb – the author of this term – opposes using it in this context. He argues that the pandemic was predictable and preventable, so the term "white swan" appears more suitable ([Bloomberg, 2020](#))

Our research findings can be used as a guide by political leaders, who seek to identify the country's weaknesses, which need to be addressed in the quest for macroeconomic stability. The study may also be of interest to different international bodies, such as the International Monetary Fund or the World Bank. Experience has shown that during extreme crises such as the Global Financial Crisis of 2008/2009 and the European Debt Crisis of 2011, the World Bank tends to launch economic support measures to different countries worldwide.² A better understanding and mapping of the possible drivers of financial immunity can a) contribute to the management of the black swan risk of countries, and ii) help to prioritize the economic aid needed. Moreover, the World Health Organization can also benefit from our research, as we examine not only economic indicators, but a wide range of country-level characteristics, including the country's healthcare infrastructure. While COVID-19 is paramount to public health around the globe, the flip side of this coin, financial vaccine, is of utmost importance for the country's financial health.

The remainder of the article is organized as follows. Section 2 summarizes the extant literature, which forms a theoretical basis for our work. Section 3 describes the data. Section 4 outlines the research design and methodology. Section 5 summarizes our baseline empirical findings. Section 6 offers further analysis and robustness checks. Finally, Section 7 concludes.

2 Literature Review and Theoretical Basis

The outbreak of COVID-19 in December 2019 and its rapid global spread has received an overwhelming attention of researchers. Below we summarize the studies most closely linked with the topics discussed in this paper. To begin with, we discuss the papers that throw light on the impact of the pandemic upon financial markets. In particular, we survey investigations of the drivers of financial immunity or vulnerability, primarily at the firm-level. Subsequently, building on the surveyed stock-level evidence, we present the potential drivers of the country-level financial immunity or vulnerability. We discuss all different groups of variables along with their basic theoretical foundations.

2.1 The Novel Coronavirus and Financial Markets

The pandemic of 2020 brought an unparalleled proliferation of studies on the effect of the novel coronavirus on financial markets (Baker et al., 2020; Spatt, 2020; Zhang et al., 2020). The examinations of the impact of COVID-19 outbreak scrutinized for example, an interplay between the pandemic and stock market returns (Al-Awadhi et al., 2020; Goodell, 2020; Li et al., 2020; Pavlyshenko, 2020; Sharif et al., 2020; Topcu and Gulal, 2020), liquidity (Haroon and Rizvi, 2020), volatility Albuлесcu (2020); Cheng (2020); Onali (2020), mutual fund investments (Pastor and Vorsatz, 2020), and corporate finances (Bretscher et al., 2020; Gormsen and Kojien, 2020; Landier and Thesmar, 2020). Importantly, studies investigated not only the role of the pandemic itself, but also the related government interventions (Ashraf, 2020a; Baig et al., 2020; Heyden and Heyden, 2020; Phan and Narayan, 2020; Zaremba et al., 2020; Zhang et al., 2020). In addition

²On June 15, during the COVID-19 crisis for example, the World Bank announced that over the next 15 months, it would provide funding of up to \$ 160 billion tailored to the health, economic and social shocks faced by countries, including \$ 50 billion of grant IDA resources and highly concessional conditions (<https://www.worldbank.org/en/about/what-we-do/brief/world-bank-group-operational-response-covid-19-coronavirus-projects-list>).

to equities, ample articles concentrated on the influence of the pandemic on other asset classes. These include, in particular, commodities (Bakas and Triantafyllou, 2020; Corbet et al., 2020b; Devpura and Narayan, 2020; Iyke, 2020a; Narayan, 2020; Umar et al., 2020), exchange rates (Iyke, 2020b), cryptocurrencies (Conlon and McGee, 2020; Corbet et al., 2020b; Mnif et al., 2020; Umar and Gubareva, 2020), real estate (Ling et al., 2020), or bonds (Arellano et al., 2020; He et al., 2020; Ji et al., 2020; Sène et al., 2020).

A separate line of studies explores the determinants of firm or market immunity to the COVID-19 outbreak. Importantly, evaluating firm exposure to the pandemic may not be straightforward, as companies rarely provide readable information on this point in their annual disclosures (Loughran and McDonald, 2020). Within this strand, some authors focus on sectoral analysis. Donadelli et al. (2017), in one of the seminal papers, investigate the reaction of pharmaceutical companies to the World Health Organization alerts. The response to the pandemic of different industries is also researched by Kanno (2020), Haroon and Rizvi (2020), Al-Awadhi et al. (2020), Mazur et al. (2020), and Yan et al. (2020).

A range of studies investigate whether firm's financial standing can improve its position in times of pandemic. This is demonstrated by, for example, Ding et al. (2020b), who shows the essential role of low debt, high profitability, and sizeable cash reserves. The importance of leverage and liquidity is also accentuated by Ramelli and Wagner (2020), and Fahlenbrach et al. (2020), who highlight the role financial flexibility. Similar studies in this context are conducted by Davison (2020), Demir and Danisman (2020), Glossner et al. (2020), and Dechow et al. (2020).

Beside the financial factors, plenty of papers investigate the role of alternative firm characteristics and circumstances. Onali and Mascia (2020) demonstrate the essential role of corporate diversification. Broadstock et al. (2020) and Albuquerque et al. (2020) show that firms with high environmental ratings and ESG scores are better prepared to cope with the pandemic. Li et al. (2020) document that firms "with a strong corporate culture do better in the midst of a pandemic than their peers without a strong culture." Lopatta et al. (2020) show the importance of reporting practices, Amore et al. (2020) test the role of family ownership, and Pagano et al. (2020) consider the ability to implement social distancing within the company.

Interesting conceptual approaches are taken also by Hassan et al. (2020) and Corbet et al. (2020a). The first study creates a text-based measure to quantify risks associated with the pandemics. The second one, on the other hand, research the role of firms' names. Corbet et al. (2020a) demonstrate that companies with the word "corona" in their names tend to be more vulnerable to the influence of COVID-19.

Our considerations so far focused solely on firm-level immunity. Studies of stock market immunity to the pandemic at the country level are more scarce. Ashraf (2020c) and Fernandez-Perez et al. (2020) demonstrate that national culture may play a crucial role, while Erdem (2020) provide similar evidence for political regime. Iyke (2020b) finds that certain exchange rates may contribute to the pandemic immunity because investors perceive them as safe havens. Finally, Narayan et al. (2020), Phan and Narayan (2020), Shanaev et al. (2020), and Zaremba et al. (2020) scrutinize the effect of government non-pharmaceutical interventions. They document that containment, closure, health, and economic policy responses may visibly influence financial markets. To sum up, while the literature on firm-level vulnerability to the COVID-19 pandemic is relatively abundant and fast-growing. To sum up, research on country-level immunity is relatively underwhelming and limited to only several articles. Our study

aims to supplement and strengthen this body of research.

2.2 Determinants of Stock Market Immunity to the Pandemic

Our study considers a range of different categories of variables that may drive the stock market immunity or vulnerability to the COVID-19 pandemic. Concretely, these categories encompass financial variables, economic and population statistics, quality of healthcare provision, government interventions, and governance and culture. Below we carry out a detailed review of these categories, along with their theoretical foundations.

The first category relates to the financial situation of firms in a given country and their ability to cope with extreme market conditions. Building on corporate finance literature (Kahle and Stulz, 2013; Giroud and Mueller, 2017), we conjecture that the companies' ability to access funding may help to cope with the adverse impact of the COVID-19 outbreak on cash flows. This conjecture is informed by the recent evidence that a healthy balance sheet and sound financial standing may serve as a shield against pandemic-induced stock market downturns (e.g., Ding et al., 2020b; Ramelli and Wagner, 2020; Albuquerque et al., 2020; Fahlenbrach et al., 2020). A particular role may be played by firm's corporate policies. Conservative investment policies are instrumental in a greater financial immunity to the pandemic, which can be attributed to the source of investment. For instance, if a firm expands aggressively, such an expansion eventually needs to be funded by issuing debt. In a business cycle recession, when the firm operates below its full capacity, revenues decrease, but expenses, particularly aimed at servicing debt obligations, remain the same. The ensuing decrease in corporate earnings translates into a less immune stock market. In line with these assertions, we hypothesize that markets populated by more profitable and less indebted companies with more conservative investment policies may be better placed to survive extreme market conditions triggered by the COVID-19 pandemic.

Our financial data also comprises a battery of the most popular valuations ratios. Valuation ratios i) predict future stock market returns in the cross-section (Zaremba, 2019; Ang and Bekaert, 2007; Golez and Koudijs, 2018), ii) indicate stock mispricing occasioned by a bias in investor's expectations (Billings and Morton, 2001; Porta et al., 1997; Skinner and Sloan, 2002), iii) are sensitive to disappointing earnings of growth firms, (Skinner and Sloan, 2002; Donnelly, 2014), and iv) may be driven by overly optimistic investors' expectations (Lakonishok et al., 1994). Furthermore, when valuations are low and generally deviate less from fundamentals, speculative bubbles are less likely to emerge, which limits the scope of financial instabilities and hence safeguards financial immunity. Thus, this expectation component may be particularly vulnerable to increases in global risk and uncertainties, driven by pandemics (Baker et al., 2020).

We also account for the industry structure of different stock markets. Certain types of business, such as hospitality are more vulnerable; others, such as pharmaceuticals or e-commerce, may even benefit from the pandemic (Donadelli et al., 2017; Mazur et al., 2020; Niederreiter and Riccaboni, 2019). This highlights the role of industry concentration and exposure to travel and leisure activities, which were the most affected by the pandemic.

We also turn to a group of asset pricing variables documented to predict returns on stock market investments. Different investment styles react to the pandemic in non-uniform ways (Baltussen and van

Vliet, 2020), which results in some groups of stocks more affected than others. It is worth noting, many of the stock level patterns have their country-level counterparts (Asness et al., 1997). Consequently, our research design factors in the most established predictors from the asset pricing universe of country-level returns on stock market investments. These predictors include momentum (Balvers and Wu, 2006), size (Keppler and Traub, 1993), long-run reversal (Balvers et al., 2000), liquidity (Amihud et al., 2015), local interest rate (Hjalmarsson, 2010), global market beta (Frazzini and Pedersen, 2014), and idiosyncratic volatility (Bali and Cakici, 2010).

The second category includes economic and population variables. Our premise is that healthy economies with solid debt capacity would be better suited to launch effective interventions and policies targeted at curbing the pandemic. We begin with gauges of overall economic conditions, such as GDP, unemployment, inflation, and credit rating. The discussion of the link between macroeconomic factors and stock market performance has a long tradition in the asset pricing literature (Birz and Lott Jr, 2011). For instance, Boyd et al. (2005) demonstrate the effects of unemployment-related news is cyclical. Rising unemployment is good news in business cycle expansions, but bad news in business cycle recessions. It is worth noting that the COVID-19 business cycle recession is likely to dwarf any previous one. For instance, countries with lower unemployment rates are likely to be more financially immune to the spread of the coronavirus pandemic. From a theoretical perspective, unemployment-related news are informative about a) future interest rates, b) equity risk premium, and c) corporate earnings and dividends. In particular, during contractions, news about rising unemployment translate into lower earnings growth rate. If, however, macroeconomic and labor market policies stabilize the rate of unemployment, the stock market becomes more immune to the pandemic.

We also consider the role of economic openness and the role of trade and tourism in GDP, since companies are connected internationally through global chains of customers and suppliers (Hertzel et al., 2008; Acemoglu and Robinson, 2012; Acemoglu et al., 2017). Thus, globalization Zimmermann et al. (2020) and international trade Ding et al. (2020b) may facilitate the spread of the disease and may act as channels of transmitting the COVID-19-induced economic disruptions. Population density and migration patterns, included in this category, may facilitate the spread of the disease. Also, as the novel coronavirus affects mostly elderly people (see, e.g., NYC Health, 2020), we consider the age of the population. Finally, the global pandemic forced many people to adapt to remote working regimes and business to move online. Such activities strongly rely on the availability of local infrastructures, such as an internet network. Hence, we hypothesize that the immunity of an economy to the pandemic may depend on the degree of technological development and Internet availability.

The third category of variables is linked to the quality of healthcare provision. We assume that countries with higher healthcare quality may be better equipped to cope with an unexpected pandemic. In our research design, the quality of healthcare provision is measured with health expenditure, numbers of beds, doctors, nurses in the population, and overall healthcare access, which provide a gauge of the healthcare provision in the country. We additionally consider indicators of the general health of the society, such as life expectancy and infant mortality rate, as well as indicators that are closely linked with the specific current pandemic, such as the ability of the local healthcare system to cope with lower respiratory diseases (Fullman et al., 2018).

The fourth category of variables concerns government interventions. The COVID-19 pandemic triggered policy responses of an unprecedented scale, such as workplace closing or stay-at-home requirements aimed at limiting social interactions. Since economic activity depends on such interactions, they could have come at a significant cost to the economy and the society (Chen et al., 2011; Epstein et al., 2007; Lempel et al., 2009; Pike et al., 2014). It should be recognized that the overall economic and financial effects of these interventions are ambiguous. The initial effects of these containment measures were found to be detrimental (Heyden and Heyden, 2020; Huo and Qiu, 2020), and even stronger than the effects induced by the pandemic itself (Shanaev et al., 2020). On the other hand, during the 1918 flu pandemic, the economy of the U.S. cities that undertook more aggressive approaches did not perform worse, and even managed to grow faster during the pandemic (Correia et al., 2020). Thus, while the initial reaction to the containment and closure actions is negative, the overall effect may benefit the economy and, in turn, stock market investments. Specifically, this study accounts for several different classes of government interventions. Building on Hale et al. (2020), we track daily changes in policies around the world to examine the role of eight containment and closure categories (school closing, workplace closing, cancellation of public events, restrictions on gatherings size, public transport closure, stay-at-home requirements, restrictions on internal movement, and restrictions on international travel), three types of health system interventions (public information campaigns, testing policy, and contact tracing), and two types of economic stimuli (income support and debt or contract relief for households). We consider each of these policies separately, as well as jointly with a single Stringency Index.

The fifth category includes governance and culture variables. The success of different policies to combat the spread of COVID-19 and revive the economy depends on the government's ability to implement them, which can be strengthened or weakened by factors such as state power, media, and freedom of expression. Countries with greater state power relative to the power of individuals and with respect of law may orchestrate a more effective response to the pandemic. This premise receives support from Cepaluni et al. (2020), who show that political regime may influence the efficiency of coping with the COVID-19 pandemic. However, the overall evidence is mixed. For instance, social scientists tend to argue that democratic governance produces better health, economic, and social outcomes through more rigorous, accountable, and better-informed decision-making processes (Acemoglu et al., 2019; Acemoglu and Robinson, 2012; Besley, 2006; Bollyky et al., 2019; Dorsch and Maarek, 2019). Nevertheless, the same features may limit the incisiveness and speed of policy implementations (Malesky and London, 2014; Weeks, 2008). To control for the governance quality, we incorporate six different indicators obtained from the World Bank that represent voice and accountability, political stability, government effectiveness, regulatory quality, rule of law, and control of corruption.

