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The role of non-critical business and telework propensity in international stock markets during the COVID-19 pandemic

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ABSTRACT

We investigate the impact of non-critical business and telework propensity on stock prices during the COVID-19 pandemic using panel data comprising 15,238 firms across 46 countries. After eight months of the COVID-19 outbreak, we find that firms operating in non-critical industrial groups have stock prices 6.52% lower than firms in the same subsector that operate in essential industrial groups. We also examine corporate characteristics that exacerbated or mitigated this effect. We find that firms in non-critical industrial groups with high leverage, high human resource management inefficiency, and low intangible intensity before the pandemic suffered even more. For non-critical firms, we find that a one-standard-deviation increase in the subsector’s telework propensity results in a 10.20% increase in the firm’s stock price relative to firms in the same sector. Our research provides valuable empirical evidence for policymakers to understand the trade-off between containing the spread of the virus and restricting non-essential businesses, monitoring firms with specific corporate characteristics, and providing extraordinary support to those with a low propensity to telework during pandemics.

1. Introduction

The COVID-19 pandemic and its rapid spread took much of the world by surprise. In less than three months, the situation evolved from a cluster of pneumonia with unknown etiology appearing in the city of Wuhan, China, to the World Health Organization (WHO) declaring a pandemic on March 11, 2020 (Sun et al., 2020; Maxmen, 2021). Anticipating the dire economic consequences that would follow, stock markets experienced their steepest declines in the early weeks of the outbreak since the Global Financial Crisis (GFC). To curb the spread of the virus, countries took very tough measures of social distancing, causing the health crisis to spread to the economy (Brodeur et al., 2021; Carlsson-Szlezak et al., 2020). Businesses providing non-essential goods and services

1 Shehzad et al. (2020) report that the market value of the MSCI World Index dropped by 17.5% between March 6 and March 18. During the same period, the US, UK, Spain, Hong Kong, and China stock markets experienced declines of 14.9%, 21.4%, 25.1%, 14.7%, and 12.1% respectively.

2 World Bank (2021) points to a 3.5% contraction in global economic activity in 2020. International Labour Organization (2021) estimates that in 2020 about 8.8% of global working hours were lost relative to the fourth quarter of 2019, equivalent to 255 million full-time jobs. Global labor income (before taking into account income support measures) is estimated to have declined by 8.3%, or 4.4% of global GDP in 2020. United Nations Conference on Trade and Development (2021) indicates that the effect of COVID-19 on global trade was most severe during the first half of 2020, with a drop in value of about 15%. Overall, world trade recorded a drop in value of about 9% in 2020.
were severely constrained in their operations. In order to continue operating, these businesses have been compelled to adapt their operations to accommodate remote work. Problematically, the transition to telework was more difficult for some than for others. These extraordinary developments motivate our research to gain a deeper understanding of the impact of the COVID-19 pandemic and its unfolding events on firm performance.

This paper examines the effect of social distancing policies on firm performance and the corporate characteristics that exacerbated or mitigated this effect. We also assess the role of telework propensity in the performance of firms operating in non-critical activities, i.e., those most dependent on an orderly transition to remote work. To the best of our knowledge, we are the first to provide evidence on these issues by combining an empirical strategy that enables causal inference with a comprehensive sample containing over 15,000 firms traded in developed, emerging, and frontier markets (46 countries).

We focus on the first wave of the pandemic because we understand it to be a more interesting event from an empirical point of view. In this first phase, economic agents could not clearly anticipate the scale of the crisis that was to come and did not have adequate time to adapt to the unfolding of the pandemic. Such features make the identification of the first wave of the COVID-19 cleaner from an empirical perspective. Evidence provided by the literature supports our reasoning. For instance, Pagano et al. (2021) show that during the “fever period” (from late February to late March 2020), U.S. high-resilience stocks greatly outperformed low-resilience ones after controlling for risk factors. However, the return differential had almost vanished by the end of the year. Some government interventions intended to provide support and temporary relief may also have affected the stock prices of specific firms, making it difficult to disentangle the pandemic’s effect from the firms’ essentiality and propensity to telework. In addition, the methodologies used to develop our variables in the identification strategy raise concerns regarding their applicability in subsequent waves.

We estimate the impact of the COVID-19 pandemic using a difference-in-differences (DiD) approach. We identify firms’ exposure to the pandemic by the essentiality of their economic activity, employing a classification provided by Papanikolaou and Schmidt (2020). As the virus spread across countries, governments implemented restrictive policies that limited most businesses, except those deemed critical or essential. The intensity and timing of the implementation of these policies varied between economies. We can also observe differences in the implementation strategy of restriction policies even across similar and geographically close countries.

In our empirical setup, firms operating in industrial groups regarded as non-critical compose the treatment group, while those in industrial groups deemed critical form the control group. To mitigate selection concerns, we compare firms within the same subsector but across industrial groups (one critical and other non-critical) by adding dynamic fixed effects for subsector. We also introduce firm fixed effects in our regressions to absorb any non-observable firm-specific and time-invariant characteristic. We employ ex-ante controls to mitigate potential omitted variable problems that could drive our results. We also conduct an event study in the surroundings of the COVID-19 outbreak to show that firms’ stock prices of the treatment and control groups are similar before the onset of the pandemic (parallel trends hypothesis).

We find that social distancing policies substantially affect firm performance. We show that firms operating in non-critical industrial groups exhibit an average 6.52% lower price after eight months of the onset of the crisis than firms of the same subsector but operating in essential industrial groups. Country-specific factors do not drive our results: they still hold when we narrow the comparison between critical and non-critical industrial groups within the same subsector in the same country. These findings reveal the extent to which non-critical companies had their performance more affected by the pandemic’s unfolding than the critical ones. We refer to this impact as the non-critical business effect.

The increased vulnerability of non-critical firms to the COVID-19 pandemic may have been amplified or moderated according to specific corporate characteristics. Companies that managed to maintain sizable cash reserves and comfortable debt levels before the pandemic faced fewer difficulties in financing the dramatic drop in cash flow (Fahlenbrach et al., 2021). Firms in intangible-intensive

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3 The authors note that one reason contributing to this market behavior was positive news regarding vaccine development. Acharya et al. (2021) find that a one-year reduction of the expected time to deployment of the vaccine increased the stock market return as a whole between 4% to 8% daily.

4 Zaremba et al. (2021) investigate how income support and debt relief programs benefited international stock markets.

5 The classification of critical economic activities developed by Papanikolaou and Schmidt (2020) is based on March 2020 recommendations made by the U.S. agency CISA. The telework propensity measure developed by Dingel and Neiman (2020) is based on pre-pandemic data. It is reasonable to expect that the first wave encouraged a profound adaptation of firms to the challenges of the pandemic and a great deal of learning by the authorities for managing restrictive business policies. In this sense, firms’ criticality and propensity to telework will likely have changed significantly in the waves after the first one.

6 Papanikolaou and Schmidt (2020) use the classification to filter out critical companies and then regress the propensity to telework on the stock returns of non-critical companies. Our work is different because we use their classification as an identification strategy in the DiD methodology, allowing us to establish a causal effect between the criticality of firms and their stock prices.

7 Oxford COVID-19 Government Response Tracker (OxCGRT) data show that only 5% of countries had implemented some type of restriction at the end of February 2020. By mid-March, that number rose to 30% and then accelerated to 87% by the end of that month. In April, restrictions began to tighten: by mid-April, about 55% of countries had imposed restrictions on all non-essential businesses. Although that number dropped to 12% by the end of May, approximately 65% of countries continued to restrict some non-essential activities.

8 France began restricting non-critical businesses a week earlier than Germany, in mid-March 2020. The intensity of these constraints was also different. While France required the closure of all non-critical businesses, Germany opted for a more flexible strategy. It was only in mid-May that France loosened restrictions and allowed some non-critical businesses to operate, unlike Germany, which always allowed some of these businesses to operate during the initial wave.

9 For example, we compare companies like Amazon, which belongs to the critical industrial group “Electronic Shopping and Mail-Order Houses”, with companies like Star Group, which belongs to the non-critical industrial group “Direct Selling Establishments”. We consider these companies similar as they belong to the same subsector “Non store Retailers”, which is characterized by the sale of products and services outside the space of a physical store. However, while Amazon’s industrial group operates primarily through electronic channels, Star Group’s industrial group also operates through alternative physical channels such as house-to-house canvassing, trucks/wagons, and other temporary locations.
industries have a greater ability to adapt to new technologies, which has made them better prepared for the digital transformations posed by the pandemic than firms in tangible-intensive industries (Demmou et al., 2021). Effective human resource management (HRM) was instrumental in redesigning work processes for the virtual environment, containing fractures between employee groups, and mitigating feelings of social isolation and high levels of anxiety in the workforce (Collings et al., 2021b,a; Caligiuri et al., 2020). We examine whether these corporate characteristics affected businesses differently during the first wave of the COVID-19 pandemic.