Moreover, certain legal heritage is demonstrated to give greater power to the state (Porta et al., 1998; La Porta et al., 1999; Levine, 2005), so we also account for the legal heritage: English, French, German, or Scandinavian. In addition to the quality and efficiency of financial regulations, the willingness of the society to adhere to such regulations should not be underestimated. Certain cultural features, such as the level of collective thinking or power distance within the society may affect human behavior during a pandemic. Other cultural characteristics, such as long-term orientation may determine how investors incorporate information in their financial investment decisions. Specifically, cultural differences can

markedly affect the way investors interpret or respond to new information (Dou et al., 2016; Schneider and De Meyer, 1991) or determine their aversion to risk (Anderson et al., 2011; Chui and Kwok, 2008; Li et al., 2013). In particular, (Fernandez-Perez et al., 2020) show that firms in countries with lower individualism and higher uncertainty avoidance tend to be affected more adversely by health disasters. To factor in these issues, we also research the role of different cultural dimensions defined by Hofstede et al. (2010). Indeed, finance literature already demonstrated that the features like short-term orientation or individualism may affect asset pricing in international equity markets (Chui et al., 2010; Docherty and Hurst, 2018).

3 Data

To investigate what determines the country’s financial immunity to the COVID-19 pandemic, we examine five categories of information pertaining to: i) financial markets, ii) economy, iii) healthcare provision quality and its capacity to cope with the pandemic, iv) government interventions and policies aimed at the containment of COVID, including containment policies, interventions in the healthcare sector, and economic stimuli, and v) governance, legal origin and national culture. Considering all these variables in conjunction with the cumulative number of confirmed cases we seek to ascertain the drivers of the country-level stock market immunity.

3.1 Equity returns

We use total returns based on Datastream Global Equity Indices. These indices are value-weighted equity portfolios, which cover around 85% of the most liquid and largest stocks in each market. Datastream indices provide a good representation of investable securities across all developed and emerging markets, and are regarded as one of the most common choices in country-level asset pricing studies.

Our sample includes 67 countries, which cover developed, emerging, and frontier markets. Specifically, to assure consistency of our calculations and avoid arbitrariness in sample selection, we examine all countries covered by Datastream indices. The detailed list of all the countries considered is provided in Table 1. In line with Fama and French (2012, 2017) and Clare et al. (2016) we express stock market returns for all countries in U.S. Dollar terms.

[Insert Table 1 about here]

To ensure that our research findings are robust to the data frequency, we perform our analyses with two different intervals: daily and weekly. Daily returns have the obvious benefit of increasing the number of degrees of freedom. On the one hand, they allow to capture daily changes in government policies, and to estimate more accurately their influence. On the other hand, trading sessions may or may not be synchronized with the timing of the announcement of numbers of cases and deaths in the country. Furthermore, information on new infections is recorded and released not only during trading days but also during non-trading days. In consequence, following weekends and holidays, the investor needs to discount case data from more than one day. To alleviate these issues, our second approach builds on Ding et al. (2020b) and utilizes weekly returns to explore the impact of the coronavirus infections on the

stock market performance. The descriptive statistics of the returns are reported along with the remaining data in Tables A.6 and A.7 in the Online Appendix.

3.2 Coronavirus case count

The growth of the pandemic could be quantified with different variables, such as the number of cases. Ashraf (2020b) compares these measures and demonstrates that the changes in the number of new infections (cases) is the most essential variable that influences the financial markets. In consequence, it is employed in the major asset pricing studies that explore the impact of the COVID-19 outbreak on financial markets (e.g., Ashraf, 2020c; Ding et al., 2020b; Iyke, 2020b; Demir and Danisman, 2020; Zaremba et al., 2020). Following these studies, we employ the change in the number of cases as our primary proxy for the spread of the disease. Specifically, we closely follow Ding et al. (2020b), who compute the growth rate of the cumulative number of confirmed cases in each country. Specifically, the growth rate, $DCC_{i,t}$, is calculated in Equation 1 below:

$$DCC_{i,t} = LN(1 + CC_{i,t}) - LN(1 + CC_{i,t-1}), \quad (1)$$

where $CC_{i,t}$ denotes the cumulative number of confirmed cases, i represents the country and t the time.

For robustness, we utilize both weekly and daily data. In terms of the latter, rather than a total change in the case count, we calculate an average daily change since the previous trading session to account for the non-trading days.

Importantly, earlier studies provide evidence of a detrimental impact of the pandemic upon stock returns around the world (Ali et al., 2020; Huo and Qiu, 2020; Ashraf, 2020b; Wang and Enilov, 2020; Zhang et al., 2020). In line with these studies, the scatter diagram in Figure 1 is indicative of an unambiguously negative relation between stock market returns and the pandemic in our sample. Our empirical analysis in Section 5 delves deeper into this research problem, which seeks to unearth the factors that alleviate or exacerbate the adverse stock market impact of COVID-19.

[Insert Figure 1 about here]

Notably, to assure the robustness of our findings, similarly as in Erdem (2020) and Iyke (2020b), we corroborate our findings with the number fatalities (see Section 6.1 for details).

The descriptive statistics of the (growth of) cumulative number of confirmed cases and death are depicted in Panel B of Tables A.6 and A.7 in the Online Appendix.

3.3 Financial data

Financial and stock market data are retrieved from Datastream. The variables are described in detail in Table A.1 in the Online Appendix. Our choice of financial data is informed by the studies that underline the financial standing of companies as a key driver of their financial immunity to COVID-19 (e.g., Ding et al., 2020b; Ramelli and Wagner, 2020; Albuquerque et al., 2020). We consider several common financial ratios. In particular, we take into account: a) three measures of profitability: return on assets (ROA),

return on equity (*ROE*), and return on sales (*ROS*); b) two proxies of indebtedness: leverage ratio (*LEV*) and interest coverage ratio (*COV*); and c) two indicators of investment activity: CAPEX-to-assets ratio (*C/A*) and 12-month asset growth (*AG*), advocated by [Cooper et al. \(2008\)](#). Firms with easier access to credit and cash are better equipped to defy the adverse impact of the coronavirus pandemic on cash flows.

In addition to the aforementioned financial ratios, we also turn to a range of different valuation indicators that were identified in country-level asset pricing studies ([Zaremba, 2019](#)): book-to-market (*BM*), earnings-to-price (*EP*), cash flow-to-price (*CP*), forward earnings-to-price (*FEP*), EBITDA-to-enterprise value (*EBEV*), as well as dividend yield (*DY*).

All these financial variables rely on aggregate-market data and are obtained directly from Datastream. The ratios are based on financial data weighted in both the numerator and the denominator according to companies' market capitalizations, i.e., in line with an index portfolio design.

Moreover, our research design incorporates two variables that represent the industry structure of stock markets in different countries. The first variable is the market share of the Travel and Leisure industry (*TRAV*), as classified by Datastream. This sector encompasses hotels, airlines, and restaurants, which were severely hit by the pandemic. Second, we hypothesize that countries with strongly concentrated activity in selected industries may be more financially vulnerable than countries with relatively diversified businesses. Hence, we compute industry concentration (*CON*) using the Gini coefficient.

Our research design is further guided by [Baltussen and van Vliet \(2020\)](#), who document that investment styles may be affected by pandemics in different ways. Hence, we also control for several well-established return predictors that are reported to predict country-level stock market returns. Momentum (*MOM*) is a 12-month trailing log-return (e.g., [Asness et al., 1997](#); [Balvers and Wu, 2006](#)). Size (*MV*) is measured by the log-market value of the index portfolio ([Keppler and Traub, 1993](#)). Long-run reversal (*REV*) is the 60-month trailing return with the 12 most recent months skipped ([Balvers et al., 2000](#)). Liquidity is proxied by the turnover ratio (*TURN*), i.e., the ratio of the 12-month average of daily dollar volume over market capitalization ([Lee, 2011](#)). Local interest rate (*BILL*) is represented by the three-month Treasury bill rate ([Hjalmarsson, 2010](#)). Stock market beta (*BETA*) and idiosyncratic volatility (*IVOL*) are estimated as the slope coefficient and the residual term, respectively, from a regression of a country's excess returns on returns on the global market portfolio using three years of daily data ([Bali and Cakici, 2010](#); [Frazzini and Pedersen, 2014](#); [Umutlu, 2015, 2019](#)).

Importantly, all financial and market variables are computed for time $t - 1$ preceding the return measurement period, to avoid any look-ahead bias. Also, the ratios are computed on an "as reported" basis; that is, at time t , they rely only on information that was publicly available at time $t - 1$. The descriptive statistics of the variables derived from financial and stock market data are presented in Panel C of Tables A.6 and A.7 in the Online Appendix.³

³For robustness, we experiment with winsorizing the financial variables at 1% and 99% levels. This exercise does not affect qualitatively our results.

3.4 Economic, demographic and technological data

The economic environment and performance in a country can be instrumental in its ability to endure the consequences of the pandemic. Therefore, we include several key economic variables, compiled from several different sources, such as the World Bank, OECD National Accounts, International Monetary Fund, and World Tourism Organization. The selected variables are described in detail in Table A.2 and Panel D in Tables A.6 and A.7 of the Online Appendix illustrates their key descriptive statistics. It is worth noting that all the variables in this category are time-invariant, and we always use the most recent data available for all the countries in our sample.

First, we include several macroeconomic variables that cast light on a country's economic growth and development, as well as the stance of business and credit cycles: overall GDP (*GDPP*), GDP per capita (*GDPC*), GDP growth (*GDPG*), unemployment (*UNEM*), inflation (*INF*), manufacturing value added (*MAN*), credit to the private sector (*CRED*), and a rescaled average credit rating from the three prime agencies: Standard & Poor's, Moody's, and Fitch Ratings (*RTNG*).

The second category of variables account for a country's exposure to the global economy, in particular, through the channels most affected by the pandemic, such as tourism. This information set includes the ratios of exports of goods and services to GDP (*EXP*), international tourism receipts in U.S. Dollar terms, as a percentage of GDP (*TOUR\$*, *TOUR%*), and trade as a percentage of GDP (*TRADE*).

The third category comprises population statistics. We conjecture that densely populated countries with older or aging population may be more vulnerable to the virus, which in turn, may also affect the economy and financial markets. Also, the migration patterns may facilitate the spread of the disease. Therefore, we consider the following variables: the share of the population aged 65 and above (*POP65*), population density (*DENS*), the share of urban population (*URBAN*), and net migration (*MIGR*).

The fourth category represents the level of technological development in the country. We hypothesize that more technologically advanced countries would be less reliant on physical contact between businesses and consumers, and they would find it easier to embrace different forms of remote work. In consequence, this would enable to cushion part of the negative financial impact of the pandemic. In addition, the more technology advanced the country is, the easier will be to i) monitor the evolution of the pandemic, ii) identify problematic contagious areas, iii) as well as quickly disseminate important information to the public. Concretely, we consider the ICT Development index (*ICT*) and the percentage of individuals using the Internet (*INET*).

3.5 Healthcare data

We also use information related to the quality of healthcare infrastructure provision in a country. The data in this section is sourced mainly from the World Health Organization (WHO), with statistics coming from the United Nations and local sources. This is a time-invariant information set, where the most recent updates are from the years 2016 to 2019. The details of the variables are reported in Table A.3 in the Online Appendix, and Panel E in Tables A.6 and A.7 displays their statistical properties.

Countries with better-developed healthcare systems may be better prepared to combat the pandemic

and, thus, alleviate the potential economic consequences. Therefore, we control for the level of health expenditures, both in per capita terms and as a percentage of GDP ($HEXPC$, $HEXP\%$), as well as the number of hospital beds, nurses, and physicians per 1,000 people ($BEDS$, $NURSE$, $PHYS$). Also, we include two variables that measure the overall population health – life expectancy at birth in years ($LIFE$) and infant mortality rate per 1,000 births ($INFMORT$). Furthermore, we consider two broad indices that evaluate the entire healthcare system: Healthcare Access and Quality Index ($HEALTH$) obtained from Institute for Health Metrics and Evaluation ($IHME$), and UHC Service Coverage Index (UHC) by WHO.

While the above-mentioned indicators reflect mostly the general healthcare infrastructure, provision and preparedness in a given country, we also include several indicators linked more closely with the vulnerability to the coronavirus pandemic. These include the lower respiratory infection score from Fullman et al. (2018) ($RESP$) that measures that extent to which the health system is prepared to cope with this particular type of infection. Furthermore, our healthcare information set highlights the importance of accounting for smoking prevalence among males and females, as a percentage of all the adults ($SMOKM$, $SMOKF$).

3.6 Government interventions data

We utilize data on government interventions collected by Hale et al. (2020). The interventions are classified into three different categories: a) containment and closure, b) health system, and c) economic stimulus. All the indicators are available on a daily basis, and are computed and represented on an ordinal scale. The precise description of the particular variables and their calculation methods are summarized in Table A.4 in the Online Appendix, and their statistical properties are displayed in Panels F of Tables A.6 and A.7.

The containment and closure category encompasses eight indicators: i) school closing ($C1$), ii) workplace closing ($C2$), iii) cancellation of public events ($C3$), iv) restrictions on gatherings size ($C4$), v) public transport closed ($C5$), vi) stay at home requirements ($C6$), vii) restrictions on internal movement ($C7$), and viii) restrictions on international travel ($C8$).

The second category includes health system interventions: i) public information campaigns ($H1$), ii) testing policy ($H2$), and iii) contact tracing ($H3$). Since these policies help to cope with the pandemic quicker, they may be also discounted in stock prices.

The third category comprises two types of economic stimuli that were widely employed in numerous territories affected by the coronavirus around the world: income support ($E1$), and debt or contract relief for households ($E2$). These stimuli affect the economy through various channels. For instance, stimuli support consumption and spending in times of distress; hence, they may significantly affect local equity markets.

Finally, besides the individual measures, we also consider the overall Stringency Index (SI) by Hale et al. (2020). The index aggregates the data pertaining to variables $C1$ – $C8$ and $H1$, and it is re-scaled to create a score between 0 and 100. SI provides a synthetic measure of the intensity of different non-medical government interventions during the pandemic.

Some of the policies in considered in this study can be implemented either as 1) targeted policies, limited to certain geographical region, category of business, or group of residents, or 2) general policies, applied to the entire country or population (for details, see Hale et al. (2020)). We consider the “scale” of these polices, and we introduce the additional “general” indicator to indicate whether the policy

applies across the entire country or population (denoted with a subscript G). For example, $C1$ indicates that school closure is ordered, regardless of the scale of the intervention (targeted or general), and $C1_G$ indicates that the schools are closed in the entire country.

All the changes in government policies are tracked daily. Therefore, when we perform the regressions based on weekly returns, we calculate the weekly averages for the considered period.

3.7 Governance, law origin and national culture data

To provide an overview of overall governance quality, state power, and freedom of expression in the country, we rely on the World Bank’s World Governance Indicators from the year 2018. We include all the six components, that is, voice and accountability (*ACCOUN*), political stability no violence (*POLSTAB*), government effectiveness (*GOVEFF*), regulatory quality (*REQUAL*), rule of law (*RULELAW*), and control of corruption (*CORRUPT*). Also, we include a dummy representing the country’s legal origin: French, German, Scandinavian, and English (*FREN*, *GERM*, *SCAN*, *ENGL*).