Among firms in non-critical industrial groups, we show that a one-standard-deviation increase in a firm’s leverage results in an additional 6.81 percentage point decline in its stock price on average following the COVID-19 crisis, when compared to firms in the same subsector with a leverage value equal to the sample mean. We also show that a one-standard-deviation increase in a firm’s HRM ineffectiveness yields an extra 13.13 percentage point decline in its stock prices on average. We also find that a one-standard-deviation increase in a firm’s intangible intensity mitigates by 2.98 percentage points the reduction of stock prices caused by the COVID-19 on average. This set of findings suggests that firms in non-essential industrial groups with a high degree of leverage, ineffective HRM, and low intangible intensity suffered even more during the pandemic.

Firms related to non-critical industrial groups, during the most stringent period of the pandemic, had to tailor their operations with a high share of their employees working from home.10 Some sectors faced fewer issues because they were more flexible to telework, while others struggled because of their reliance on tasks that were more challenging, or even impossible, to adapt to telework.11 In this sense, we explore the role of telework propensity in the stock prices of firms related to non-critical activities during the COVID-19 pandemic. In this investigation we also use the DiD approach, but this time we identify non-critical firms’ exposure to the pandemic by the telework propensity of their economic activity.12 Bai et al. (2021) conduct a similar investigation to ours using the DiD framework. However, their findings are limited to firms traded in the U.S. market, whereas our results extend to different economies.13

We show that, for firms in non-essential industrial groups, a one-standard-deviation increase in the telework propensity of the firm’s subsector drives an average 10.20% increase in its stock price after eight months of the COVID-19 outbreak, compared to firms in the same sector and with a telework propensity of the subsector equal to the sample mean value. These findings suggest that, for firms selling non-essential products/services, having a higher proportion of workers able to work from home was critical in mitigating the adverse effects of the policies restricting their operations during the COVID-19 pandemic.

Our empirical research questions stem from the theoretical literature that seeks to explain how rare events impact asset pricing and their transmission channels that either mitigate or amplify these effects. This interest dates back to an attempt to solve the Mehra–Prescott puzzle, when Rietz (1988) extended the Lucas (1978)’s model to explain the high equity risk premium and low risk-free returns. This allowed the model to account for risk-averse equity investors who demanded a higher return to offset the substantial losses they could experience in an adverse and rare event. Reinforcing Rietz (1988)’s argument, several authors have expanded the model, allowing for the explanation of other puzzles such as the high stock price volatility (Barro, 2006; Wachter, 2013). Inspired by this theoretical background, Pagano et al. (2021) found that, with the emergence of the pandemic, firms less resilient to social distancing not only experienced a more significant negative impact on their stock returns, but their expected returns were higher than those of more resilient firms, indicating a market pricing a risk factor similar to that of a rare disaster, which they refer to as pandemic risk. Although our work does not pretend to investigate or measure the risk premium relative to rare disasters, our empirical strategy allows us to establish a cause-and-effect relationship between the pandemic and stock prices, which is absent in Pagano et al. (2021)’s work. Therefore, our analysis enriches this line of investigation with evidence that allows us to understand the phenomenon from a different but complementary perspective.

Our work provides important policy implications to counter undesirable public health and economic consequences during pandemics. First, we show that imposing strict foreclosure policies has a severe negative impact on firms that provide non-essential goods/services. This finding implies that policymakers must carefully analyze the trade-off between containing the virus and restricting non-essential businesses, avoiding unintended consequences that could threaten their survival and, consequently, employees’ income. Second, we provide evidence that firms in non-critical industrial groups with high leverage, inefficient HRM, and low intangible intensity suffered even more from the restriction policies implemented during the pandemic. This finding means that, if constraints on these firms’ activities cannot be avoided, close monitoring of firms exhibiting these corporate characteristics is necessary to avoid bankruptcies and job losses. Finally, we show that propensity to telework was a key factor in mitigating the adverse effects of the pandemic among firms in non-essential industrial groups. If policymakers choose to impose restrictions on these businesses, it is critical to provide assistance that enables these businesses’ processes to adapt to remote work. Additional assistance could be required for those with a very low proclivity for remote work.

10 Ker et al. (2021) show that working from home increased markedly – by around one-third on average – between 2019 and 2020 in OECD countries. For instance, telecommuting more than doubled in France relative to pre-pandemic levels, while in the United Kingdom, it increased by about 80%.

11 Ker et al. (2021) note that industries associated with physical production such as health and social care, construction, transportation and warehousing, and accommodation and food services had relatively low rates of teleworking. By contrast, industries that are already highly digitalized, including financial services, information and communication services, and professional, scientific and technical services, achieved significantly higher rates of remote working—over 50% on average.

12 We employ the telework propensity measure provided by Dingel and Neiman (2020). This variable indicates the proportion of the labor force – at the NAICS subsector level – capable of telework.

13 Papanikolaou and Schmidt (2020) also assess the relationship between telework propensity and stock returns, but as Bai et al. (2021), their sample is limited to firms traded in the U.S. market. Favilakis et al. (2021) examine the association between the propensity to telework and stock returns of firms in the G7 countries. Our work differs in that we employ a methodology that allows us to infer a causal relationship and that our sample is broader, including firms traded in 46 countries.
2. Related literature

Most of the studies that analyze the effect of the COVID-19 pandemic on stock returns at the firm level are limited to a single country. A recurrent result is the critical role of liquidity and indebtedness in firms’ sensitivity to the COVID-19 shock. Ramelli and Wagner (2020) employ a sample of U.S. public firms and show that, when we compare within the same industry and control for standard firm characteristics, investors disfavored companies with high corporate debt and low cash. On the same note, Fahlenbrach et al. (2021) discover that U.S. public companies with a high degree of financial flexibility – as measured by cash holdings, debt, and leverage – experienced a lower stock price drop. Liu et al. (2021a) supply similar findings, showing that the COVID-19 shock significantly increased the credit default swap spread and decreased the shareholder value for U.S. public firms facing higher debt rollover risk. Alfaro et al. (2020) present results in the same direction, COVID-19 related losses in the market value of U.S. listed companies rise with leverage and are more profound in industries more conducive to disease transmission. Dechow et al. (2021) complement showing that pandemic shutdowns primarily impacted short-term cash flows of U.S. listed firms. They demonstrate that the underperformance of value stocks during this period is a rational response to their lower durations. We also evaluate the role of leverage on firms’ performance during the pandemic. However, we employ a much larger sample (about 15,000 stocks traded in 46 countries), extending the results to a broader range of firms traded in different markets.

Disruptions in the credit market and banking sector also highlight how firms have become more or less vulnerable to the COVID-19 pandemic due to liquidity and debt issues. Elnahass et al. (2021) find that the COVID-19 outbreak has significantly harmed bank financial performance and bank financial stability. Their findings are observed for various geographical regions, bank sizes and countries’ income classifications. Li et al. (2020) show that firms drew funds on a massive scale from preexisting credit lines in anticipation of cash flow and financial disruptions stemming from the COVID-19 crisis in the U.S. The increase in liquidity demands was concentrated at the largest banks, which serve the largest firms. Acharya and Steffen (2020) provide similar evidence by finding a corporate “dash for cash” induced by the COVID-19 pandemic for a sample of U.S. listed firms. In the first phase of the crisis, all firms used bank credit lines and raised cash levels. In the second phase, only the highest-rated firms switched to capital markets to raise cash. Halling et al. (2020) point out that asset tangibility has a highly significant negative effect on corporate bond spreads during normal times. However, during COVID-19, this reversed, especially in industries heavily affected by lockdown measures, reflecting the inflexibility associated with fixed assets. Jiang et al. (2022) find that bonds with higher pre-crisis fragility experienced more negative returns and more significant reversals around March 2020. Apergis et al. (2021) show that the COVID-19 pandemic drove up U.S. corporate credit default swap spreads, where both the magnitude and significance were heterogeneous across sectors.

A smaller subset of the literature investigates the effects of the COVID-19 pandemic on stock returns at the firm level using a broader sample containing firms from several countries. Ding et al. (2021) expand on results found by Ramelli and Wagner (2020) and similar studies, on the importance of firms’ liquidity and indebtedness. They observe that the pandemic-induced drop in stock returns, across 61 economies, was milder among firms with stronger pre-2020 finances (more cash and undrawn credit, less total and similar studies, on the importance of firms’ liquidity and indebtedness. They observe that the pandemic-induced drop in stock returns, across 61 economies, was milder among firms with stronger pre-2020 finances (more cash and undrawn credit, less total and shorter-term debt, and larger profits). Heyden and Heyden (2021) also present evidence with respect to the important role of firms’ liquidity. This feature has the power to strengthen or weaken stock reactions of U.S. and European firms to monetary and fiscal policy announcements during the pandemic. Kaczmarek et al. (2021) find results in the same direction, highlighting how limited leverage strengthened stock returns of travel and leisure firms, over 52 countries, during the COVID-19 crisis. Hyun et al. (2020) find evidence, using data on more than 7,000 firms in 71 countries, that companies with greater global connectivity and market power exhibit greater resilience (in terms of market value growth) to domestic COVID-19 shocks. Hu and Zhang (2021) observe that the impact of COVID-19 on firm performance, measured by return on assets rather than stock returns, are less pronounced in countries with better healthcare systems, more advanced financial systems, and better institutions. Our work differs from the above in the econometric modeling: the DiD framework we employ allows us to infer a causal relationship between the COVID-19 pandemic and stock prices.