Besides the governance, we incorporate information on national culture. Similarly to (Fernandez-Perez et al., 2020), we rely on the classification by Hofstede et al. (2010). To provide a comprehensive overview of national culture, we incorporate all the six components obtained from Hofstede (2018): power distance (*POWDIST*), individualism (*INDIV*), masculinity (*MASC*), uncertainty avoidance (*UNCAV*), long-term orientation (*LTOR*), and indulgence (*INDUL*).

A detailed description of the governance, legal origin, and national culture indicators is outlined in Table A.5 in the Online Appendix, and Panel G in Tables A.6 and A.7 summarizes their basic statistics. Similar to other variables, also these categories are time-invariant and were retrieved upon their availability.

4 Methodology

In this section, we outline our research design that we employ to study the effects of financial, economic, healthcare, government and governance variables on financial immunity to the coronavirus pandemic. Our research design deals with a multidimensional information set, which has not been used before to study financial immunity in international stock markets. We ask whether innovations to this information set alleviate or exacerbate the negative effect of the officially confirmed cases on financial immunity. Our rigorous empirical methodology proceeds in three steps, which are necessary for the identification of an optimal set of variables capable of explaining the response of international stock markets to the outbreak of the pandemic.

In Step 1, we seek to determine the optimal set of *in-sample* determinants of financial immunity. To this end, we interact the rate of growth in the total number of confirmed cases with financial, economic, healthcare, government interventions, and governance variables. Subsequently, We estimate single-interaction panel data regressions, while controlling for an array of asset pricing factors, identified in the related body of studies.

In Step 2, we turn to machine learning methods. This novel framework is rapidly growing in popularity as a tool for efficient stock characteristic selection for return predictability (Gu et al., 2020; Feng et al., 2020; Sun, 2018; Bryzgalova et al., 2019). Specifically, we validate the individually significant interaction

with an elastic net. The elastic net, a machine-learning technique, seeks to ascertain if the individually significant interaction terms, identified in Step 1, carry significant information about financial immunity. In particular, the elastic net determines the set of variables, which lead to the largest value of the *out-of-sample* Adjusted R^2 or the smallest mean prediction error of *out-of-sample* forecasts.

In Step 3, we use multiple-interaction panel data regressions to evaluate the relative importance of financial, economic, healthcare, government interventions, and governance variables for financial immunity in international stock markets. In the baseline approach we use random-effects panel-data regressions, but we also ratify our findings with alternative approaches in Section 6.

4.1 Single interaction panel data regression

In Step 1, our empirical methodology is founded on a single-interaction panel-data regression, which appears in Equation 2 below:

$$R_{i,t} = \gamma_0 + \gamma_1 \times DCC_{i,t} + \Gamma'_1 \times \mathbf{X}_{1,i,t} + \beta \times X_{2,i,t} \times DCC_{i,t} + u_{i,t}, \quad (2)$$

where $R_{i,t}$ is stock market return in country i at time t , defined as $R_{i,t} = 100 \times [LN(P_{i,t}) - LN(P_{i,t-1})]$, and $P_{i,t}$ is country's i stock market index. The single-interaction regression is used to identify individually significant interaction terms $X_{2,i,t} \times DCC_{i,t}$, while controlling for an array of key asset pricing factors, $\mathbf{X}_{1,i,t}$. Specifically, $\mathbf{X}_{1,i,t} \equiv (BETA_{i,t}, BM_{i,t}, MOM_{i,t}, MV_{i,t})'$. In Equation 2, $BETA_{i,t}$ is a country's i beta in period t , $BM_{i,t}$ is the book-to-market ratio, $MOM_{i,t}$ is momentum factor (Carhart, 1997), and $MV_{i,t}$ is the market value. These asset pricing factors are well established in international studies, such as Fama and French (2012), Assness et al. (2013), Griffin (2015), Hou et al. (2011), *inter alia*.⁴ Importantly, beta, book-to-market, ratio, momentum, and size are key predictors of country-level returns in the cross-section (Asness et al., 1997; Assness et al., 2013; Balvers and Wu, 2006; Frazzini and Pedersen, 2014; Keppler and Traub, 1993; Zaremba, 2019). Controlling for these factors allows us to disentangle the effect of the pandemic from the regular cross-sectional return patterns.

All regressions also include the rate of growth in total confirmed cases ($DCC_{i,t}$), and the random disturbance term ($u_{i,t}$). The random disturbance term can be decomposed into two components, $u_{i,t} = v_i + \varepsilon_{i,t}$, where v_i captures unobservable country-specific heterogeneity, and $\varepsilon_{i,t}$ is the idiosyncratic error. We use both daily and weekly return data from 01/01/2020 to 28/04/2020.

We expect that a larger change in the total confirmed cases exerts a negative effect on returns in international stock markets; hence, $\gamma_1 < 0$. Also, the coefficient β can be positive or negative, depending on a specific covariate. The coefficient β measures the extent to which a change in $X_{2,i,t}$ is associated with higher or lower financial immunity. For instance, if $\beta > 0$, a rise in $X_{2,i,t}$ reduces the negative effect of the change in confirmed cases on stock market returns, insofar as $\gamma_1 < 0$.

⁴A full definition of the RHS variables and their measurements appear in Tables A.1 – A.5 in the Online Appendix.

4.2 Machine learning methodology

In Step 2, our empirical methodology builds on an elastic net, which can be formulated as a constrained optimization problem à la [Zou and Hastie \(2005\)](#), as follows in [Equation 3](#) below:

$$\hat{\Gamma} = \arg \min_{\Gamma} \frac{1}{N \times T} \left\{ \sum_{i=1}^N \sum_{t=1}^T [R_{i,t} - \gamma_0 - \gamma_1 \times DCC_{i,t} - \Gamma'_1 \times \mathbf{X}_{1,i,t} - \Gamma'_2 \times \mathbf{X}_{2,i,t} \times DCC_{i,t}] \right\} + \lambda \left[\alpha (\|\Gamma\|_1) + \frac{1-\alpha}{2} (\|\Gamma\|_2^2) \right], \quad (3)$$

where $\|\Gamma\|_1$ is the ℓ_1 -norm (also referred to as the ℓ_1 -penalty), and $\|\Gamma\|_2$ is the ℓ_2 -norm (also referred to as the ℓ_2 -penalty) of the coefficient vector Γ . The elastic net optimizes over the vector of coefficients, $\Gamma = (\gamma_0, \gamma_1, \Gamma'_1, \Gamma'_2)'$. The optimization problem needs to satisfy certain pre-assignment constraints (as well as other constraints), which seek to retain the coefficients of the control variables, γ_0 , γ_1 , Γ_1 . Conditional on retaining all coefficient in γ_0 , γ_1 , Γ_1 , elastic net iteratively chooses an optimal set of covariates from Γ_2 . The elastic net is a combination of least absolute shrinkage and selection operator (*lasso*) with the ℓ_1 -penalty (when $\alpha=1$) and ridge regression the ℓ_2 -penalty ($\alpha=0$). Lasso is a machine learning method for selecting and fitting covariates that appear in the model. Ridge regression is a method designed to retain highly collinear variables in a regression model that is employed for forecasting.

This machine learning technique highlights at least two distinctive features of our research design. First, when predictors are highly correlated, the ordinary least squares (OLS) estimator becomes increasingly unstable as the correlation among the covariates grows. In fact, OLS gives rise to wild coefficient estimates on highly correlated regressors that cancel each other out in terms of the fit. The ridge regression penalty remedies this issue by removing this instability and giving rise to coefficient estimates that can be used for out-of-sample forecasting. Thus, coefficient estimates from the elastic net are more robust to the presence of highly correlated covariates than are lasso solutions ([Zou and Hastie, 2005](#)). This is relevant for time invariant covariates, particularly pertaining to economic, healthcare and governance information sets.

Second, since research into the catalysts and inhibitors of financial immunity is embryonic, the true model of financial immunity is unknown. Including too many covariates may lead to over-fitting, whereas including too few covariates may lead to an omitted variable bias. When the number of covariates is 'large', some of them are likely to be significant 'by chance' and, subsequently, perform poorly out of sample. In this regard, the elastic net allows us to minimise the scope of 'p-hacking', when a researcher falsely finds evidence of an effect ([Simmons et al., 2011](#)). We also recognize that individually significant variables are not necessarily those that lead to substantial changes in the out-of-sample R^2 . Therefore, elastic net can be regarded as an effective remedy to a false-positive outcome, which seeks to ensure that individually significant covariates also maximize the out-of-sample Adjusted R^2 (or minimize the mean prediction error). Therefore, the ensuing optimal set of variables can be deemed "economically" significant, as opposed to the single interaction panel data model, where covariates are selected based on their individual significance. Conditional on the elastic net selection outcome in Step 2, Step 3 consists of post-selection inference ([Lee et al., 2016](#)).

4.3 Multiple interaction panel data regression

In Step 3, we construct a multiple interaction panel data regression model, as outlined in Equation 4 below:

$$R_{i,t} = \gamma_0 + \gamma_1 \times DCC_{i,t} + \Gamma'_1 \times \mathbf{X}_{1,i,t} + \Gamma'_2 \times \mathbf{X}_{2,i,t} \times DCC_{i,t} + u_{i,t} \quad (4)$$

In Equation 4, We now consider M interaction terms that appear to be significant in Section 4.1. These interaction terms will involve an optimal subset of variables, selected from financial, economic, healthcare, government interventions, and governance variables. As previously, the $DCC_{i,t}$ is the rate of growth in the cumulative number of confirmed cases. As in Section 4.1, we control for the four key asset pricing factors, beta ($BETA_{i,t}$), the book-to-market ratio ($BM_{i,t}$), momentum ($MOM_{i,t}$), and market value ($MV_{i,t}$). The random disturbance term can be decomposed into two components, $u_{i,t} = v_i + \varepsilon_{i,t}$, where v_i captures unobservable country-specific heterogeneity, and $\varepsilon_{i,t}$ captures the idiosyncratic error. We employ a random-effects panel-data regression to estimate Equation 4. The justification for the random effects estimation model is five-fold. First, our multidimensional information set mainly comprises time-invariant variables, which would be correlated with country-specific fixed effects, if a fixed-effect panel-data regression is used instead. Whilst single-interaction panel-data regressions are essentially free from the multicollinearity issue, we preserve the consistency of the estimation method across all of our model specifications. Second, we are particularly interested in the population, from which the sample is drawn, rather than unobserved country specific characteristics *per se* (Gelman, 2005; Searle et al., 2009, p. 15-16). Third, our sample is a relatively small share of the population (Gelman, 2005; Green and Tukey, 1960). Fourth, it is worth noting that random effects vary across individual countries, whereas fixed effects are constant (Gelman, 2005; Kreft and De Leeuw, 1998, p. 12). Fifth, the fixed effects estimation method requires estimating country-specific intercepts, which significantly reduces the number of degrees of freedom (Zaremba et al., 2020).

5 Baseline empirical findings

We begin the analysis of our baseline findings with the panel regressions that account for single interaction terms. We then continue with the application of the elastic net. Finally, we perform the multivariate test of multiple features simultaneously.

5.1 Single interaction panel data regression

In this subsection, we first focus on the examination of individual interactions with different categories of variables: financial, economic, healthcare, government interventions, and governance. Subsequently, we turn to comprehensive examinations of multiple factors jointly.

5.1.1 Financial variables and valuations

Table 2 demonstrates the results of the examinations with the single-interaction regressions following Equation 2. To assure robustness of our findings, for all of our tests we report simultaneously the results

based on both daily and weekly data, and we focus mainly on the variables significant in both approaches. For the sake of brevity, we present only the slope coefficients of the considered interactions and leave out of the presentation the control variables and the coefficients on *DCC*.

[Insert Table 2 about here]

Several financial variables stand out in Table 2 as reliable determinants of the stock market reaction to the pandemic. First, the interaction of asset growth with the growth of the cumulative number of confirmed cases has a negative and significant effect on returns on international stock markets. In other words, stock markets populated with companies with aggressive investment policies tend to underperform markets with conservative investment policies during the pandemic. Indeed, extensive investment relies on a steady source of financing, either internal or external (Hou et al., 2015). Not did only the pandemic adversely affect companies' ability to generate revenue, but also "froze" credit markets, making external financing more costly and challenging (Nozawa and Qiu, 2020; De Vito and Gómez, 2020; Sinagl, 2020; Fahlenbrach et al., 2020; Banerjee et al., 2020). The subsequent cash crunch may lead to massive insolvencies (Baldwin and Weder di Mauro, 2020; Benassy-Quere et al., 2013). Hence, companies that embark on aggressive investment programs are particularly vulnerable to the pandemic-induced liquidity and lending constraints. Relatively similar reasons may lie behind the positive and significant effect of the interaction that involves *ROS*. Also, Ding et al. (2020b) argue that more profitable firms may cope better with funding problems, which manifests their immunity to the COVID-19 pandemic.

Furthermore, we record a negative and significant coefficient on stock market beta. High beta markets were more negatively affected by the pandemic. This finding is aligned with the abundant literature on the "flight to safety" phenomena, which demonstrates that during extreme market conditions investors tend to prefer securities with stable payoff (Baele et al., 2020). Hence, investors may decide to stay away from volatile markets, opting for safer ones. The valuation indicators considered in our sample are predominantly insignificant, but the forward earnings-price ratio (*FEP*) is a notable exception. The high *FEP* markets performed visibly better than low *FEP* markets. This is in line with our conjecture that the growth firms may be more affected due to the bigger role of the "growth component" in the valuation. The overvaluation of elevated expected profits may face brutal reality during a pandemic-scale disaster, which effectively brings down the valuations.

Nonetheless, it is interesting why the performance of *FEP* differs qualitatively from the other (insignificant) valuation ratios. Indeed, Doukas et al. (2002) and Cen et al. (2006) argue that *FEP* displays certain differences from other valuation ratios. On the one hand, unlike, for instance, high BM stocks, high *FEP* stocks are actually safer than low *FEP* stocks in terms of market risk, liquidity, and financial standing. Hence, while the value factor underperformed during the pandemic (Anderson, 2020), the flight to safety phenomena may actually benefit the high *FEP* stocks. On the other hand, among all of our valuation ratios, only *FEP* has its numerator adjusted to the dramatic changes in the economic situation and market conditions. Following the outbreak of the pandemic, many analysts cut their forecasts, decreasing the expected earnings per share. In consequence, *FEP* is better equipped to capture the expected cash flow, compared with the backward-looking *EP* or *CP* ratios.

Industry concentration (CON) is the last variable that significantly influences international stock markets during the pandemic. Astonishingly, the coefficient takes on a positive value, which suggests that more concentrated industries were more immune during the pandemic. This may stem from the weight of certain sectors, which were less adversely affected by the COVID-19-induced bear market. The positive effect may be linked to the financial standing of companies, as some sectors may be financially better prepared to cope with the crisis. The role of CON is revisited in Section 5.3, which centres on the multiple-interaction panel-data model.

5.1.2 Economy, demographics and technological development

Table 3 summarizes the results of the panel regressions that comprise the economic, demographic, as well as technological variables. While some of the variables appear significant in one specification only – daily or weekly – let us just remind that to ensure robustness we require significance in both types of time intervals. The findings indicate that population and access to modern technology do not appear to significantly influence the country-level financial immunity to the pandemic. In other words, equity investors do not seem to factor in the potential risks, associated with the spread of the disease in aging societies and densely populated countries, nor they consider the opportunity to absorb the pandemic consequence with modern technology.

[Insert Table 3 about here]

With regard to the economy, although several variables display some significance for only one of the return measurement frequencies, unemployment is the only significant factor for both weekly and daily returns. Labor market conditions are associated with financial immunity in two ways. First, the unemployment level forms an acid test of the business cycle stance. It can help to identify ailing economies, which may find it difficult to launch and finance vigorous actions to quickly cope with the COVID-19 pandemic. Second, labor markets were severely hit by the pandemic Bernstein et al. (2020); Blustein et al. (2020); Coibion et al. (2020), and many countries recorded unprecedented levels of jobless claims (Kretchmer, 2020).⁵ Elevated unemployment adversely impacts consumption, thus, directly affecting the revenues of the stock market companies.

5.1.3 Healthcare quality

Table 4 reports the results of our investigations for the quality of healthcare infrastructure and provision. Remarkably, none of the slope coefficients in this section is significant in both daily and weekly approaches. In other words, neither the quality of healthcare provision in the country — measured with the number of medical staff or beds in — nor the overall population health seems to drive the country-level financial immunity to the pandemic. Even the variables directly related to lower respiratory system infections prove insignificant. To conclude, though the quality of healthcare in a country may influence the development of a pandemic (Levin et al., 2007; Armocida et al., 2020), this information is not priced in by stock market investors.

⁵In April 2020, International Labour Organization predicted that about 1.6 billion workers may face the immediate risk of job loss (Organization, 2020).

[Insert Table 4 about here]

5.1.4 Government interventions

We now turn the effect of the government policy response to the COVID-19 pandemic (Zaremba et al., 2020). As aforementioned, this type of intervention may exert a significant effect on stock market returns and volatility. However, there is no consensus as to whether their impact on the economy and financial markets is positive or negative. While some studies accentuate the immediate negative reaction of the equity market (Heyden and Heyden, 2020; Shanaev et al., 2020; Huo and Qiu, 2020), others argue that timely and decisive measures may actually limit the economic consequence of the pandemic (Correia et al., 2020). It is worth noting that our findings, summarized in in Table 5, support the latter view.

[Insert Table 5 about here]

First of all, the slope coefficient on the Stringency Index is positive and significant (Table 5, Panel A). In other words, the application of different stringency measures does not appear to exacerbate stock market declines. On the contrary, government interventions help to build the country-level financial immunity. In other words, market downturns are driven predominantly by the evolution of the pandemic itself. However, the adverse stock market effect provoked by the COVID-19 pandemic is partially offset by the positive stock market effect of government interventions.

The subsequent panels of Table 5 provide insights into the effects of specific types of interventions. Panel B concentrates on different containment and closure measures. Many of the variables display positive and significant coefficients. When we consider the joint positive impact on weekly and daily returns, workplace closing (C2), closure of public transportation (C5), stay at home requirements (C6), and the restrictions on internal movement (C7) appear to have significant effects on financial immunity. Moreover, the government interventions exert a similar influence, irrespective of whether they are implemented country-wide or in targeted regions. In fact, investors may interpret targeted interventions as the first step towards comprehensive and decisive actions. Noteworthy, these specific government interventions feature increased correlations, since many countries launched policies against the COVID-19 pandemic at similar times. Therefore, disentangling their individual influences poses a challenge, which is addressed by way of the multivariate tests in Section 5.3.

Table 5, Panel C, presents the results for different healthcare interventions. Out of the three tested variables, contact tracing (H3) lends the strongest support for the equity market. Investors tend to price in the potential benefits from the contact tracing policies, as they allow to control the pandemic. Recent studies argue that modern contact tracing methods can be highly effective. In particular, it is argued that when combined with case isolation, the coronavirus outbreak could be controlled within just a few months (Hellewell et al., 2020; Salathé et al., 2020). Thus, implementation of such policies may spur expectations for quicker economic revival, which subsequently would benefit the local equity markets.

Finally, the last category of government interventions contains information about two types of economic stimuli: income support and debt relief. Intuitively, these interventions stimulate consumption and decrease risks in the economy. Consequently, they are expected to exert a positive effect on returns from

international stock markets. In line with this reasoning, the coefficient on the two variables, both in the targeted and general setting, is positive and significant. In other words, both types of interventions help to mitigate the influence of the pandemic on the stock market. Remarkably, however, the two types of actions may be correlated, as they were sometimes implemented together. In consequence, dissecting their specific effects can be a daunting task, which is addressed in Section 5.3.

5.1.5 Governance, law heritage, and national culture

The last category of our multidimensional information set encompasses variables pertaining to corporate governance, legal origin, and national culture (See Table 6). The legal heritage does not appear to be a reliable predictor of the country-level financial immunity to the COVID-19 pandemic. None of variables in this class is significant across both weekly and daily returns. Nevertheless, in the remaining two categories, we identify several significant influences.

[Insert Table 6 about here]

Among the World Governance Indicators, we record a negative influence of Voice and Accountability (*ACCOUN*). This variable captures perceptions of the extent to which citizens can participate in electing their government, as well as freedom of expression, freedom of association, and free media. The observed negative sign indicates that the pandemic is more detrimental to the stock market in more democratic countries. This lends support to the premise that autocratic regimes can impose and execute rapidly strict regulations, which be unthinkable in liberal societies. Nonetheless, regardless of their ethical assessment, the strong power may help to suppress the pandemic and limit its negative influence on the economy and stock-listed firms.

We also witness a significant effect of some national cultural characteristics. In particular, long-term orientation (*LTOR*) plays a positive and significant role. A plausible explanation for this finding is that long-term oriented investors are better placed to evaluate the temporary character of certain consequences of the pandemic and thus are less likely to overreact. Along similar lines, Hofstede (2020) points out that long-run oriented societies are likely to cope well with the COVID-19 pandemic. In fact, all the countries that managed to curb the pandemic fast – notably, Singapore, Korea, Taiwan, and Japan – have traditionally long-term oriented cultures. The citizens of these countries are prepared for uncertain events and are used to adapting to new circumstances. In this regard, China is a perfect example. It is also long-term oriented, and it responded very rapidly to the novel coronavirus outbreak. Finally, long-term oriented societies are more likely to have savings and hospital capacity to defy pandemics.

Another significant cultural trait is *INDUL*. Its negative sign indicates that restrained societies are associated with more immune stock markets than indulgent societies. Restrained societies can suppress the gratification of needs and control it by means of strict social norms. On the contrary, relatively free gratification and human drives related to having fun and enjoying lives prevail in more indulgent societies. The negative coefficient on *INDUL* lends support to the argument of Hofstede (2020) that more restrained societies commonly endorse the idea that life is typically hard. Thus, these cultures are more likely to accept the utter misery of different containment and closure measures imposed on them.

Interestingly, our findings regarding the national culture do not support the conclusions of [Fernandez-Perez et al. \(2020\)](#), who argue that the two most important cultural traits that strengthen the financial immunity to health disasters are low uncertainty avoidance and high individualism. These differences may stem from differing methodological approaches. [Fernandez-Perez et al. \(2020\)](#) concentrates only on the reaction to the first case, and examines only the overall impact of culture on returns rather than interactions. On the other hand, we account for interactions during the period when the pandemic was developing.

5.2 Machine learning

Our examinations of individual interactions in Tables 2 – 6 demonstrate that many of them are potential determinants of the country-level financial immunity to the COVID-19 pandemic. We now continue with multivariate tests, considering multiple variables jointly.

As it is indicated in Section 4.2, to decide which predictors should be considered in the joint regression, we apply the elastic net methodology to all the variables that proved significant in the single-interaction tests. Naturally, some of these variables may contain overlapping information contents that influence the overall out-of-sample predictability. By applying the elastic net method, we aim to determine the optimal set of covariates that can be deemed “economically” significant.

[Insert Table 7 about here]

Table 7 visualizes a two-dimensional grid of values for the elastic-net penalty parameter α and for the lasso penalty parameter λ . The values of α are confined to the interval $[0,1]$. When $\alpha=0$, the objective function, outlined in Equation 3, reduces to the objective function for the ridge-regression estimator. When $\alpha = 1$, the elastic-net objective function reduces to the lasso objective function. When $\lambda = 0$, Equation 3 becomes the objective function for the unpenalized maximum-likelihood estimator. The elastic net uses the coordinate descent algorithm for given values of α and λ ([Friedman et al., 2007, 2010](#); [Hastie et al., 2015](#)). For any given value of α , λ is allowed to decrease from ∞ to 0. Such a descent creates a vector of coefficient paths. When λ is “large” the solution to the objective function in Equation 3, $\hat{\Gamma}$, is zero. Holding α while decreasing λ induces coefficient paths, in which each element of the coefficient vector $\hat{\Gamma}$ emerges from 0. The algorithm repeatedly cycles over individual elements of the coefficient vector and updates single coefficient estimates until the convergence criteria are met. Specifically, the elastic net selects $\alpha=0.01$. It shows that the relative contribution of the ℓ_2 -penalty (ridge-type) is unambiguously larger than the contribution of the ℓ_1 -penalty (lasso-type). Since the ℓ_2 -penalty dominates the optimal solution, the elastic net retains for post-selection inference correlated, albeit economically significant covariates.

The results of this exercise, reported in Table 7 of the Online Appendix, consistent with the proportionally large ℓ_2 -penalty, indicate that nearly all of the considered variables have economically significant information contents about financial immunity. The optimal solution of the elastic net validates 26 out of the 27 individually significant interaction terms. The only discarded variable is *ROS*. These 26 individually significant covariates subsequently enter in the multiple interaction regressions in Step 3.⁶

⁶As it is indicated, the elastic net method rejected *ROS* as redundant. To assure the robustness of our findings, we nevertheless repeat the multivariate panel data regressions with this variable included. Notably, this modification in methodology leads to no qualitative difference in the results. For brevity, we do not report these results in details.

5.3 Multiple interaction panel data regression

We now turn to the multivariate tests applied to the 26 variables selected in the previous step. Table 8 displays the results of the multiple interaction panel data regression estimated by means of the random-effects method. We scrutinize the results for both daily and weekly returns. Also, to evaluate the effects of government policy responses, we include both the aggregate Stringency Index, as well as individual interventions that proved significant in earlier tests. In consequence, Table 8 contains four different specifications.

[Insert Table 8 about here]

The results are largely in agreement with our earlier findings, which validate the important role of several key variables. First, the role of *AG* is negative and significant across all the specifications. In other words, companies that engage in aggressive investments are hit the hardest. Moreover, conservative investment policies provide relative immunity to the COVID-19 pandemic. The second key variable is *FEP*. Similarly to the outcomes in Table 2, stock markets, in which firm value is low relative to expected profits, are more immune to the pandemic.

Notably, several other financial variables, such as *BETA*, *CON*, or *ROS*, as well *EXP*, prove insignificant in the multivariate tests, or significant only in limited specifications. Apparently, their information content is already overlapped by other return predictors.

Among the macroeconomic variables, Table 8 attests the vital role of *UNEM*. Countries with low unemployment levels are better placed to cope with the pandemic than countries characterized by high unemployment. This agrees with our earlier observation in Table 3.

The role of governance quality and cultural dimensions loses its significance when considered jointly with other variables. The partial slope coefficients on *ACCOUN* and *INDUL* become insignificant, while *LTOR* retains its significance only for daily data. To sum up, our multivariate analysis shows that the predictive power of these variables are already contained by other factors considered in our regression.

Finally, we continue to observe the positive impact of the government policy responses synthesized in the aggregate Stringency Index (*SI*), but only for weekly data (specification [2]). In this case, the partial slope coefficient is positive and significant, which ratifies our earlier observations that government interventions can help to avert the adverse impact of the pandemic on the stock market. In particular, specifications [2] and [4] are indicative of a positive and significant impact of closing public transport (*C5*). Contact tracing (*H3*) and debt relief (*E2*) are exert positive and significant effects for weekly and daily data, respectively. Nevertheless, it should be noted that many of the government interventions are correlated in time, and distinguishing their unique roles can be a daunting task.

Overall, our results in Table 8 indicate that some of the variables identified in the single interaction models are likely to be manifestations of similar phenomena or contain the same information. The most essential market characteristics contributing to COVID-19 immunity are conservative investment policy (low *AG*), low valuations relative to expected profits (high *FEP*), limited unemployment (low *UNEM*), and, partially, government policy responses (high *SI*).⁷

⁷To assure the robustness of our findings, we perform an additional experiment. Specifically, we control for the three most essential variables determined in our study – *AG*, *FEP*, and *UNEM* – through an alternative approach, i.e., through

6 Robustness checks and further analysis

Our baseline empirical findings pointed to the significant roles of several variables in determining a market's financial immunity to the pandemics, with special emphasis on asset growth, valuations based on expected profits, unemployment, and government policy responses. To assure the robustness of our findings, we now turn to additional investigations.

First, we examine an alternative proxy for the development of the pandemics. Specifically, in lieu of the confirmed cases, we focus on the confirmed deaths. By doing so, we aim to verify that our research findings are not just a statistical artifact, but present a real link with the growth of the novel coronavirus outbreak. Second, we concentrate on the potential data endogeneity concerns built into our regressions. To alleviate these issues, we replace the random-effects method employed in the multivariate panel data tests with two-stage least squares regressions. Finally, to account more carefully for the multicollinearity problems in our dataset, we carry out factor analysis. To this end, latent extract latent common factors that influence the markets' immunity to the pandemic, and explore their composition.

6.1 Growth of confirmed deaths

To avoid arbitrariness in the selection of the proxy of the pandemic, we use an alternative measure. Specifically, instead of relying on the growth in the cumulative number of confirmed cases, we utilize the growth rate in the cumulative number of confirmed deaths ($DCD_{i,t}$). The growth rate is calculated similar to [Equation 1](#):

$$DCD_{i,t} = LN(1 + CD_{i,t}) - LN(1 + CD_{i,t-1}), \quad (5)$$

where $CD_{i,t}$ is the cumulative number of confirmed deaths in country i at time t . Having computed weekly and daily values of $DCD_{i,t}$, we now proceed with a similar analysis as presented in [Table 8](#). Specifically, we employ the random-effects method to estimate a multiple interaction panel data regression and explore the interactions of $DCD_{i,t}$ with the identical set of potential determinants of the country-level financial immunity. Results of this exercise are summarized in [Table 9](#).