Other firms’ characteristics proved important to explain their resilience or fragility to the shock arising from the COVID-19 pandemic. The unfolding of the pandemic in the vicinity of the headquarters or important assets has influenced their stock returns. Bretscher et al. (2020) observe using a DiD framework that, on average, daily returns of U.S. public firms are lower in the 10-day window right after the first case of COVID-19 is recorded in the county where the firm is headquartered. Ling et al. (2020)

14 Firms with high financial flexibility experienced a stock price drop lower by 26% or 9.7 percentage points than those with low financial flexibility.
15 Value stocks tend to be stocks for which earnings and cash flows are in secular decline. Consequently, a more significant proportion of their value is represented by near-term cash flows. The bond duration measure often represents interest rate risk for fixed income securities, Dechow et al. (2004) adapt this measure to equity securities.
16 They also notice that the lowest-quality BBB-rated firms behaved more similarly to non-investment grade firms, revealing the significant impact of credit risk on corporate cash holdings.
17 They also find that firms with less exposure to COVID-19 through global supply chains and customer locations, more corporate social responsibility activities, and less entrenched executives also presented lower drop in their stock returns. Furthermore, the stock returns of firms controlled by families, large corporations, and governments performed better, and those with greater ownership by hedge funds and other asset management companies performed worse.
18 Fiscal policy measures negatively affect stock returns, and monetary policy measures have the potential to calm markets. Other important firm-specific characteristics are tangible assets and institutional holdings.
19 Firms with low valuations and high investments have been more immune to the pandemic-induced crash also.
20 Authors argue that while global production and export networks expose firms to international shocks, they likely moderate firms’ sensitivity to domestic shocks through global diversification. Increases in market power can yield buffers by allowing margins for adjustment.
find a consistent negative relationship between abnormal returns of U.S. real estate investment trusts (REITs) and GeoCOVID. \(^{21}\) Ren et al. (2021) quantify the influence of regional COVID-19 outbreaks on the stock returns of Chinese firms by using a DiD framework. \(^{22}\) Exposure to international markets is another factor that has the potential to affect firms’ stock returns. Ramelli and Wagner (2020) show that as China was effectively shut down, investors shunned U.S. stocks with China exposure and internationally oriented companies. Takahashi and Yamada (2021) find that stock returns of Japanese firms were lower for companies with China and U.S. exposure during the COVID-19 outbreak. Yong and Laing (2021) observe that, while international exposure of U.S. listed firms is significant and negatively associated with standardized cumulative abnormal returns in the short-run, the effect reverses in the long run. \(^{23}\) The literature also highlights the following features: firm’s industry (Ling et al., 2020; Mazur et al., 2021); operating flexibility (Liu et al., 2021b); top brands (Huang et al., 2021); firm efficiency (Neukirchen et al., 2022) and role of earnings forecast (Landier and Thesmar, 2020). Like Ren et al. (2021) and Bretscher et al. (2020), we also employ the DiD framework, but instead of assessing firms’ exposure to regional cases of COVID-19, we identify the vulnerability of firms to the pandemic by their nexus to products/services regarded as essential during the pandemic. We also show that some firm attributes (intangible intensity, HRM ineffectiveness and leverage) were responsible for heterogeneities of the non-critical business effect on stock prices.

Another key feature of firms that proved to be important in making them more or less resilient to the pandemic was the propensity to telework. \(^{24}\) Papanikolaou and Schmidt (2020) show that U.S. sectors in which a higher share of the workforce is able to work from home observed a more significant downturn in indicators such as employment and stock returns. Along the same lines, Favlukis et al. (2021) find that U.S. firms in industries with high telework propensity significantly outperformed (in terms of stock returns) firms in industries with low propensity. They observe this result for the G7 countries as well. Unlike the previous ones, Bai et al. (2021) employ a DiD approach that allows establishing a causal relationship between telework propensity and firm performance. They show that U.S. firms with high pre-pandemic telework propensity had significantly higher sales, net incomes, and stock returns than their peers during the pandemic. Like Bai et al. (2021), we apply a DiD approach. However, they focus on U.S. firms. The comprehensiveness of our sample allows us to provide evidence of the causal effect of telework propensity on the performance of non-critical firms traded in major developed, emerging, and frontier markets.

Our work also relates to a broader literature that explores the effect of dangerous infectious diseases on stock markets. Hassan et al. (2020) evaluate firm-level exposure to COVID-19, SARS, and H1N1 using a new word pattern-based method. \(^{25}\) They find that demand shocks stemming from the COVID-19 pandemic have significantly depressed firm valuations, investment activities, and employment. Baker et al. (2020a) also use text-based methods to investigate the role of COVID-19 and past infectious diseases in U.S. stock market volatility. They notice that the COVID-19 pandemic impact was much stronger than the effect of past pandemics. Donadelli et al. (2017) examine whether investor mood, driven by WHO alerts and media news on dangerous infectious diseases, is priced in pharmaceutical companies’ stocks in the U.S. They find that disease-related news has a positive and significant effect on the returns of these stocks. Cakici and Zaremba (2021) estimate U.S. firm exposure to a pandemic index representing global concerns of infectious diseases between 2002 and 2019. They provide evidence that such a pandemic index reliably predicts the cross-section of future stock returns. McTier et al. (2013) study the impact of influenza on stock markets. They show that for the U.S., a higher incidence of flu is associated with decreased trading, decreased volatility, decreased returns, and higher bid–ask spreads. Ichev and Marinè (2018) investigate whether the geographic proximity of information disseminated by the 2014–2016 Ebola outbreak events combined with intense media coverage affected stock prices in the U.S. They show that information about the Ebola outbreak is more relevant for companies closer to the birthplace of the epidemic.

3. Data

This section describes the data on firms/stocks, countries, and COVID-19. Table 1 reports the summary statistics of the variables used in our empirical setup. We build a firm-time panel data comprising 15,238 firms with stocks traded across 46 countries. Table A.1 shows the number of stocks per country, as well as the geographic location and level of capital market development of countries. \(^{26}\) We use the North American Industry Classification System (NAICS) to identify the firm’s main economic activity. This classification has several granularity levels, which we explore in our empirical setup: sector (19), subsector (87), and industrial group (283). Table A.2 displays the number of stocks held by each sector. The manufacturing sector stands out with the largest quantity of stocks.

\(^{21}\) GeoCOVID is a measure of geographically weighted exposure to COVID-19 growth.

\(^{22}\) They show that when there is a COVID-19 outbreak in a province, treated firms first underperform by daily lower returns of 0.54% but abruptly regain their value by daily higher returns of 0.76%.

\(^{23}\) Authors measure international exposure through foreign sales, foreign assets, imports, and exports. In the long-run, multinational firms are more resilient to economic shocks caused by COVID-19.

\(^{24}\) The literature often measures the propensity to telework by the fraction of workers – at the industry or firm level – able to work from home. Some papers close to this subset of the literature explore how sensitivity to social distancing affected firm performance during the pandemic. Social distancing is measured by the sector’s share of workers whose job requires a high level of teamwork, customer contact, and physical presence. Pagano et al. (2021) observe that from late February to late March 2020, stocks of U.S. firms less sensitive to social distancing performed much better compared to the more sensitive ones. Laeven (2022) add to the previous result finding that U.S. companies whose downstream sectors are more sensitive to social distancing experienced a more profound drop in stock prices in the first wave of the COVID-19 pandemic.

\(^{25}\) The method automatically classifies firms’ primary concerns related to the spread of epidemic diseases raised in their quarterly earnings conference calls.

\(^{26}\) We follow the ratings of the major financial market index providers (S&P Dow Jones, MSCI Inc., and FTSE Group,) to establish the stage of development of stock markets.
Table 1
Summary statistics of the collected variables.

| Variable | N     | Mean   | St. Dev. | Min   | Pctl(25) | Med.   | Pctl(75) | Max          |
|----------|-------|--------|----------|-------|----------|--------|----------|--------------|
| Price    | 1,584,752 | 58.53  | 2,747.95 | 0.01  | 0.71     | 4.59   | 18.56    | 437,260.00   |
| Level of Variation: Firm |
| Intangible intensity | 15,062 | 1.17   | 2.52     | 0.01  | 0.28     | 0.59   | 1.19     | 123.45       |
| HRM ineffectiveness | 10,630 | 10.69  | 105.83   | 0.001 | 1.01     | 2.96   | 7.79     | 7,840.98     |
| Leverage | 14,886 | 48.57  | 664.07   | 0.00  | 6.04     | 25.25  | 52.06    | 66,172.71    |
| Market capitalization | 15,234 | 4.256  | 25.748   | 0.001 | 0.057    | 0.245  | 1.477    | 1,287.658    |
| Price-to-book | 15,066 | 1.17   | 2.52     | 0.01  | 0.28     | 0.59   | 1.19     | 123.45       |
| Employees | 10,631 | 10,214.55 | 39,418.09 | 10   | 380      | 1,471  | 6,000    | 2,200,000    |
| Total assets | 15,066 | 11.661 | 86.822   | 0.001 | 0.103    | 0.455  | 2.597    | 2,807.099    |
| EBITDA | 14,862 | 546.132 | 2,638.739 | −2,700.367 | 4.633    | 32.954 | 200.601  | 76,477.000   |
| Non-critical | 13,435 | 0.61   | 0.49     | 0.00  | 0.00     | 1.00   | 1.00     | 1.00         |
| Telework propensity | 15,146 | 0.39   | 0.25     | 0.02  | 0.18     | 0.28   | 0.54     | 0.95         |
| Level of Variation: Country |
| GDP per capita | 46 | 29,346.39 | 22,382.01 | 2,104.15 | 9,216.27 | 26,379.36 | 46,242.84 | 81,993.73   |
| Unemployment rate | 46 | 6.47   | 5.08     | 0.75  | 3.40     | 4.58   | 7.85     | 28.18        |
| Inflation | 46 | 128.41 | 36.57    | 18.70 | 112.46   | 117.65 | 133.92   | 267.51       |
| Country openness | 46 | 0.91   | 0.67     | 0.25  | 0.51     | 0.74   | 1.10     | 3.53         |
| Population | 46 | 81.671 | 204.340  | 4.207 | 9.232    | 32.230 | 68.984   | 1,366.417    |

Note: Number of non-missing observations for the variable is represented by N. Mean, St. Dev. and Med represent the sample mean, standard deviation and median of the variable respectively. Price has weekly frequency and range from 2019-05-24 to 2021-05-14. Firm variables referring to the last values observed in 2019. Country variables corresponding to 2019 values. Market capitalization and Total assets (US$ billion); EBITDA (US$ million); HRM ineffectiveness (employees per US$ million); Population (million).

3.1. Stock prices data

We collect stock price information from the Datastream data set provided by Thomson Reuters Eikon. The data represents the dividend-adjusted closing prices, measured in U.S. dollars, on the last trading day of the week, covering the period from 2019-05-17 to 2021-05-14. Fig. 1 shows the evolution of the median stock prices in the period, highlighting the dramatic drop in stock prices around the date (2020-03-11) on which the WHO recognizes COVID-19 as a pandemic. In our regressions, we apply a logarithmic transformation on stock prices to reduce skewness and kurtosis of the original data and approximate a normal distribution. Another point of concern when examining stock prices in an econometric analysis is the presence of trends. While this is an important issue for time series data, our research design in the form of a DiD specification mitigates this concern. Since we are comparing treatment firms before and after the COVID-19 outbreak against similar control firms in the same two periods, pre-pandemic trends cancel out with during-pandemic trends.

Fig. 1. Evolution of the median stock prices from 2019-05-17 to 2021-05-14. This figure highlights the dramatic drop in stock prices around WHO pandemic announcement (2020-03-11).

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27 If the distribution of the raw data is approximately log-normal, then the distribution of the logarithmically transformed data will be approximately normal (Changyong et al., 2014). The finance literature often employs the log-normal distribution model for stock prices (Black and Scholes, 1973). Therefore, we expect that the logarithmic transformation will reduce the skewness and kurtosis found in the raw data. Indeed, comparing both statistics before and after the logarithmic transformation, skewness reduces from 114.73 to −0.21, and kurtosis reduces from 13,922.01 to −0.39.
3.2. Non-critical business and propensity to telework

We need to distinguish whether a given firm provides essential goods/services or not to establish the causal effect of non-critical business on stock prices. We follow Papanikolaou and Schmidt (2020) and create the dummy variable Non-critical, which assumes the value of one if the firm’s industrial group was considered non-critical during the pandemic, and zero if it was considered critical. We display in Fig. A.1 the share of critical industrial groups by sector. Some sectors were heavily impacted (e.g., accommodation and food services; arts, entertainment, and recreation) because no industrial groups related to them were deemed essential. Others were safeguarded (e.g., utilities and financial/insurance) as all their industrial groups were deemed critical.

To assess the role of telework propensity in stock prices during the pandemic, we gather measures developed by Dingel and Neiman (2020). Telework propensity estimates the fraction of the workforce capable of working from home—at the firm’s NAICS subsector level. Fig. A.2 displays the relationship between the share of critical industrial groups and the telework propensity at the sectoral level. Within the sectors with no or a few industrial groups identified as critical, we observe a substantial diversity in telework propensity. While some had a high propensity to telework (e.g., information), others had only a minor share of their workforce that could work from home (e.g., arts, entertainment, and recreation).

3.3. Firm data

We obtain firm-level information before the pandemic (2019) from the Worldscope database available at Thomson Reuters Eikon. In this subsection, we address one set of firm attributes that potentially worked as transmission channels during the pandemic and another that serves as firm-specific controls.

3.3.1. Firm features as transmission channels

In our paper, we examine how some firm attributes influence the non-critical business effect. We use Leverage, which we calculate as the ratio of total debt to enterprise value at fiscal year-end 2019, to proxy for the firm’s leverage prior to the pandemic outbreak. The sample mean of this variable is 48.57%. We employ the measure Intangible intensity, evaluated as the market capitalization to total assets at fiscal year-end 2019, to proxy for intangible-intensive companies prior to the pandemic outbreak. We refer to the literature that addresses the relationship between intangible capital and Tobin’s q (Peters and Taylor, 2017). The sample mean of intangible intensity is 1.17. The measure the HRM ineffectiveness, which is the number of employees to market capitalization at fiscal year-end 2019, is a proxy for the HRM ineffectiveness of firms prior to the pandemic. We reference the literature that studies the relationship between HRM and firm performance (Posthuma et al., 2013; Fey et al., 2009; Ichniowski et al., 1997). The sample mean of HRM ineffectiveness is 10.69 employees per US$ million in market capitalization.

3.3.2. Firm-specific controls

We employ firm variables measured at fiscal year-end 2019 to control for firm size, financial performance, and market valuation prior to the pandemic outbreak. We measure firm size using Total assets – the book value of the firm’s assets – with a sample mean of US$11.7 billion. We also use Employees – which stands for the size of the company’s workforce – with a sample mean of about 10,214 employees. We assess the firm’s market valuation by Price-to-book – which is the ratio of the market value of a company’s stock over its book value of equity – with a sample mean of 1.98. We also use Market capitalization – which represents the market-assigned value of firms – with a sample mean of about US$4.3 billion. We gauge the firm’s financial performance by employing EBITDA – the earnings before interest, taxes, depreciation, and amortization – with a sample mean of about US$546 million.

3.4. Country-specific controls

We use country-level variables as controls for macroeconomic climate before the pandemic as well as other relevant features. We obtain data from databases provided by World Bank and International Monetary Fund. We assess income per capita using GDP per capita with a sample mean of about US$29,348. Country openness is the ratio between the sum of exports and imports over GDP with a sample mean of 0.91. Unemployment is the country’s unemployment rate, with a sample mean of 6.47%. Population is the number of residents of the country, with a sample mean of about 81.6 million. Inflation is measured by the consumer price index. Fig. 2 displays the relationship between the economy’s size and economic growth of countries in 2019. Most countries achieved economic growth between −5% and 5%, with some exceeding this range like Argentina (−15.6%) and Egypt (17.2%).
Fig. 2. Pre-pandemic macroeconomic environment (2019). This figure illustrates that, while some countries presented a solid macroeconomic background when the pandemic started, others were suffering from a very fragile situation. We highlight countries (represented by ISO-2 code) with economic growth outside the −5% to 5% range, as well as countries with inflation or unemployment rates above 5%. GDP data in US dollars.

displays the relationship between inflation and unemployment rates before the pandemic. A significant number of countries reported a robust situation with inflation and unemployment rates below 5%. However, some countries exceeded this level, such as Argentina (inflation rate of 30%) and South Africa (unemployment rate of 28.2%). The data implies that when the pandemic started in the early months of 2020, some countries enjoyed a solid economic environment, while others were suffering from an already turbulent situation.

4. Empirical results

Our results are delivered in two steps. First, Section 4.1 shows our baseline findings: the quantification of the causal effect of non-critical business on stock prices during the COVID-19 pandemic. We then extend these results by examining how firm-specific characteristics (intangible intensity, HRM ineffectiveness and leverage) exacerbated or mitigated our baseline estimations. Finally, Section 4.2 displays the beneficial effect of telework propensity on stock prices of firms engaged in non-critical goods and services.