[Insert Table 9 about here]

Our scrutiny of the estimation results in [Table 9](#) confirms the robustness of our earlier findings. Similarly to the previous estimations, DCD , as an independent variable, negatively affects stock returns. In other words, an increase in the number of new COVID-19 related deaths results in a decline in stock

sorting. In this exercise, each month we rank all the countries in our sample on these variables and determine the top and bottom quartiles. Subsequently, we perform our usual regressions within these subsets, dropping AG, FEP, and UNEM from the equations, as these variables are already controlled for through sorting. The results of this analysis are reported in [Table A.8](#) in the Online Appendix. In line with our earlier results, we find that the exposure to the pandemic risk in countries with low AG, high FEP, and low UNEM is lower than in their counterparts with high AG, low FEP, and high UNEM. The absolute values of the partial slope coefficients of DCC are visibly lower in the first country group than in the second. These observations additionally corroborate our baseline findings.

market returns. The partial slope coefficients on the interactions with *AG* and *UNEM* are negative and significant across all the specifications, while the interactions with *FEP* and *SI* positively impact on the stock returns. These observations match our earlier findings, which endorse our conclusions that equity markets with conservative investment policies, low unemployment rates, low valuation ratios, and effective policy responses can cope better with the adverse consequences of the pandemic.

One noteworthy difference presented by the regressions based on the death count, is that it highlights the importance of a different set of particular government interventions. In this case, the partial slope coefficients of two types of responses – restrictions on internal movement and income support – are significant and positive for both daily and weekly returns. Nevertheless, as aforementioned, the different types of policies are frequently highly correlated. Consequently, disentangling among the information contents pertaining to individual responses may be a challenging task.

6.2 Two-stage least squares panel data regression

We now turn to the two-stage least squares panel data regressions. A critical issue in the identification of the catalysts and inhibitors of financial immunity of countries may be related to endogeneity concerns. Endogeneity arises because of simultaneity, reverse causality, or omitted variable bias. For instance, changes in unobserved drivers of financial immunity (i.e., the spread of the coronavirus pandemic) can also concurrently trigger a change in the number of confirmed cases. In other words, $DCC_{i,t}$ may be correlated with the idiosyncratic error term ($v_{i,t}$) in Equation 4, which can give rise to a bias in coefficient estimates. In particular, the testing for COVID-19 varies dramatically across countries; therefore, it is not unreasonable to assume that $DCC_{i,t}$ may not be adequately capturing the spread of the coronavirus pandemic. The ensuing measurement errors of the pandemic spread are likely to be captured in the idiosyncratic error term in Equation 4. The first remedy to this issue is to use the growth rate of confirmed deaths, $DCD_{i,t}$, that pursue in Section 6.1. A second solution is to employ a two-stage least squares (2SLS) panel data model that tackles the potential endogeneity issue.

The 2SLS panel data regression model proceeds in two stages. In the first stage, we regress $DCC_{i,t}$ on exogenous variables (instruments). Our instruments should i) be associated with $DCC_{i,t}$ but not with $R_{i,t}$, and ii) be conceptually valid. We select three instruments that satisfy the exogeneity conditions. First, we include $DCC_{i,t-1}$, the first lag of $DCC_{i,t}$. The resulting model can be regarded as an autoregressive process of order 1, AR(1), which indicates that the today's value of $DCC_{i,t}$ is determined by its past values (Benvenuto et al., 2020). Second, we include population density of each country as a risk factor responsible for the transmission of the coronavirus (Sajadi et al., 2020). Third, pollution is a significant catalyst of the spread of the coronavirus, as demonstrated in the literature of epidemiology (Frontera et al., 2020; Shi et al., 2020). As a proxy for pollution, we use the environmental health index (EHI) for each country, which is produced by The Yale Center for Environmental Law Policy (Wendling et al., 2018). The index consists of variables on the air quality, water and sanitation, and heavy metals.

We assume that $DCC_{i,t}$ can be endogenous, while $\mathbf{X}_{i,t} \equiv (\mathbf{X}'_{1,i,t}, \mathbf{X}'_{2,i,t})'$ comprises exogenous variables. If $DCC_{i,t}$ is endogenous, then the resulting vector of interaction terms, $\mathbf{X}_{2,i,t} \times DCC_{i,t}$ becomes endogenous too. Therefore, it needs to be instrumented with a suitable set of instruments. The resulting

model can be written as:

$$R_{i,t} = \pi_0 + \pi_1 \times DCC_{i,t} + \Pi'_1 \times \mathbf{X}_{1,i,t} + \Pi'_2 \times \mathbf{X}_{2,i,t} \times DCC_{i,t} + \epsilon_{i,t} \quad (6)$$

where $DCC_{i,t}$ is instrumented with $\mathbf{Z}_{i,t} \equiv (DCC_{i,t-1}, DENS_{i,t}, EHI_{i,t})'$ variables. Similarly, the vector of interactions $\mathbf{X}_{2,i,t} \times DCC_{i,t}$ is instrumented with a valid set of instruments $\mathbf{X}_{2,i,t} \otimes \mathbf{Z}_{i,t}$. More specifically, an m^{th} element from $\mathbf{X}_{2,i,t} \times DCC_{i,t}$, $X_{2,i,t}^{(m)} \times DCC_{i,t}$ is instrumented with $\mathbf{Z}_{i,t} \times X_{2,i,t}^{(m)}$.

The first stage consists of regressing $\mathbf{X}_{2,i,t} \times DCC_{i,t}$ on $\mathbf{X}_{2,i,t} \otimes \mathbf{Z}_{i,t}$, while the second stage uses the fitted values from the first stage as covariates. The two-stage panel data regression is estimated by means of the random-effects estimation method with robust standard errors. The validity of instruments is tested by means of the Hansen-J test for over-identifying restrictions.

Table 10 reports the results of coefficients estimated with the two-stage regressions. In all four regressions, Hansen test indicates that the instruments satisfy the over-identifying conditions. The regression outcome perfectly matches our earlier findings. Among all the considered interactions, there are four main variables that stand out in their significance: *UNEM*, *AG*, *FEP*, and *SI*. In line with our earlier observations, the countries with low unemployment, populated with companies with conservative investment policies, low valuations relative to future earnings, and stringent policy responses tend to perform better. To sum up, the two-stage regressions corroborate our overall conclusions. Furthermore, the eyeballing of individual policy responses highlights the role of closure of public transportation, identically as in our baseline results, summarized in Table 8, as well as income support for citizens and residents.

[Insert Table 10 about here]

6.3 Factor analysis

This subsection proposes the construction of factors by means of factor analysis. Subsequently, these factors can be used in interaction with *DCC* to test for the country-level financial immunity. The use of factor analysis has two advantages. First, this method allows us to reconstruct the variation of a high-dimensional information contents by means of just a few latent factors. Second, it allows us to alleviate the problem of multicollinearity in the subset of individually significant variables. Specifically, the presence of a considerable number of variables with similar characteristics (see Table A.9 in the Online Appendix) highlights the need to reduce the dimensionality of the data. Performed on large data sets, factor analysis enables us to synthesize a large amount of economic information in fewer latent common factors (see for example, Stock and Watson, 2002; Ludvigson and Ng, 2007). The factor analysis describes a set of P variables (i.e. $X^{(1)}, X^{(2)}, \dots, X^{(P)}$) in smaller set of M factors (i.e. $FACTOR^{(1)}$),

$FACTOR^{(2)}, \dots, FACTOR^{(M)}$). The model for country i at time t is given below:

$$\begin{aligned}
X_{i,t}^{(1)} &= a_{1,1}FACTOR_{i,t}^{(1)} + a_{1,2}FACTOR_{i,t}^{(2)} + \dots + a_{1,M}FACTOR_{i,t}^{(M)} + \epsilon_{i,t}^{(1)} \\
X_{i,t}^{(2)} &= a_{2,1}FACTOR_{i,t}^{(1)} + a_{2,2}FACTOR_{i,t}^{(2)} + \dots + a_{2,M}FACTOR_{i,t}^{(M)} + \epsilon_{i,t}^{(2)} \\
&\vdots \\
X_{i,t}^{(P)} &= a_{P,1}FACTOR_{i,t}^{(1)} + a_{P,2}FACTOR_{i,t}^{(2)} + \dots + a_{P,M}FACTOR_{i,t}^{(M)} + \epsilon_{i,t}^{(P)},
\end{aligned} \tag{7}$$

where P represents the number of original variables, the factor loadings $a_{p,m}$ are extracted from the rotated factors⁸ and the errors $\epsilon_{i,t}^{(p)}$, are independently distributed with mean zero. We retain the factors that have eigenvalues greater than unity (OECD, 2008)⁹.

For instance, in our case, we consider 17 variables and we run the model. We retain three factors that feature eigenvalues greater than unity. It should be noted that Table A.10 (in the Online Appendix) is based on weekly data. The extracted factors for daily data are identical, and thus are not reported. In addition, rotated factor loadings in Table A.10 are displayed in order to enhance their interpretability. Then, the factors are used as interaction terms in Equation 4, where $\mathbf{X}_{2,i,t}$ is an M -dimensional vector of extracted factors with eigenvalues greater than 1.

The factor analysis indicates that the clear majority (15 of the 17 variables that interact with DCC) can be synthesized in three main factors (see Table A.10 in the Online Appendix). AG is the variable with the highest percentage of uniqueness and thus cannot be ascribed to any factor. Moreover, although ROS features a lower uniqueness score, it does not add value to the factors, and thus is excluded. Occasionally, factors are not easily named or explained; however, in our case, the factors seem to be synthesized in a meaningful way. The first factor selects all government response variables, as well as FEP . Therefore, the first factor primarily quantifies governments' efforts to i) ensure effective social distancing, ii) monitor and control the spread of the pandemic, and iii) offset the income lost by businesses and households. To sum up, the first factor represents the short-term government response to the coronavirus pandemic. The total percentage of variance explained by the first factor is approximately 51%. In Table 11, this factor in interaction with DCC has a positive effect on stock market returns. The second factor, which accounts for 28.5% of the variance, has positive and economically significant loadings on $INDUL$ and $ACCOUN$. It also provides information contents about financial variables, such as $BETA$ (positive sign), FEP (negative sign) and CON (negative sign). Therefore, the second factor consists of two sides. The first side can be thought to reflect democratic freedom of the society, whereas the flip side captures investment opportunities available for the society. The interaction of the second factor has a negative coefficient on stock market returns. The third factor significantly loads on $LTOR$ (positive sign), EXP (positive sign) and $UNEMP$ (negative sign),

⁸Factor rotation is a method that minimizes the number of variables that have high scores on a factor. Rotation can be performed using, among others, the Oblimin or Varimax method.

⁹According to Kaiser criterion, factors, with eigenvalues lower than unity should not be included in the analysis. In other words, the Kaiser criterion advises against adding a factor that explains less variance than is contained in one individual variable.

as well as *INDUL* (negative sign) and *H3* (positive sign). Based on the weighted information contents of the third factor, it can be thought of as an indicator of long-term socio-economic stability. This factor, which represents 19% of the total variance of the variables, has a positive impact on stock market returns.

[Insert Table 11 about here]

A detailed scrutiny of the variables underlying different factors reveals similarities to our earlier findings. First of all, we observe that government interventions help to curb the detrimental effect of the pandemic on the stock markets. Also, a high *FEP* increases a country's immunity to the pandemic. Finally, similarly to the earlier results, we record a positive influence of low unemployment (*UNEM*). On the other hand, several variables such as *CON*, *BETA*, *INDUL*, and *ACCOUN*, which mattered in univariate tests in Tables 2 to 6 – but lost their significance in the latter multivariate regressions – still seem to provide significant information contents about the country-level financial immunity, albeit via the factor analysis.

Despite these minor differences, our three robustness checks in Section 6 – regressions based on the death count, two-stage regression, and factor analysis lead to consistent conclusions as our baseline regressions demonstrated in Table 8. Overall, our examinations point out to several variables that prove significant in the majority of tests. These are: asset growth, forecast earnings-to-price ratio, unemployment, and government interventions. The role of other issues is limited or contained by these four variables.

7 Concluding Remarks

What are the determinants that ensure stronger financial immunity to crises? What can make a country be more financially immune to unexpected events such as the coronavirus pandemic? What could make a stable capital market in normal times a volatile one, making the economy back to business a tough mission? These important questions are essential for a wide range of decision makers ranging from ordinary citizens to national or supranational policy makers and politicians. However, just as the discussion itself is important, the findings we document in this study are of utmost importance, as they may assist in the decision-making process of various market participants. To the best of our knowledge, this is the first time that such a thorough analysis has been conducted on the drivers of country-level stock market immunity.

This study seeks to examine the determinants of a country's stock market immunity to the outbreak of epidemics such as COVID-19. To solve this research problem, we examine data from 67 countries from January to April 2020. We explore about a hundred of different variables from diverse domains, including economic conditions, quality of the healthcare system, demographics, national culture, law, governance, as well as financial and valuation ratios. Our dataset also accounts for various government interventions, such as containment and closure policies, and economic stimuli. We propose the use of a variety of novel statistical tools such as panel regressions, machine learning tools, and factor analysis to ascertain what makes some countries more vulnerable to the pandemic than others. Our tests reveal several key features that shape a country's financial immunity to the pandemic. Specifically, stock markets populated by firms with conservative investment policies, low valuations relative to future earnings, as well as countries with low unemployment are best equipped to deal with the adverse consequences of the COVID-19-induced

crash. Moreover, our research findings reveal that efficient government interventions – both containment and closure policies and economic stimuli – can provide support for the local stock market.

Our research findings are relevant for a variety of decision-makers, such as individuals, economists, managers, and legislators, at both the firm and the state level. International investors can use our findings for the allocation of investments and diversification of risks, including the risk of pandemics. The results may be essential and improve investors' portfolio management towards future black swans. The state level decision makers may also find this research useful from a macroeconomic perspective, since it helps to understand the effects of their policy decisions. Policy decisions that aim at improving the local economy's immunity to crises is paramount to a more stable economy, and an economy that recovers quickly to the pre-crisis level.

Economists can use this information to value the degree of a country's exposure to pandemic risk, and consequently determine an additional sensitivity factor to their valuation of projects. The study may also be of interest to different international bodies with global policy mandate.

A better mapping and understanding of the possible factors that affect financial immunity may contribute to a more effective management of the black swan risk of countries, and to ascertain the priority of the economic aid needed. Furthermore, governments and policy makers may also use the findings of this study, as we examine not only economic indicators, but also a wide range of explanatory variables, including variables related to the country's healthcare system. In addition, policymakers may find interest in this study, in order to identify their country's weak points and where improvement may be needed for strengthening the country's economic stability during financial market turbulence.

To sum up, the results in this paper may help to provide ground for more informed decision making to manage the risks of unexpected disasters similar to the novel coronavirus pandemic. This study offers an opportunity to witness the weaknesses and threats alongside the opportunities and strengths of countries struggling with COVID-19 pandemic.

The comprehensive approach employed in this study may enhance the understanding of the nature of the relationship between country's financial immunity and variables from different aspects such as health, financial, cultural, and government actions. In this respect, an important insight, which enhances our understanding as to the impact of variables from different fields is that the strength of the capital market is not limited to classical economic variables such as the unemployment level, but also to a range of factors from different fields including proactive and preemptive government actions, which contribute to the shaping and improving of the financial immunity of the local capital market.

Our study is limited by the relatively short study period dictated by the nature of the abrupt pandemic. Also, due to data availability constraints, we are not able to account for many environmental and climate issues, such as the mere temperature, which may potentially influence the country's immunity to a pandemic. Future studies, taking advantage of fresher and richer datasets, may potentially fill these gaps. Moreover, further research could potentially extend a list of predictors of markets' immunity to a pandemic. Variables capturing the interplay with commodity returns, which play an essential role for equity markets (Iyke and Ho, 2020), may serve as an example.