4.1. The non-critical business effect

As the crisis triggered by COVID-19 escalated, countries chose to impose restrictive measures to contain the spread of the virus. These restrictions constrained businesses in nearly every economic sector, except those deemed critical or essential. According to the OxCGRT workplace closure indicator, the timing and intensity of business closure varied across countries.31 Fig. A.3 indicates that the percentage of countries restricting non-critical businesses was above 80% already between late March and early June 2020.32

The emergence of the COVID-19 health crisis constitutes a natural experiment, with similar firms being impacted differently according to the essentiality of their products/services. This feature creates the opportunity to perform causal inference analysis in empirical finance, a field where it is exceedingly difficult to obtain data collected from well-designed randomized experiments. We select DiD as our methodological strategy because it is a conceptual framework that allows the examination of specific sources of variation in quasi/natural experiments, allowing the research design to approximate a real experiment.33
We comprise the treatment group with companies involved in non-critical goods/services, which experienced severe restrictions in their operations with the onset of the pandemic. The control group includes companies engaged in essential activities, which did not have their operations severely restricted. We follow Papanikolaou and Schmidt (2020) to identify which companies conduct essential activities and which do not. The authors provide a NAICS taxonomy classification table of the businesses identified as essential at the industrial group level. Therefore, we seek to test the following empirical hypothesis:

**Hypothesis 1.** COVID-19 affected more firms from the non-critical industrial groups than those operating in critical ones ($\beta < 0$ in Eq. (1)).

We use the following DiD econometric model to test Hypothesis 1:

$$\log(p_{i,g,s,c,t}) = \alpha_i + \alpha_s + \beta \cdot COVID_{19} \cdot Non\text{-}critical_g + \gamma^T C_{i,s} + \epsilon_{i,g,s,c,t}$$

where $i, g, s, c, t$ index firm, industrial group, subsector, country, and time (weekly), respectively. The variable $\log(p_{i,g,s,c,t})$ represents the logarithm of the week’s closing price of firm $i$’s stock. The dummy variable $Non\text{-}critical_g$ assumes the value of 1 if the industrial group $g$ (of firm $i$) is engaged in non-essential activities and 0 otherwise. The dummy variable $COVID_{19}$, is equal to 1 if $t \geq 2020\text{-}01\text{-}31$, and 0 otherwise. One natural concern in our empirical setup is that firms declared as non-essential could be fundamentally different from those declared as essential. We address this concern by including subsector-time fixed effects $\alpha_s$ in Eq. (1), which ensures within-comparison of firms in the same subsector. Additionally, we add firm fixed effects to absorb any firm-specific non-observable and time-invariant characteristics. $C_{i,s}$ is a set of controls covering ex-ante country- and firm-specific characteristics interacted with time to avoid collinearity with fixed effects. Due to the introduction of the fixed effects, we interpret the coefficient $\beta$ as the effect of COVID-19 on stock prices of firms engaged in non-critical industrial groups compared to firms in the same subsector but operating in critical industrial groups. Following Abadie et al. (2020), we cluster the errors at the industrial group level, which matches the level of variation of our main variable $Non\text{-}critical_g$.

It is critical in the DiD framework to determine accurately when the shock begins to affect stock prices. To accomplish this task, we refer to the pandemic timeline provided by WHO, which we summarize with the main events in Table A.4. An evident date to consider is when WHO recognized COVID-19 as a pandemic (2020-03-11). Two concerns compel us to consider an earlier date. First, there is evidence that authorities lack incentives to declare epidemics due to political and economic issues, resulting in delays in recognizing these types of events (Rull et al., 2015). Four days before WHO formally recognized the outbreak as a pandemic, the number of confirmed cases worldwide exceeded 100,000, suggesting a delay in WHO’s decision. Second, there is a substantial body of literature indicating that stock price movements reflect the market’s expectations for future economic developments (Beaudry and Portier, 2006). In this regard, prior to WHO’s official recognition, market agents were likely foreseeing this event and embedding these expectations into stock prices. Because of these issues, we chose the day (2020-01-30) on which WHO recognized the outbreak as a Public Health Emergency of International Concern (PHEIC). We argue that this event clearly signaled the emergence of an international public health risk to economic agents, potentially evolving into a pandemic in the near future.

Table 2 reports the coefficient estimates of the specification in Eq. (1) for an eight-month time window surrounding the WHO’s PHEIC declaration to cover the entire first wave of the pandemic. In Spec. (1), we find that firms operating in non-critical industrial groups exhibit an average 6.52% lower price following eight months of the COVID-19 outbreak than firms of the same subsector but operating in industrial groups considered essential. Our findings indicate that the essentiality of a firm’s industrial group had a significant effect on its stock prices: less essential industrial groups were disproportionately harmed by COVID-19 due to the restrictions imposed by governments worldwide.

Even though we are comparing firms of the same subsector, they could be located in different countries with varying COVID-19 intensities. Therefore, our results could be driven by some country-specific non-observable factors unrelated to the essentiality of the sector. We address this concern in Spec. (2) by including subsector and also country dynamic fixed effects. As a result, we make within-comparisons of firms of the same subsector in the same country. Our findings still hold, and the coefficient's magnitude becomes even higher: firms related to non-essential industrial groups experience an average drop of 7.82% in their stock prices after eight months of the onset of the COVID-19 than firms of the same subsector and country but related to essential industrial groups.

The previous specifications rely on a comprehensive set of fixed effects, as we can observe by the high $R^2$. We also test whether our results still hold when we do not saturate the model. In Spec. (3), we remove all controls and firm fixed effects. Our results still hold. Overall, our findings imply that it was very important for firms during the COVID-19 pandemic to be associated with essential industries – provided by Papanikolaou and Schmidt (2020) – is based on guidelines issued by a U.S. agency (CISA) to U.S.

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34. Papanikolaou and Schmidt (2020) base their classification on the Cybersecurity and Infrastructure Security Agency (CISA) guidelines to U.S. states regarding which businesses should remain open. They use data on foot traffic from SafeGraph to validate their construction. The authors show that establishments in critical industries experienced significantly smaller declines in traffic than establishments in non-critical industries, which contrasts sharply with nearly identical trends in foot traffic in January-February 2020.

35. According to World Health Organization (2005), a PHEIC is “an extraordinary event that may pose a public health risk to other countries through the international spread of disease and may require a coordinated international response”.

36. We consider that the first wave is over at the end of October 2020 because, after this date, we observe the percentage of countries applying tougher business restrictions (scales 2 and 3) increasing again (see Fig. A.3).
states. One criticism that could be made is that while one industrial group was deemed critical in the United States, the same could have been considered non-critical in other countries due to differences in the economy’s structure. In other words, there is no guarantee that the recommendations implemented in the U.S. were comparable to those implemented in other countries. To address this problem, Spec. (4) of Table 2 reruns our baseline model in Eq. (1) without including stocks of firms traded on the U.S. market. Our main results still hold (both sign and statistical significance). Another criticism along the same lines is that, while the recommendations applied in the United States may have been similar to those made in other more similar economies (developed markets), a greater discrepancy may have occurred in economies more dissimilar to the United States (emerging markets). In this sense, Spec. (5) of Table 2 reruns the baseline estimation in Eq. (1) but removing all stocks of firms traded in developed markets. Again, our results are still qualitatively preserved.

We also provide an additional piece of empirical evidence to show that our treatment and control groups are similar ex-ante to the COVID-19 outbreak. We perform an event study to test for the parallel trends assumption for the treatment and control groups’ outcome variables. For this purpose, we employ the following specification:

$$
\log(p_{i,g,s,c,t}) = \alpha_i + \alpha_{s,t} + \sum_{r=May}^{M} \beta_r \cdot \text{Non-critical}_r \cdot I_{[t==r]} + \gamma^T C_{g,s,c,t} + \epsilon_{i,g,s,c,t}
$$

(2)

in which $i$ indexes the firm, $g$ the industrial group of firm $i$, $s$ the subsector of firm $i$, $c$ the country of the firm $i$, and $t$ the time (weekly). $I_{[t==r]}$ is an indicator function that returns 1 when $t = r$, and 0 otherwise. Eq. (2) has the same format as Eq. (1), but instead of using the step variable $COVID_{-19}$, weekly pulse time dummies are introduced, represented by $\beta_r$ coefficients and considering a eight-month time window centered on the event. If our empirical setup for defining the control and treatment groups is reasonable, the two groups’ stock price trends should evolve similarly prior to the COVID-19 outbreak. Only after its onset should they diverge. In this sense, the $\beta_r$ coefficients must be statistically insignificant before the COVID-19 and statistically different from zero following the event’s occurrence (if COVID-19 had any impact on stock prices). Fig. 3 illustrates this event study. Following the declaration of PHEIC by WHO, the $\beta$ coefficients become negative and statistically significant, indicating the adverse effect of the COVID-19 pandemic on the stock prices of companies related to non-essential businesses.