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Figures and Tables

Figure 1: Scatter plot between stock returns and growth of confirmed cases. The line shows a linear regression between and Stock returns and *DCC* with no other covariates. The sample period runs from 01/01/2020 to 28/04/2020.

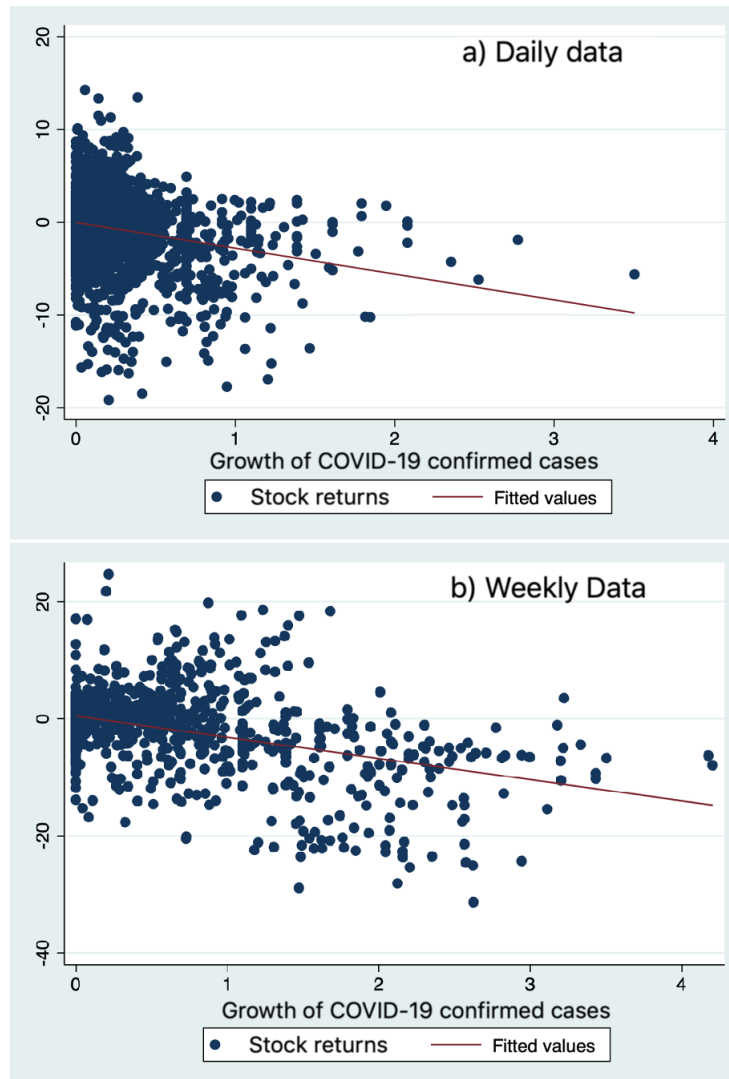


Table 1: Countries

This table visualises the countries that are included in our sample. The sample period runs from 01/01/2020 to 28/04/2020.

#	Country	#	Country	#	Country
1	Argentina	24	India	46	Portugal
2	Australia	25	Indonesia	47	Qatar
3	Austria	26	Ireland	48	Romania
4	Bahrain	27	Israel	49	Russia
5	Belgium	28	Italy	50	Saudi Arabia
6	Brazil	29	Japan	51	Singapore
7	Bulgaria	30	Jordan	52	Slovakia
8	Canada	31	Kuwait	53	Slovenia
9	Chile	32	Luxembourg	54	South Africa
10	China	33	Malaysia	55	South Korea
11	Colombia	34	Malta	56	Spain
12	Croatia	35	Mexico	57	Sri Lanka
13	Cyprus	36	Morocco	58	Sweden
14	Czechia	37	Netherlands	59	Switzerland
15	Denmark	38	New Zealand	60	Taiwan
16	Egypt	39	Nigeria	61	Thailand
17	Estonia	40	Norway	62	Turkey
18	Finland	41	Oman	63	UAE
19	France	42	Pakistan	64	United Kingdom
20	Germany	43	Peru	65	United States
21	Greece	44	Philippines	66	Venezuela
22	Hong Kong	45	Poland	67	Vietnam
23	Hungary				

Table 2: Single Interaction Panel Data Regression: Financial variables

This table summarises the coefficient estimates (β) of the single-interaction panel data model, outlined in Equation 2 for daily (Column 1) and weekly (Column 2) data. The model is estimated by means of the random effects estimation method. Robust standard errors are indicated in round parentheses. Asterisks ***, **, * denote significance at 1%, 5% and 10%, respectively. The dependent variable is the percentage continuously compounded rate of return, $R_{i,t} = 100 \times [\ln(P_{i,t}) - \ln(P_{i,t-1})]$, where $P_{i,t}$ is country's i stock market index in period t . The sample period runs from 01/01/2020 to 28/04/2020. In this model, financial covariates, described in Table A.1 in the Online Appendix, are interacted interchangeably with the rate of growth in the total number of confirmed cases, $DCC_{i,t}$. The model also includes $DCC_{i,t}$, and it controls for the key four asset pricing factors, $\mathbf{X}_{1,i,t} \equiv (BETA_{i,t}, BM_{i,t}, MOM_{i,t}, MV_{i,t})'$. Coefficient estimates of the control variables are not reported for brevity.

$R_{i,t} = \gamma_0 + \gamma_1 \times DCC_{i,t} + \Gamma'_1 \times \mathbf{X}_{1,i,t} + \beta \times FINANCIAL_{i,t} \times DCC_{i,t} + u_{i,t}$				
	(1) Daily		(2) Weekly	
	Coef.	SE	Coef.	SE
<i>Valuation</i>				
$DY \times DCC$	-7.8808	(12.9765)	-30.3046**	(12.5566)
$EBEV \times DCC$	-0.8431	(2.0338)	-0.1910	(2.0002)
$FEP \times DCC$	23.7187***	(6.0837)	24.8062***	(5.4447)
$CP \times DCC$	-4.3361	(3.5610)	-7.9037**	(3.3764)
$EP \times DCC$	2.0701	(3.9450)	2.7918	(3.4818)
$BM \times DCC$	0.2401	(1.2038)	-1.7268	(1.2009)
<i>Investment</i>				
$C/A \times DCC$	-10.6561**	(4.9816)	0.2297	(3.8385)
$AG \times DCC$	-7.0495*	(4.2085)	-9.3922**	(3.8514)
<i>Profitability</i>				
$ROA \times DCC$	-2.9785	(2.4655)	-2.8577	(2.3963)
$ROE \times DCC$	-11.0182	(7.5885)	-0.5600	(7.3392)
$ROS \times DCC$	11.5583**	(5.8191)	11.2545*	(5.9546)
<i>Indebtedness</i>				
$COV \times DCC$	-4.4329	(3.1515)	-2.4403	(3.0231)
$LEV \times DCC$	-2.9785	(2.4655)	-2.8577	(2.3963)
<i>Industry structure</i>				
$CON \times DCC$	6.5722***	(1.8960)	6.8382***	(2.3261)
$TRAV \times DCC$	3.1612	(4.4509)	2.4121	(4.1585)
<i>Other valuation pricing variables</i>				
$MOM \times DCC$	1.6231	(1.2461)	8.1683***	(1.2917)
$MV \times DCC$	-0.0867	(0.1223)	0.0771	(0.1309)
$BILL \times DCC$	-1.9049	(4.5084)	-5.8718	(4.0497)
$REV \times DCC$	-1.0262	(0.8212)	-0.8202	(0.7652)
$TURN \times DCC$	-0.2218	(0.1350)	0.3985	(0.4622)
$IVOL \times DCC$	-230.6611***	(60.8133)	-25.3192	(21.0435)
$BETA \times DCC$	-2.7244***	(0.6048)	-1.2372*	(0.7020)

Table 3: Single interaction panel data regression: Economic variables

This table summarises the coefficient estimates (β) of the single-interaction panel data model, outlined in Equation 2 for daily (Column 1) and weekly (Column 2) data. In this model, economic covariates (*ECONOMIC*), described in Table A.2 in the Online Appendix, are interacted interchangeably with the rate of growth in the total number of confirmed cases, $DCC_{i,t}$. The model also includes $DCC_{i,t}$, and it controls for the key four asset pricing factors, $\mathbf{X}_{1,i,t} \equiv (BETA_{i,t}, BM_{i,t}, MOM_{i,t}, MV_{i,t})'$. The dependent variable is the percentage continuously compounded rate of return, $R_{i,t} = 100 \times [LN(P_{i,t}) - LN(P_{i,t-1})]$, where $P_{i,t}$ is country's i stock market index in period t . The sample period runs from 01/01/2020 to 28/04/2020. The model is estimated by means of the random effects estimation method. Robust standard errors are indicated in round parentheses. Asterisks ***, **, * denote significance at 1%, 5% and 10%, respectively. Coefficient estimates of the control variables are not reported for brevity.

	$R_{i,t} = \gamma_0 + \gamma_1 \times DCC_{i,t} + \Gamma_1' \times \mathbf{X}_{1,i,t} + \beta \times ECONOMIC_{i,t} \times DCC_{i,t} + u_{i,t}$			
	(1) Daily		(2) Weekly	
	Coef.	SE	Coef.	SE
<i>Economy</i>				
$GDPP \times DCC$	0.0000	(0.0000)	0.0000	(0.0000)
$GDPC \times DCC$	0.0000*	(0.0000)	0.0000	(0.0000)
$GDPG \times DCC$	0.1324	(0.1166)	0.0361	(0.1166)
$EXP \times DCC$	0.0170***	(0.0052)	0.0061	(0.0054)
$UNEM \times DCC$	-0.1935***	(0.0470)	-0.1014**	(0.0448)
$INF18 \times DCC$	-0.1216*	(0.0688)	0.0190	(0.0603)
$INF19 \times DCC$	-0.1180	(0.0788)	0.0243	(0.0690)
$TOUR\% \times DCC$	0.0104	(0.0274)	0.0196	(0.0263)
$TOUR\$ \times DCC$	-0.0000	(0.0000)	0.0000	(0.0000)
$TRADE \times DCC$	0.0092***	(0.0028)	0.0032	(0.0030)
$MAN \times DCC$	0.0000	(0.0000)	0.0000	(0.0000)
$CRED \times DCC$	0.0011	(0.0057)	0.0037	(0.0057)
$RTNG \times DCC$	-0.0347	(0.0444)	-0.0382	(0.0448)
<i>Population</i>				
$POP65 \times DCC$	-0.0395	(0.0297)	-0.0179	(0.0315)
$DENS \times DCC$	0.0004**	(0.0002)	0.0003	(0.0002)
$URBAN \times DCC$	0.0069	(0.0115)	0.0083	(0.0124)
$MIGR \times DCC$	0.1239***	(0.0432)	0.0595	(0.0477)
<i>Technology</i>				
$ICT \times DCC$	0.0951	(0.1124)	0.0114	(0.1098)
$INET \times DCC$	0.0105	(0.0109)	0.0130	(0.0121)

Table 4: Single interaction panel data regression: Healthcare variables

This table summarises the coefficient estimates (β) of the single-interaction panel data model, outlined in Equation 2 for daily (Column 1) and weekly (Column 2) data. In this model, healthcare covariates (*HEALTHCARE*), described in in Table A.3 in the Online Appendix, are interacted interchangeably with the rate of growth in the total number of confirmed cases, $DCC_{i,t}$. The model also includes $DCC_{i,t}$, and it controls for the key four asset pricing factors, $\mathbf{X}_{1,i,t} \equiv (BETA_{i,t}, BM_{i,t}, MOM_{i,t}, MV_{i,t})'$. The dependent variable is the percentage continuously compounded rate of return, $R_{i,t} = 100 \times [LN(P_{i,t}) - LN(P_{i,t-1})]$, where $P_{i,t}$ is country's i stock market index in period t . The sample period runs from 01/01/2020 to 28/04/2020. The model is estimated by means of the random effects estimation method. Robust standard errors are indicated in round parentheses. Asterisks ***, **, * denote significance at 1%, 5% and 10%, respectively. Coefficient estimates of the control variables are not reported for brevity.

	$R_{i,t} = \gamma_0 + \gamma_1 \times DCC_{i,t} + \Gamma_1' \times \mathbf{X}_{1,i,t} + \beta \times HEALTHCARE_{i,t} \times DCC_{i,t} + u_{i,t}$			
	(1) Daily		(2) Weekly	
	coef.	SE	coef.	SE
<i>BEDS</i> × <i>DCC</i>	-0.0174	(0.0859)	0.0145	(0.0847)
<i>HEXP%</i> × <i>DCC</i>	-0.1386*	(0.0716)	-0.0573	(0.0719)
<i>HEXPC</i> × <i>DCC</i>	0.0001	(0.0001)	0.0001	(0.0001)
<i>NURSE</i> × <i>DCC</i>	0.0018	(0.0477)	0.0049	(0.0465)
<i>PHYS</i> × <i>DCC</i>	-0.3079**	(0.1516)	-0.1698	(0.1568)
<i>LIFE</i> × <i>DCC</i>	0.0357	(0.0404)	0.0310	(0.0419)
<i>RESP</i> × <i>DCC</i>	0.0134	(0.0097)	0.0083	(0.0093)
<i>HEALTH</i> × <i>DCC</i>	0.0101	(0.0128)	0.0154	(0.0134)
<i>UHC</i> × <i>DCC</i>	-0.0092	(0.0214)	0.0043	(0.0238)
<i>SMOKM</i> × <i>DCC</i>	0.0016	(0.0197)	0.0158	(0.0182)
<i>SMOKF</i> × <i>DCC</i>	-0.0313	(0.0205)	-0.0120	(0.0204)

Table 5: Single interaction panel data regression: Government intervention variables

This table summarises the coefficient estimates (β) of the single-interaction panel data model, outlined in Equation 2 for daily (Column 1) and weekly (Column 2) data. In this model, government intervention covariates (*GOVERNMENT*), described in Table A.4 in the Online Appendix, are interacted interchangeably with the rate of growth in the total number of confirmed cases, $DCC_{i,t}$. The model also includes $DCC_{i,t}$, and it controls for the key four asset pricing factors, $\mathbf{X}_{1,i,t} \equiv (BETA_{i,t}, BM_{i,t}, MOM_{i,t}, MV_{i,t})'$. The dependent variable is the percentage continuously compounded rate of return, $R_{i,t} = 100 \times [LN(P_{i,t}) - LN(P_{i,t-1})]$, where $P_{i,t}$ is country's i stock market index in period t . The sample period runs from 01/01/2020 to 28/04/2020. The model is estimated by means of the random effects estimation method. Robust standard errors are indicated in round parentheses. Asterisks ***, **, * denote significance at 1%, 5% and 10%, respectively. Coefficient estimates of the control variables are not reported for brevity.