### Table 2

| Specification: | Time window: | May|Oct|20 (± 8 months) |
|---------------|--------------|--------------------------------|
| Sample:       | Full         | Full                           | Full                           | Ex-U.S.           | Ex-Dev.          |
| Specification:| (1)          | (2)                            | (3)                            | (4)               | (5)              |
| COVID-19, × Non-critical$_g$ | -0.0652**   | -0.0782**                     | -0.0681**                     | -0.0760**         | -0.1530**        |
|               | (0.032)      | (0.031)                        | (0.032)                        | (0.033)           | (0.043)          |

**Note:** This table reports coefficient estimates for the specification in Eq. (1). The dependent variable $\log(p_{i,g,s,c,t})$ represents the logarithm of the week’s closing price of the stock of firm $i$. We include ex-ante firm-specific controls (fixed with the latest observed values in 2019): Market capitalization, Total assets, EBITDA, and Price-to-book. We also include ex-ante controls for the COVID-19 outbreak. We perform an event study to test for the parallel trends assumption for the treatment and control groups’ stock price trends. Following the declaration of PHEIC by WHO, the event's occurrence (if COVID-19 had any impact on stock prices). Fig. 3 illustrates this event study. Following the declaration of PHEIC by WHO, the $\beta$ coefficients become negative and statistically significant, indicating the adverse effect of the COVID-19 pandemic on the stock prices of companies related to non-essential businesses.

**Ex-ante controls**

|               | Firm | Country | Time × Subsector | Time × Subsector × Country |
|---------------|------|---------|------------------|----------------------------|
| Full          | Yes  | Yes     | No               | Yes                        |
| Full          | Yes  | Yes     | No               | Yes                        |
| Full          | Yes  | No      | Yes              | Yes                        |
| Full          | No   | Yes     | No               | No                         |

**Fixed effects**

|               | Firm | Country | Time × Subsector | Time × Subsector × Country |
|---------------|------|---------|------------------|----------------------------|
| Full          | Yes  | Yes     | No               | Yes                        |
| Full          | Yes  | No      | Yes              | Yes                        |
| Full          | No   | Yes     | No               | No                         |

**Error clustering**

|               | Industrial group | Firm | Country | Time × Subsector | Time × Subsector × Country |
|---------------|------------------|------|---------|------------------|----------------------------|
| Full          | Yes              | Yes  | Yes     | No               | Yes                        |
| Full          | Yes              | Yes  | No      | Yes              | Yes                        |
| Full          | Yes              | No   | Yes     | No               | No                         |

| Observations | 1,007,391       | 1,007,391  | 1,007,391  | 840.532          | 254.331                   |
|-------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| $R^2$       | 0.990           | 0.992           | 0.104          | 0.990           | 0.985          |

**Note:** Table reports coefficient estimates for the specification in Eq. (1). The dependent variable $\log(p_{i,g,s,c,t})$ represents the logarithm of the week’s closing price of the stock of firm $i$. We include ex-ante firm-specific controls (fixed with the latest observed values in 2019): Market capitalization, Total assets, EBITDA, and Price-to-book. We also include ex-ante controls for the COVID-19 outbreak. We perform an event study to test for the parallel trends assumption for the treatment and control groups’ stock price trends. Following the declaration of PHEIC by WHO, the event's occurrence (if COVID-19 had any impact on stock prices). Fig. 3 illustrates this event study. Following the declaration of PHEIC by WHO, the $\beta$ coefficients become negative and statistically significant, indicating the adverse effect of the COVID-19 pandemic on the stock prices of companies related to non-essential businesses.
Firm features as transmission channels. The worsening of the COVID-19 outbreak prompted several countries to implement lockdowns, resulting in a dramatic drop in consumption and, consequently, in company revenues.\(^{37}\) This has resulted in liquidity shortages, making it more difficult for many firms to meet their financial commitments to employees, suppliers, and creditors. Companies that managed to maintain sizable cash reserves and comfortable debt levels before the pandemic faced fewer difficulties in financing the dramatic decline in cash flow (Fahlenbrach et al., 2021). Some studies have pointed out that high leverage was a significant factor in firms being negatively impacted by the emergence of COVID-19 (Ramelli and Wagner, 2020; Alfaro et al., 2020; Ding et al., 2021).\(^{38}\) In this regard, we examine how firms’ leverage influences the effect of non-critical business on stock prices. Following the literature, we expect that highly leveraged firms will experience larger declines in their stock prices due to the increased financing costs observed during the pandemic (negative effect).

Innovative technologies were critical in sustaining goods and services production and establishing sales and customer service channels during the pandemic. Firms in intangible-intensive industries were better equipped to deal with these challenges than firms in tangible-intensive industries, owing to their more remarkable ability to adopt new technologies (Demmou et al., 2021). We investigate the impact of the firm’s intangible intensity on the non-critical business effect. We expect that high intangible-intensity firms will experience fewer adverse effects on their stock prices following the COVID-19 outbreak (positive effect).

The digital transformation of organizations has entailed the redesign of work processes for the virtual environment, requiring the HRM of firms to effectively coordinate the training and learning of new skills by employees (Collings et al., 2021b). HRM also had to handle increased fractures between groups of employees due to a variety of factors (Collings et al., 2021a).\(^{39}\) HRM was critical in assisting managers in leading remote teams for the first time, overcoming barriers to employee collaboration, and enabling the achievement of key business goals during the pandemic (Caligiuri et al., 2020). Numerous employees reported experiencing issues related to social isolation and elevated levels of anxiety and stress during the pandemic. Effective HRM was able to alleviate these concerns without adversely affecting employee productivity (Collings et al., 2021b). We examine how the firm’s HRM ineffectiveness shapes the non-critical business effect. We expect firms with more inefficient HRM will experience a further decline in their stock prices (negative effect).

To examine how these firm-specific transmission channels contribute to exacerbating or mitigating the effect of non-critical business on stock prices, we expand the specification in Eq. (1) as follows:

$$
\log (p_{i,g,s,c,t}) = \alpha_i + \alpha_{t,s} + \beta \cdot COVID-19_i \cdot Non-critical_g \cdot Factor_s + \lambda \cdot COVID-19_i \cdot Factor_t + \gamma \cdot C_{i,s,t} + \epsilon_{i,g,s,c,t}
$$

(3)

in which \(i\) indexes the firm, \(g\) the industrial group of firm \(i\), \(s\) the subsector of firm \(i\), \(c\) the country of the firm \(i\), and \(t\) the time (weekly). Eq. (3) has the same format as Eq. (1), except for the interactions (i) \(COVID-19_i \cdot Non-critical_g \cdot Factor_s\), and (ii) \(COVID-19_i \cdot Factor_t\).\(^{40}\) The coefficient of the first interaction (\(\beta\)) holds our measure of interest: it quantifies the extent to which

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\(^{37}\) Baker et al. (2020b) report a 25%–30% decline in overall spending by U.S. consumers during the second half of March, coinciding with the spread of the disease. Chen et al. (2021) estimate that China’s offline consumption fell by more than 1.22 trillion RMB, or 1.2% of the country’s 2019 GDP, in the three months following the COVID-19 outbreak. Carvalho et al. (2021) point out that total consumption in Spain was rising before the nationwide lockdown and then fell precipitously after that (almost 50% below previous year levels).

\(^{38}\) These findings are consistent with empirical evidence found for the GFC (Fosu et al., 2016; Arslan-Ayaydin et al., 2014) and the Great Recession (Giroud and Mueller, 2017).

\(^{39}\) Divisions between groups of employees occurred in many dimensions. They include employees who were able to work from home and those who were unable to, those who remained on the payroll and those who were furloughed, and employees in less affected units and those in heavily affected ones by the pandemic.

\(^{40}\) The remaining interaction \(Non-critical_g \cdot Factor_s\) is collinear with the firm fixed effects \(\alpha_i\).
firm-specific transmission channels (leverage, HRM ineffectiveness and intangible intensity) influence the non-critical business effect on stock prices.

Table 3 exhibits our coefficient estimates of specification in Eq. (3) regarding firm-specific characteristics that enhanced or mitigated the role of non-critical businesses on stock prices during the COVID-19 pandemic. In Spec. (1), we find that among firms in non-critical industrial groups, a one-standard-deviation increase in a firm’s leverage promotes a further 6.81 percentage point decline in its stock price on average after eight months from the onset of the crisis, when compared to firms in the same subsector and with a leverage value equal to the sample mean. This leverage effect is relevant because its magnitude is comparable to the baseline effect. We note in Spec. (2) that, within firms related to non-essential goods/services, a one-standard-deviation increase in a firm’s intangible intensity leads to an average positive effect on its stock prices of 2.98 percentage points after the COVID-19 outbreak, compared to firms in the same subsector and with intangible intensity value equal to the sample mean. This effect is significant since it mitigates approximately half of the baseline effect. Spec. (3) provides evidence that, among firms in non-essential industrial groups, a one-standard-deviation increase in a firm’s HRM ineffectiveness yields an extra decrease in its stock price of 13.13 percentage points on average eight months after the shock, relative to firms in the same subsector and with HRM ineffectiveness value equal to the sample mean. This is the most prominent transmission channel, with a magnitude of about twice the baseline effect. This set of findings suggests that leverage and HRM ineffectiveness are corporate characteristics that exacerbated the negative impact of the COVID-19 pandemic on firms in non-critical industrial groups. On the other hand, intangible intensity represents a firm attribute that softened the adverse effect of the pandemic.