$R_{i,t} = \gamma_0 + \gamma_1 \times DCC_{i,t} + \Gamma_1' \times \mathbf{X}_{1,i,t} + \beta \times GOVERNMENT_{i,t} \times DCC_{i,t} + u_{i,t}$				
	(1) Daily		(2) Weekly	
	coef.	SE	coef.	SE
<i>Aggregate index</i>				
$SI \times DCC$	0.0211**	(0.0091)	0.0417***	(0.0075)
<i>Containment and closure</i>				
$C1 \times DCC$	0.0539	(0.1466)	0.0575	(0.1460)
$C1_g \times DCC$	0.2284	(0.1519)	0.1603	(0.1417)
$C2 \times DCC$	0.5195**	(0.2230)	0.7944***	(0.1745)
$C2_g \times DCC$	0.7463***	(0.2534)	0.7245***	(0.1862)
$C3 \times DCC$	-0.4125*	(0.2284)	0.2038	(0.2221)
$C3_g \times DCC$	-0.0405	(0.2321)	0.3471*	(0.2102)
$C4 \times DCC$	0.0983	(0.1628)	0.3535***	(0.1345)
$C4_g \times DCC$	0.2903	(0.1793)	0.4154***	(0.1483)
$C5 \times DCC$	1.4716***	(0.3871)	1.5710***	(0.2794)
$C5_g \times DCC$	1.6900***	(0.4790)	1.7356***	(0.3487)
$C6 \times DCC$	0.7476**	(0.3513)	1.4159***	(0.2408)
$C6_g \times DCC$	1.3139***	(0.4400)	1.6982***	(0.2820)
$C7 \times DCC$	0.5663**	(0.2543)	1.2145***	(0.2228)
$C7_g \times DCC$	1.1783***	(0.3389)	1.0138***	(0.2560)
$C8 \times DCC$	0.0965	(0.1467)	0.3903***	(0.1370)
<i>Health system</i>				
$H1 \times DCC$	-0.6893**	(0.2801)	-0.0904	(0.3290)
$H2 \times DCC$	0.3121	(0.2858)	0.8206***	(0.2816)
$H3 \times DCC$	0.8160***	(0.2516)	1.0415***	(0.2548)
<i>Economic stimulus</i>				
$E1 \times DCC$	1.6407***	(0.5856)	1.4284***	(0.4288)
$E1_g \times DCC$	1.8531***	(0.7021)	1.1708**	(0.5301)
$E2 \times DCC$	1.4417***	(0.4414)	1.2222***	(0.3781)

Table 6: Single interaction panel data regression: Governance variables

This table summarises the coefficient estimates (β) of the single-interaction panel data model, outlined in Equation 2 for daily (Column 1) and weekly (Column 2) data. In this model, governance covariates (*GOVERNANCE*), described in Table A.5 in the Online Appendix, are interacted interchangeably with the rate of growth in the total number of confirmed cases, $DCC_{i,t}$. The model also includes $DCC_{i,t}$, and it controls for the key four asset pricing factors, $\mathbf{X}_{1,i,t} \equiv (BETA_{i,t}, BM_{i,t}, MOM_{i,t}, MV_{i,t})'$. The dependent variable is the percentage continuously compounded rate of return, $R_{i,t} = 100 \times [LN(P_{i,t}) - LN(P_{i,t-1})]$, where $P_{i,t}$ is country's i stock market index in period t . The sample period runs from 01/01/2020 to 27/04/2020. The model is estimated by means of the random effects estimation method. Robust standard errors are indicated in round parentheses. Asterisks ***, **, * denote significance at 1%, 5% and 10%, respectively. Coefficient estimates of the control variables are not reported for brevity.

	(1) Daily		(2) Weekly	
	coef.	SE	coef.	SE
<i>Governance</i>				
<i>ACCOUN</i> × <i>DCC</i>	-0.3946*	(0.2035)	-0.4447**	(0.2106)
<i>POLSTAB</i> × <i>DCC</i>	0.2850	(0.2310)	0.0719	(0.2388)
<i>GOVEFF</i> × <i>DCC</i>	0.4553*	(0.2620)	0.1680	(0.2623)
<i>REQUAL</i> × <i>DCC</i>	0.3831	(0.2569)	0.0709	(0.2543)
<i>RULELAW</i> × <i>DCC</i>	0.4683*	(0.2427)	0.1282	(0.2340)
<i>CORRUPT</i> × <i>DCC</i>	0.3413	(0.2140)	0.0787	(0.2112)
<i>Legal origin</i>				
<i>FREN</i> × <i>DCC</i>	-1.2313***	(0.4236)	-0.3922	(0.4005)
<i>GERM</i> × <i>DCC</i>	0.7692	(0.4904)	0.4700	(0.4660)
<i>SCAN</i> × <i>DCC</i>	-1.0799	(0.7983)	-0.7217	(0.7927)
<i>ENGL</i> × <i>DCC</i>	1.0669**	(0.4464)	0.3118	(0.4671)
<i>Natural Culture</i>				
<i>POWDIST</i> × <i>DCC</i>	0.0098	(0.0097)	0.0171*	(0.0095)
<i>INDIV</i> × <i>DCC</i>	-0.0061	(0.0096)	-0.0075	(0.0092)
<i>MASC</i> × <i>DCC</i>	0.0128	(0.0113)	0.0023	(0.0107)
<i>UNCAV</i> × <i>DCC</i>	-0.0161*	(0.0097)	0.0025	(0.0098)
<i>LTOR</i> × <i>DCC</i>	0.0334***	(0.0109)	0.0206**	(0.0098)
<i>INDUL</i> × <i>DCC</i>	-0.0185*	(0.0111)	-0.0193*	(0.0106)

Table 7: Elastic net optimal set

This table displays results of the elastic net optimisation problem (Zou and Hastie, 2005), postulated in Equation 3. The problem is solved by optimally choosing a vector of coefficients $\Gamma \equiv (\gamma_0, \gamma_1, \Gamma_1', \Gamma_2')$ conditional on retaining the coefficients $\gamma_0, \gamma_1, \Gamma_1$. Elastic net combines least absolute shrinkage and selection operator (henceforth, *lasso*, when $\alpha=1$) and ridge regression ($\alpha=0$). Lasso is a machine learning method for selecting and fitting covariates that appear in the model. Ridge regression seeks to retain highly correlated covariates in a regression model that is employed for out-of-sample forecasting. Coefficient estimates from elastic net are more robust to the presence of highly correlated covariates than are lasso solutions. This machine learning technique selects covariates that maximise the out-of-sample Adjusted R^2 . The elastic net uses the coordinate descent algorithm for given values of α and λ to solve the optimisation problem. This table provides a grid of values of α , over which the coordinate descent algorithm is set to iterate. The optimal solution is obtained at $\alpha = 0.01$ and $\lambda = 1.5599$. The elastic net validates 26 out of the 27 individually significant covariates, and discards only *ROS*. Therefore, the individually significant interaction terms are also regarded as “economically” significant. Thus our multiple interaction panel data models exclude *ROS* in Table 8. As a robustness check, we also estimate multiple interaction panel data models with *ROS*, and the results remain qualitatively similar.

$$\hat{\Gamma} = \arg \min_{\Gamma} \left\{ \frac{1}{NT} \sum_{i=1}^N \sum_{t=1}^T [R_{i,t} - \gamma_0 - \gamma_1 \times DCC_{i,t} - \Gamma_1' \times \mathbf{X}_{1,i,t} - \Gamma_2' \times \mathbf{X}_{2,i,t} \times DCC_{i,t}] + \lambda (\alpha \|\Gamma\|_1 + \frac{1-\alpha}{2} \|\Gamma\|_2^2) \right\}$$

α	Description	λ	Nonzero coeffs	Out-of-sample R^2	MPE
1	first lambda	85.7920	5	0.1744	37.8734
	last lambda	0.2125	13	0.1818	37.5311
0.9	first lambda	85.7920	5	0.1744	37.8734
	last lambda	0.2332	14	0.1829	37.4829
0.8	first lambda	85.7920	5	0.1744	37.8734
	last lambda	0.2560	14	0.1839	37.4356
0.7	first lambda	85.7920	5	0.1744	37.8734
	last lambda	0.2809	14	0.1849	37.3913
0.6	first lambda	85.7920	5	0.1744	37.8734
	last lambda	0.3384	15	0.1868	37.3030
0.5	first lambda	85.7920	5	0.1744	37.8734
	last lambda	0.3714	16	0.1878	37.2562
0.4	first lambda	85.7920	5	0.1744	37.8734
	last lambda	0.4076	18	0.1891	37.1949
0.3	first lambda	85.7920	5	0.1744	37.8734
	last lambda	0.2332	20	0.1893	37.1870
0.2	first lambda	85.7920	5	0.1744	37.8734
	last lambda	0.2809	20	0.1913	37.0972
0.1	first lambda	85.7920	5	0.1744	37.8734
	last lambda	0.4076	20	0.1943	36.9598
0.01	first lambda	85.7920	5	0.1744	37.8732
	lambda before	1.5887	26	0.1997	36.7089
	selected lambda	1.5599	26	0.1997	36.7088
	lambda after	1.5320	26	0.1997	36.7088
	last lambda	0.9861	26	0.1988	36.7506

Table 8: Multiple interaction panel data regression

This table summarises the coefficient estimates, $\Gamma \equiv (\gamma_0, \gamma_1, \Gamma'_1, \Gamma'_2)'$, of the multiple-interaction panel data model, outlined in Equation 4 for daily (Columns 1 and 2) and weekly (Columns 3 and 4) data. In Columns 1 and 3, the composite government stringency index measures the degree of government response to the coronavirus pandemic. In Columns 2 and 4, individual elements of government response are utilised in the model. Individually significant interactions in Tables 2 – 6 of the rate of growth in the total number of confirmed cases, $DCC_{i,t}$, with financial, economic, healthcare, government intervention and governance variables. The multidimensional information set is described in Tables A.1 – A.5 in the Online Appendix. The model also includes $DCC_{i,t}$, and it controls for the key four asset pricing factors, $\mathbf{X}_{1,i,t} \equiv (BETA_{i,t}, BM_{i,t}, MOM_{i,t}, MV_{i,t})'$. The dependent variable is the percentage continuously compounded rate of return, $R_{i,t} = 100 \times [LN(P_{i,t}) - LN(P_{i,t-1})]$, where $P_{i,t}$ is country's i stock market index in period t . The sample period runs from 01/01/2020 to 28/04/2020. The model is estimated by means of the random effects estimation method. Robust standard errors are indicated in round parentheses. Asterisks ***, **, * denote significance at 1%, 5% and 10%, respectively.

	$R_{i,t} = \gamma_0 + \gamma_1 \times DCC_{i,t} + \Gamma'_1 \times \mathbf{X}_{1,i,t} + \Gamma'_2 \times \mathbf{X}_{2,i,t} \times DCC_{i,t} + u_{i,t}$			
	Daily		Weekly	
	(1)	(2)	(3)	(4)
<i>DCC</i>	-4.8744*** (1.7235)	-4.3273** (1.7809)	-5.8599*** (1.6563)	-5.3131*** (1.6788)
<i>BETA</i>	-0.0395 (0.1360)	-0.0270 (0.1363)	0.6879 (0.8962)	0.9408 (0.8914)
<i>BM</i>	0.0319 (0.2548)	0.0575 (0.2585)	-1.6719 (1.3517)	-1.2307 (1.3610)
<i>MOM</i>	-1.0544*** (0.2187)	-0.7832*** (0.2207)	0.5141 (1.2083)	1.4580 (1.2108)
<i>MV</i>	0.0507* (0.0266)	0.0356 (0.0270)	0.0756 (0.1557)	-0.0129 (0.1573)
<i>AG</i> × <i>DCC</i>	-7.1470 (4.8354)	-9.1783* (5.0052)	-12.5437*** (4.2961)	-12.4355*** (4.4986)
<i>BETA</i> × <i>DCC</i>	-1.8104** (0.9190)	-1.4198 (0.9624)	0.1096 (0.9355)	-0.0038 (0.9813)
<i>FEP</i> × <i>DCC</i>	32.7551*** (9.2440)	29.2519*** (9.6054)	31.4503*** (7.6370)	23.5086*** (8.1645)
<i>CON</i> × <i>DCC</i>	-5.2824 (4.0135)	-7.2409* (4.1405)	-2.1752 (3.9317)	-1.6662 (4.0727)
<i>EXP</i> × <i>DCC</i>	0.0077 (0.0062)	0.0047 (0.0066)	-0.0005 (0.0064)	-0.0031 (0.0068)
<i>UNEM</i> × <i>DCC</i>	-0.1287** (0.0604)	-0.1513** (0.0612)	-0.1289** (0.0527)	-0.1289** (0.0530)
<i>LTOR</i> × <i>DCC</i>	0.0253* (0.0141)	0.0310** (0.0148)	0.0090 (0.0124)	0.0102 (0.0132)
<i>INDUL</i> × <i>DCC</i>	0.0062 (0.0152)	0.0042 (0.0155)	-0.0049 (0.0139)	-0.0084 (0.0142)
<i>ACCOU</i> × <i>DCC</i>	0.4790 (0.3373)	0.2549 (0.3609)	0.3399 (0.3160)	0.3286 (0.3412)
<i>SI</i> × <i>DCC</i>	0.0114 (0.0106)		0.0283*** (0.0085)	
<i>C2</i> × <i>DCC</i>		0.5501 (0.4755)		0.6376* (0.3697)
<i>C2_g</i> × <i>DCC</i>		-0.5239 (0.5177)		-0.6012 (0.3785)
<i>C5</i> × <i>DCC</i>		1.9056*** (0.7114)		0.9860** (0.4760)
<i>C5_g</i> × <i>DCC</i>		-0.0442 (0.8925)		0.0289 (0.6165)
<i>C6</i> × <i>DCC</i>		-0.6568 (0.7518)		-0.4611 (0.5216)
<i>C6_g</i> × <i>DCC</i>		-0.0705 (0.9034)		1.0761* (0.5934)

$C7 \times DCC$		-0.7314 (0.5067)		0.0720 (0.4158)
$C7_g \times DCC$		1.0683* (0.6106)		0.2780 (0.4294)
$H3 \times DCC$		0.1558 (0.3352)		0.5530* (0.3136)
$E1 \times DCC$		0.4671 (1.1392)		1.1756 (0.7695)
$E1_g \times DCC$		-0.2051 (1.3491)		-1.1217 (0.8961)
$E2 \times DCC$		1.6200*** (0.6119)		0.7274 (0.5132)
$CONST$	-0.7517** (0.3433)	-0.6117* (0.3478)	-0.2077 (1.8980)	0.3376 (1.9107)
OBS	4648	4645	896	896
R^2	0.0463	0.0522	0.2312	0.2568

Table 9: Multiple interaction panel data regression: Confirmed deaths

This table summarises the coefficient estimates, $\Gamma \equiv (\gamma_0, \gamma_1, \Gamma'_1, \Gamma'_2)'$, of the multiple-interaction panel data model, outlined in Equation 4 for daily (Columns 1 and 2) and weekly (Columns 3 and 4) data. In Columns 1 and 3, the composite government stringency index measures the degree of government response to the coronavirus pandemic. In Columns 2 and 4, individual elements of government response are utilised in the model. Individually significant interactions in Tables 2 – 6 of the rate of growth in the total number of confirmed deaths, $DCD_{i,t}$, with financial, economic, healthcare, government intervention and governance variables. The multidimensional information set is described in Tables A.1 – A.5 in the Online Appendix. The model also includes $DCD_{i,t}$, and it controls for the key four asset pricing factors, $\mathbf{X}_{1,i,t} \equiv (BETA_{i,t}, BM_{i,t}, MOM_{i,t}, MV_{i,t})'$. The dependent variable is the percentage continuously compounded rate of return, $R_{i,t} = 100 \times [\ln(P_{i,t}) - \ln(P_{i,t-1})]$, where $P_{i,t}$ is country's i stock market index in period t . The sample period runs from 01/01/2020 to 28/04/2020. The model is estimated by means of the random effects estimation method. Robust standard errors are indicated in round parentheses. Asterisks ***, **, * denote significance at 1%, 5% and 10%, respectively.