### Table 3

Heterogeneities in the non-critical business effect on stock prices during the COVID-19 pandemic.

| Dependent variable: \( \log(p_{i,2020}) \) | Time window: May 19-Oct 20 (± 8 months) |
|---------------------------------------------|------------------------------------------|
| Specification:                             | (1)                                      | (2)                                      | (3)                                      |
| COVID-19, × Non-critical,                  | −0.0676**                                | −0.0553*                                 | −0.0585*                                 |
|                                            | (0.033)                                  | (0.030)                                  | (0.032)                                  |
| COVID-19, × Leverage,                      | 0.0018**                                 |                                          |                                          |
|                                            | (0.001)                                  |                                          |                                          |
| COVID-19, × Non-critical, × Leverage,      | −0.0681*                                 |                                          |                                          |
|                                            | (0.038)                                  |                                          |                                          |
| COVID-19, × Intangible intensity,          |                                          | 0.0269***                               |                                          |
|                                            |                                          | (0.010)                                  |                                          |
| COVID-19, × Non-critical, × Intangible intensity, |                                          | 0.0298**                               |                                          |
|                                            |                                          | (0.014)                                  |                                          |
| COVID-19, × HRM ineffectiveness,           |                                          |                                          | −0.0010                                  |
|                                            |                                          |                                          | (0.002)                                  |
| COVID-19, × Non-critical, × HRM ineffectiveness, |                                          | −0.1313***                              |                                          |
|                                            |                                          | (0.045)                                  |                                          |

Error clustering Industrial group | Yes | Yes | Yes |
Ex-ante controls Firm | Yes | Yes | Yes |
Country | Yes | Yes | Yes |
Fixed effects Firm | Yes | Yes | Yes |
Time × Subsector | Yes | Yes | Yes |
Observations 986,216 | 1,007,391 | 711,172 |
\( R^2 \) | 0.990 | 0.990 | 0.990 |

Note: This table reports coefficient estimates for the specification in Eq. (3). The dependent variable \( \log(p_{i,2020}) \) represents the logarithm of the week’s closing price of the stock of firm \( i \). We use the following firm-specific characteristics to compose the transmission factor \( Factor \): leverage (Spec. 1), intangible intensity (Spec. 2), and HRM ineffectiveness (Spec. 3). We include ex-ante controls for firm (fixed with the latest observed values in 2019): Market capitalization, Total assets, EBITDA and Price-to-book. We also include ex-ante controls for country (fixed with 2019 values): GDP per capita, Unemployment, Inflation, Country openness and Population. All ex-ante controls are interacted with time to avoid collinearity with fixed effects. Non-critical\( g \) identifies whether the industrial group \( g \) of firm \( i \) is a non-essential economic activity. COVID-19\( i, t ≥ 2020-01-31 \) and \( 0 \) otherwise. We cluster errors at the industrial group level, which coincides with the level of variation of the variable Non-critical\( g \). We report results for a time window of eight months centered on the event in order to cover the first wave of the pandemic. Statistical significance: * \( p \)-value < 0.10; ** \( p \)-value < 0.05; *** \( p \)-value < 0.01.

4.2. The effect of telework propensity on non-critical firms

As we show in Section 4.1, firms engaged in non-essential activities suffered a more significant impact on their performance during the pandemic than businesses associated with essential goods and services. The non-critical business effect was moderated in the case of firms with high intangible intensity, consistent with the idea that they were more suited to embrace new technologies, allowing them to adapt more quickly to constraints requiring a high percentage of their employees to work from home. However, as we previously observed, increased proficiency in implementing new technologies is not sufficient to fully mitigate the non-critical
business effect. A plausible explanation for this outcome is that some tasks were inherently easier to adapt to remote work than others. In this sense, some sectors faced fewer issues because they were more prone to telework, while others struggled more due to their dependency on activities that were more difficult to adapt to remote work. We use a measure devised by Dingel and Neiman (2020) to assess the telework propensity of each firm, which identifies the proportion of jobs that can be done from home at the subsector level of the NAICS taxonomy. Hence, we aim to investigate the following empirical hypothesis:

**Hypothesis 2.** In non-critical industrial groups, COVID-19 had a lower impact on firms related to subsectors with a high propensity to telework than firms in the same sector, but operating in subsectors less prone to work from home ($\beta > 0$ in Eq. (4)).

We use the following econometric model to test Hypothesis 2:

$$\log(p_{i,s,z,c,t}) = \alpha + \alpha_{2} + \beta \cdot COVID-19 \cdot Telework\ propensity + \gamma C_{i,s,t} + \epsilon_{i,s,z,c,t}$$  \hspace{1cm} (4)

where $i, s, z, c, t$ are indices related to firm, subsector, sector, country and time (weekly), respectively. The variable $\log(p_{i,s,z,c,t})$ represents the logarithm of the week's closing price of the stock of firm $i$. The variable $Telework\ propensity$ represents the share of the workforce in subsector $s$ of firm $i$ that is capable of working from home. The binary variable $COVID-19$, is equal to 1 if $i \geq 2020-01-31$ and 0 otherwise. The coefficient $\beta$ captures the effect of a one-standard-deviation increase in Telework\ propensity on firms' outcomes in the same non-critical sector. $C_{i,s,t}$ is a set of controls covering ex-ante country- and firm-specific characteristics interacted with time to avoid collinearity with fixed effects. $\alpha$ stands for fixed effects of firm $i$ and $\alpha_{2}$ represents dynamic fixed effects referring to sector $z$ of firm $i$. We cluster errors at the subsector level, which matches the level of variation of Telework\ propensity, our variable of interest.

Table 4 reports our coefficient estimates of specification in Eq. (4), which shows how the propensity to telework affected stock prices of firms in non-essential industrial groups during the COVID-19 pandemic. We report results for a time window of eight months centered on the event to cover the first wave of the pandemic. In Spec. (1), we find that, for firms in non-essential industrial groups, a one-standard-deviation increase in the telework propensity of the firm's subsector drives an average 10.20% increase in its stock price. In Spec. (2), we remove all controls and firm fixed effects to reduce the model's saturation level. To address potential problems with our identification strategy in Spec. (3), we perform the estimation without stocks of firms traded on the U.S. market. In Spec. (4), we further remove stocks of firms traded in developed markets.

### Table 4

| Time window: | May 19-Oct 20 (± 8 months) |
|-------------|-----------------------------|
| Sample:     | Non-critical | Non-critical | Non-critical (Ex-U.S.) | Non-critical (Ex-Dev.) |
| Specification: | (1) | (2) | (3) | (4) |
| COVID-19 $\times$ Telework\ propensity | 0.1020*** | 0.1119*** | 0.0907*** | 0.0847*** |
| (0.021) | (0.022) | (0.020) | (0.019) |

**Ex-ante controls**

| | Firm | Country |
|---|---|---|
| Yes | No | Yes |

**Fixed effects**

| | Firm | Time $\times$ Sector |
|---|---|---|
| Yes | No | Yes |

**Error clustering**

| Subsector | Yes |
|---|---|
| Yes |

$R^2$ = 0.989, 0.037, 0.989, 0.985

**Note:** This table reports coefficient estimates for the specification in Eq. (4) using a sample restricted to firms in non-critical industrial groups. The dependent variable $\log(p_{i,s,z,c,t})$ represents the logarithm of the week's closing price of the stock of firm $i$. We include ex-ante firm-specific controls (fixed with the latest observed values in 2019): Market capitalization, Total assets, EBITDA, and Price-to-book. We also include ex-ante controls for country (fixed with 2019 values): GDP per capita, Unemployment, Inflation, Country openness and Population. All ex-ante controls are interacted with time to avoid collinearity with fixed effects.

We use the following econometric model to test Hypothesis 2:

$\log(p_{i,s,z,c,t}) = \alpha + \alpha_{2} + \beta \cdot COVID-19 \cdot Telework\ propensity + \gamma C_{i,s,t} + \epsilon_{i,s,z,c,t}$

We cluster errors at the subsector level, which coincides with the level of variation of Telework\ propensity, our variable of interest.

41 They classify each occupation as able or unable to be performed entirely from home using pre-pandemic surveys from the Occupational Information Network (O*NET). These surveys are comprehensive because they describe the typical experience of US workers in nearly 1000 occupations.
Our identification strategy that uses the propensity to telework may suffer from the same issues as the critical business identification that relies on the classification provided by Papanikolaou and Schmidt (2020). The share of the subsector’s labor force that can work from home, as provided by Dingel and Neiman (2020), is based on U.S. data. Our identification strategy assumes that the telework propensity in the U.S. subsectors is a reasonable approximation for the other economies. As we did before, Spec. (3) reruns the specification in Eq. (4) by excluding stocks of firms traded on the U.S. market as a robustness test. Our results still hold even when we do not consider U.S. stocks. Additionally, Spec. (4) also removes stocks from firms in developed markets. The results remain qualitatively unchanged.