	$R_{i,t} = \gamma_0 + \gamma_1 \times DCD_{i,t} + \Gamma'_1 \times \mathbf{X}_{1,i,t} + \Gamma'_2 \times \mathbf{X}_{2,i,t} \times DCD_{i,t} + u_{i,t}$			
	Daily		Weekly	
	(1)	(2)	(3)	(4)
<i>DCD</i>	-6.1363*** (1.6323)	-4.2161*** (1.6287)	-16.3116*** (2.6256)	-13.2595*** (2.5838)
<i>BETA</i>	-0.2110 (0.1316)	-0.2099 (0.1315)	-0.7023 (0.8984)	-0.4344 (0.8938)
<i>BM</i>	0.0466 (0.2548)	0.0187 (0.2553)	-2.5257* (1.4040)	-2.6069* (1.4012)
<i>MOM</i>	-0.7038*** (0.2107)	-0.7058*** (0.2113)	6.6656*** (1.2624)	6.1313*** (1.2722)
<i>MV</i>	0.0510* (0.0262)	0.0520** (0.0264)	0.0400 (0.1594)	0.0354 (0.1597)
<i>AG × DCD</i>	-11.1081** (4.7080)	-9.9574* (5.1755)	-11.9987* (7.2370)	-8.4372 (7.7490)
<i>BETA × DCD</i>	1.7536** (0.8362)	1.1394 (0.8957)	5.3041*** (1.4596)	3.9311** (1.5800)
<i>FEP × DCD</i>	29.2953*** (7.0347)	31.2147*** (7.3528)	50.5626*** (10.0784)	55.1007*** (10.8649)
<i>CON × DCD</i>	0.8533 (4.1441)	4.0571 (4.3873)	-6.7685 (6.4909)	0.5169 (6.9198)
<i>ROS × DCD</i>	-0.7296 (8.6464)	-8.9825 (9.5851)	22.3911* (12.5910)	8.3288 (14.2873)
<i>EXP × DCD</i>	-0.0143** (0.0072)	-0.0137* (0.0075)	0.0011 (0.0120)	-0.0035 (0.0124)
<i>UNEM × DCD</i>	-0.3102*** (0.0542)	-0.2752*** (0.0570)	-0.2578*** (0.0792)	-0.2128*** (0.0833)
<i>LTOR × DCD</i>	-0.0080 (0.0126)	-0.0002 (0.0140)	-0.0313* (0.0186)	-0.0264 (0.0213)
<i>INDUL × DCD</i>	-0.0035 (0.0144)	-0.0091 (0.0148)	0.0084 (0.0214)	0.0095 (0.0223)
<i>ACCOUN × DCD</i>	0.4757 (0.3287)	0.3282 (0.3561)	0.7671* (0.4570)	0.8053 (0.5569)
<i>SI × DCD</i>	0.0705*** (0.0096)		0.1571*** (0.0165)	
<i>C2 × DCD</i>		0.5309 (0.3284)		0.8948* (0.4959)
<i>C2_g × DCD</i>		0.2082 (0.3159)		0.3014 (0.4110)
<i>C5 × DCD</i>		0.4990 (0.4832)		-0.2238 (0.6551)
<i>C5_g × DCD</i>		0.6892 (0.5529)		2.5187*** (0.7788)
<i>C6 × DCD</i>		-0.9347** (0.4626)		-0.7635 (0.6061)

$C6_g \times DCD$		0.5754 (0.5136)		0.9904 (0.6509)
$C7 \times DCD$		1.1250** (0.4427)		2.7763*** (0.7467)
$C7_g \times DCD$		-0.1811 (0.3767)		-0.4618 (0.5200)
$H3 \times DCD$		-0.5735* (0.3360)		0.1006 (0.4922)
$E1 \times DCD$		1.3818*** (0.5220)		1.9289*** (0.6944)
$E1_g \times DCD$		-0.9623 (0.6318)		-2.5901*** (0.7719)
$E2 \times DCD$		0.0238 (0.4045)		-0.0645 (0.5701)
$CONST$	-0.8129** (0.3404)	-0.8170** (0.3419)	-0.2953 (1.9428)	-0.4210 (1.9426)
OBS	4648.0000	4645.0000	896.0000	896.0000
R^2	0.0335	0.0393	0.1708	0.1976

Table 10: Two-stage multiple interaction panel data regression

This table summarises the coefficient estimates, $\Gamma \equiv (\pi_0, \pi_1, \Pi'_1, \Pi'_2)'$, of the multiple-interaction panel data model, outlined in Equation 6 for daily (Columns 1 and 2) and weekly (Columns 3 and 4) data. In Columns 1 and 3, the composite government stringency index measures the degree of government response to the coronavirus pandemic. In Columns 2 and 4, individual elements of government response are utilised in the model. Individually significant interactions in Tables 2 – 6 of the rate of growth in the total number of confirmed cases, $DCC_{i,t}$, with financial, economic, healthcare, government intervention and governance variables. The multidimensional information set is described in Tables A.1 – A.5 in the Online Appendix. The model also includes $DCC_{i,t}$, and it controls for the key four asset pricing factors, $\mathbf{X}_{1,i,t} \equiv (BETA_{i,t}, BM_{i,t}, MOM_{i,t}, MV_{i,t})'$. The dependent variable is the percentage continuously compounded rate of return, $R_{i,t} = 100 \times [LN(P_{i,t}) - LN(P_{i,t-1})]$, where $P_{i,t}$ is country's i stock market index in period t . The sample period runs from 01/01/2020 to 28/04/2020. The panel data model is estimated by means of the two-stage random effects estimation method. This estimation methods addresses the potential endogeneity issue of $DCC_{i,t}$. $DCC_{i,t}$ is instrumented with $\mathbf{Z}_{i,t} \equiv (DCC_{i,t-1}, DENS_{i,t}, EHI_{i,t})'$ variables. Similarly, the vector of interactions $\mathbf{X}_{2,i,t} \times DCC_{i,t}$ is instrumented with a valid set of instruments $\mathbf{X}_{2,i,t} \otimes \mathbf{Z}_{i,t}$. More specifically, a p^{th} element from $\mathbf{X}_{2,i,t} \times DCC_{i,t}$, $X_{2,i,t}^{(p)} \times DCC_{i,t}$ is instrumented with $\mathbf{Z}_{i,t} \times X_{2,i,t}^{(p)}$. Robust standard errors are indicated in round parentheses. Asterisks ***, **, * denote significance at 1%, 5% and 10%, respectively.

	$R_{i,t} = \pi_0 + \pi_1 \times \widehat{DCC}_{i,t} + \Pi'_1 \times \mathbf{X}_{1,i,t} + \Pi'_2 \times \mathbf{X}_{2,i,t} \times \widehat{DCC}_{i,t} + \epsilon_{i,t}$			
	Daily		Weekly	
	(1)	(2)	(3)	(4)
\widehat{DCC}	-18.2522*** (4.2119)	-9.8280** (4.9843)	-17.5199*** (3.9820)	-9.4538*** (3.6682)
$BETA$	-0.3509*** (0.1229)	-0.2256 (0.1508)	-3.1295 (1.9340)	0.6807 (2.2308)
BM	-0.1194 (0.2462)	-0.0300 (0.2188)	-2.8707* (1.4958)	-2.4953* (1.3003)
MOM	-0.9266*** (0.2319)	-1.0629*** (0.1981)	5.2195** (2.0474)	1.4022 (1.3481)
MV	0.0691** (0.0307)	0.0534* (0.0274)	0.2289 (0.1909)	0.0898 (0.1928)
$AG \times \widehat{DCC}$	-19.6608** (8.5671)	-29.2574*** (8.6446)	-23.0464* (13.6222)	-17.7580 (12.2612)
$BETA \times \widehat{DCC}$	2.2022 (1.8361)	0.7994 (2.1367)	8.1240** (3.9951)	-0.2751 (3.7818)
$FEP \times \widehat{DCC}$	58.7564*** (22.3435)	47.7066** (19.1506)	46.7582*** (15.9072)	38.9788** (17.8511)
$CON \times \widehat{DCC}$	9.4292 (9.7892)	6.0427 (9.5596)	-0.6879 (10.7294)	2.5679 (6.9219)
$ROS \times \widehat{DCC}$	-22.1657 (23.1261)	-37.5505 (26.2794)	-17.8229 (19.4480)	-34.3284 (21.1876)
$EXP \times \widehat{DCC}$	-0.0157 (0.0179)	-0.0153 (0.0188)	0.0149 (0.0152)	0.0044 (0.0157)
$UNEM \times \widehat{DCC}$	-0.1778** (0.0887)	-0.2387*** (0.0894)	-0.1589* (0.0886)	-0.1373* (0.0703)
$LTOR \times \widehat{DCC}$	0.0507** (0.0252)	0.0380 (0.0259)	-0.0162 (0.0225)	0.0229 (0.0210)
$INDUL \times \widehat{DCC}$	0.0331 (0.0363)	0.0046 (0.0334)	-0.0121 (0.0353)	0.0047 (0.0281)
$ACCOUN \times \widehat{DCC}$	1.1154 (0.7928)	0.7528 (0.9199)	0.7803 (0.8014)	0.5967 (0.8462)
$SI \times \widehat{DCC}$	0.1054*** (0.0210)		0.1526*** (0.0241)	
$C2 \times \widehat{DCC}$		0.6007 (0.9526)		0.9642 (0.7554)
$C2_g \times \widehat{DCC}$		-0.6332		-0.7960

$C5 \times \widehat{DCC}$		(0.7562)		(0.6413)
		3.4949***		1.7282**
		(1.1936)		(0.8523)
$C5_g \times \widehat{DCC}$		-1.6888		-0.3100
		(1.5702)		(1.3094)
$C6 \times \widehat{DCC}$		-2.7696***		-0.7907
		(0.9564)		(0.8175)
$C6_g \times \widehat{DCC}$		1.6460*		0.5882
		(0.9733)		(0.8712)
$C7 \times \widehat{DCC}$		1.0870		1.3822*
		(1.0508)		(0.8321)
$C7_g \times \widehat{DCC}$		1.5921		0.7877
		(1.1237)		(0.8398)
$H3 \times \widehat{DCC}$		0.6322		0.9055*
		(0.7444)		(0.5384)
$E1 \times \widehat{DCC}$		2.7599*		2.1315*
		(1.5780)		(1.1043)
$E1_g \times \widehat{DCC}$		-2.2044		-1.3480
		(1.6113)		(1.3182)
$E2 \times \widehat{DCC}$		0.5723		0.0659
		(0.8399)		(0.8359)
<i>CONST</i>	-0.4945	-0.4472	2.2054	0.8894
	(0.3397)	(0.2956)	(2.5997)	(2.5815)
<i>Hansen-J test</i> [p-value]	[0.15243]	[0.13678]	[0.14915]	[0.11209]
<i>OBS</i>	4509	4506	847	794
<i>R</i> ²	0.0387	0.0460	0.1650	0.2329

Table 11: Multiple interaction panel data regression: Factor analysis

This table summarises the coefficient estimates, $\Gamma \equiv (\gamma_0, \gamma_1, \Gamma'_1, \Gamma'_2)'$, of the multiple-interaction panel data model, outlined in Equation 4 for daily (Columns 1) and weekly (Columns 2) data. In Step 1, single-interaction panel data models are estimated. In Step 2, the factor analysis was performed for each of the financial, economic, healthcare, government intervention, and governance categories. The factor model retains three key factors. The first factor selects all government response variables, as well as *FEP*. Therefore, the first factor represents the short-term government response to the coronavirus pandemic. The total percentage of variance explained by the first factor is approximately 51%. The second factor, which accounts for 28.5% of the variance, has positive and economically significant loadings on *INDUL* and *ACCOUN*. It also provides information contents about financial variables, such as *BETA* (positive sign), *FEP* (negative sign) and *CON* (negative sign). Therefore, the second factor consists of two sides. The first side can be thought to reflect democratic freedom of the society, whereas the flip side captures investment opportunities available for the society. The third factor significantly loads on *LTOR* (positive sign), *EXP* (positive sign) and *UNEMP* (negative sign), as well as *INDUL* (negative sign) and *H3* (positive sign). This factor can be thought of as an indicator of long-term socio-economic stability. This factor represents 19% of the total variance. In Step 3, the extracted factors are interacted with the rate of growth in the total number of confirmed cases, $DCC_{i,t}$. The multidimensional information set is described in Tables A.1 – A.5 in the Online Appendix. The model also includes $DCC_{i,t}$, and it controls for the key four asset pricing factors, $\mathbf{X}_{1,i,t} \equiv (BETA_{i,t}, BM_{i,t}, MOM_{i,t}, MV_{i,t})'$. The dependent variable is the percentage continuously compounded rate of return, $R_{i,t} = 100 \times [LN(P_{i,t}) - LN(P_{i,t-1})]$, where $P_{i,t}$ is country's i stock market index in period t . The sample period runs from 01/01/2020 to 28/04/2020. The model is estimated by means of the random effects estimation method. Robust standard errors are indicated in round parentheses. Asterisks ***, **, * denote significance at 1%, 5% and 10%, respectively.

$R_{i,t} = \gamma_0 + \gamma_1 \times DCC'_{i,t} + \Gamma'_1 \times \mathbf{X}_{1,i,t} + \Gamma'_2 \times \mathbf{X}_{2,i,t} \times DCC'_{i,t} + u_{i,t}$				
	(1) Daily		(2) Weekly	
	Coef.	SE	Coef.	SE
<i>DCC</i>	-3.280***	(0.3400)	-3.595***	(0.2868)
<i>BETA</i>	-0.153	(0.0998)	0.554	(0.6572)
<i>BM</i>	0.159	(0.1797)	-0.835	(0.9492)
<i>MOM</i>	-1.046***	(0.1460)	1.253	(0.7883)
<i>MV</i>	0.0591**	(0.0252)	0.0740	(0.1124)
<i>FACTOR1</i> × <i>DCC</i>	0.971***	(0.3399)	1.496***	(0.3892)
<i>FACTOR2</i> × <i>DCC</i>	-0.515*	(0.2875)	-0.504**	(0.2375)
<i>FACTOR3</i> × <i>DCC</i>	0.941***	(0.3200)	0.992**	(0.4205)
<i>CONST</i>	-0.845**	(0.3306)	-0.579	(1.2921)
<i>OBS</i>	4647		896	
R^2	0.0421		0.2268	