5. Conclusion

COVID-19 took the world by surprise, rapidly escalating into an international crisis and posing a threat to public health in all countries. Governments have decided to impose restrictive policies to slow down the spread of the virus, limiting the operations of the vast majority of businesses, particularly those engaged in goods/services deemed non-critical. Anticipating the severe economic consequences that were to follow, stock markets recorded their worst losses since the GFC. Our work provides empirical evidence of the impact of the COVID-19 pandemic on stock prices. We contribute to the literature by documenting how the firms’ relationship with non-critical goods/services increased their vulnerability to the pandemic. Furthermore, we show that specific firm-specific characteristics exacerbated or mitigated this vulnerability.

We employ a DiD methodology to infer a causal relationship between the COVID-19 pandemic and stock prices. We use microdata covering 15,238 firms with stocks traded in 46 countries. We use the criticality of the firm’s economic activity at the industrial group level as a tool to identify how it is exposed to restrictive policies aimed at mitigating the COVID-19 effects. We find that firms operating in non-critical industrial groups exhibit an average 6.52% lower price after eight months of the onset of the crisis than firms on the same subsector but operating in industrial groups deemed essential. Results are persistent when we narrow the comparison to stocks traded in the same country. This vulnerability was magnified/moderated according to specific corporate characteristics. We document empirical evidence that firms in non-critical industrial groups that are highly leveraged, have ineffective HRM, and have low intangible intensity suffered even more. These findings imply that it was critical for firms during the COVID-19 pandemic to be associated with essential goods/services, as this shielded them from policy constraints.

Firms related to non-critical industrial groups were forced to tailor their operations with a high share of their employees working from home. For these firms, we show that a one-standard-deviation increase in the telework propensity of the firm’s subsector drives an average 10.20% increase in its stock price after eight months of the COVID-19 outbreak, compared to firms in the same sector and with a telework propensity of the subsector equal to the sample mean value. This result suggests that having a higher proportion of workers able to work from home was crucial in mitigating the adverse effects of restriction policies.

Our research provides valuable evidence for firms and policymakers on the adverse economic and financial effects of pandemics or, more generally, catastrophic events that necessitate substantial restrictions on business activity. In order to avoid unintended consequences that could ultimately threaten the survival of firms deemed non-essential and, consequently, the jobs they support, policymakers must conduct a critical analysis of the circumstances that genuinely necessitate their restriction. This investigation requires that health and economic policymakers maintain a close and constructive dialogue that leads to a desirable trade-off between containing the health crisis and worsening the economic crisis. This dialogue should also include market participants who can assist policymakers in understanding the effects of specific measures on firm performance during exceptional periods.

If it is unavoidable to restrict the activities of non-critical firms, policymakers should consider offering specialized assistance to those firms that are more sensitive to restrictions, particularly those with high leverage, HRM inefficiency, and low intangible intensity. This assistance should not be limited to firms alone but also to the employees who are ultimately affected by the adverse effects on firm performance. Managers of firms with these traits should devise contingency plans to prepare their organizations better for the occurrence of catastrophic events with the potential to restrict non-core activities. They must also look for innovative ways to make their businesses more resilient to these events. It may be difficult for a company to increase its intangible intensity due to the nature of the product or service it offers, its production method, or the market it serves. In this case, they should invest in HRM to make it more effective and focus on operating with less leverage.

The contingency plans of non-critical firms should include a particular section regarding teleworking, as this feature has proven to be crucial in mitigating the adverse effects arising from the constraints. In order to reduce the risk of bankruptcies and job losses, policymakers should seek measures that promote and facilitate telecommuting during these periods. Particular support may be required for businesses with a low propensity to telecommute. Non-critical companies with low leverage, high HRM efficiency, and high intangible intensity should be aware that they can still become vulnerable if they have a very low propensity to telework.

As a potential avenue for future research, we intend to expand our analysis to include the pandemic’s effects on operating results, corporate structure, and workforce. Additionally, we intend to assess potential impacts on firm outcomes resulting from network effects (e.g., return and air traffic networks) during the COVID-19 pandemic.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
Funding

Thiago C. Silva (Grant no. 308171/2019-5, 408546/2018-2) and Benjamin M. Tabak (Grant no. 310541/2018-2, 425123-2018-9) gratefully acknowledge financial support from the CNPq foundation.

Appendix. A

Table A.1
Number of stocks per country, geographic location and level of capital market development.

| Americas | Europe | Asia–Pacific | Middle East–Africa |
|----------|--------|-------------|-------------------|
| Developed |        |             |                   |
| Canada (682) | Austria (36) | Australia (460) | Israel (319) |
| United States (2,468) | Belgium (71) | Hong Kong (807) | |
| | Denmark (82) | Japan (2297) | |
| | Finland (93) | New Zealand (62) | |
| | France (373) | South Korea (1,337) | |
| | Germany (378) | Singapore (141) | |
| | Italy (172) | | |
| | Netherlands (64) | | |
| | Norway (113) | | |
| | Portugal (22) | | |
| | Spain (80) | | |
| | Sweden (278) | | |
| | Switzerland (157) | | |
| | United Kingdom (682) | | |
| Emerging |        |             |                   |
| Brazil (138) | Greece (60) | India (1506) | Kuwait (108) |
| Chile (39) | Hungary (22) | Malaysia (498) | Turkey (282) |
| Colombia (26) | Poland (239) | Philippines (88) | South Africa (132) |
| Mexico (53) | Russia (110) | Thailand (856) | |
| Peru (10) | | | |
| Frontier |        |             |                   |
| Argentina (47) | Bulgaria (6) | Vietnam (266) | Nigeria (32) |
| Romania (20) | | Tunisia (24) | |
| Serbia (2) | | | |

Table A.2
Number of stocks by economic sector.

| Sector | Stocks |
|--------|--------|
| Accommodation and Food Services | 277 |
| Administrative and Support and Waste Management and Remediation Services | 239 |
| Agriculture, Forestry, Fishing and Hunting | 110 |
| Arts, Entertainment, and Recreation | 93 |
| Construction | 823 |
| Educational Services | 53 |
| Finance and Insurance | 1,664 |
| Health Care and Social Assistance | 126 |
| Information | 886 |
| Management of Companies and Enterprises | 1 |
| Manufacturing | 6,272 |
| Mining, Quarrying, and Oil and Gas Extraction | 918 |
| Other Services (except Public Administration) | 51 |
| Professional, Scientific, and Technical Services | 985 |
| Real Estate and Rental and Leasing | 761 |
| Retail Trade | 599 |
| Transportation and Warehousing | 454 |
| Utilities | 361 |
| Wholesale Trade | 565 |

Table A.3
Business constraints according to the scales of the OsCGRT workplace closing indicator.

| Scale | Description |
|-------|-------------|
| 0     | No measures |
| 1     | Recommend closing (or recommend work from home) or all businesses open with alterations resulting in significant differences compared to non-Covid-19 operation |
| 2     | Require closing (or work from home) for some sectors or categories of workers |
| 3     | Require closing (or work from home) for all-but-essential workplaces |
Table A.4
Summary of the COVID-19 pandemic timeline provided by WHO. This table presents the main events between the beginning of the outbreak and the declaration of the pandemic by WHO.

| Date | Event |
|------|-------|
| 2019-12-31 | WHO's Country Office in China picked up a media statement by the Wuhan Municipal Health Commission on cases of “viral pneumonia” in Wuhan. |
| 2020-01-09 | WHO reported that Chinese authorities have determined that the outbreak is caused by a novel coronavirus. |
| 2020-01-11 | Chinese media reported the first death. |
| 2020-01-14 | WHO said additional investigation was needed to ascertain the presence of human-to-human transmission. |
| 2020-01-15 | Japan's first confirmed case, person who traveled to Wuhan. Second confirmed case detected outside China. |
| 2020-01-19 | WHO Western Pacific Regional Office stated there was evidence of limited human-to-human transmission. |
| 2020-01-21 | United States reported its first confirmed case (first case in the Americas). |
| 2020-01-22 | WHO Director-General convened an IHR Emergency Committee (EC) charged with advising as to whether the outbreak constituted a public health emergency of international concern (PHEIC). The Committee was not able to reach a conclusion. |
| 2020-01-24 | France informed of three cases, all of whom had traveled from Wuhan (first confirmed cases in Europe). |
| 2020-01-29 | United Arab Emirates reported the first cases in the Middle East. |
| 2020-01-30 | WHO Director-General reconvened the IHR EC. The EC advised the Director-General that the outbreak now met the criteria for a PHEIC. The Director-General declared the novel coronavirus outbreak a PHEIC. At that time there were 98 cases in 18 countries outside China (four with evidence of human-to-human transmission). |
| 2020-02-11 | WHO announced that the disease would be named COVID-19. |
| 2020-03-07 | Number of confirmed cases surpasses 100,000 globally. |
| 2020-03-11 | WHO made the assessment that COVID-19 could be characterized as a pandemic and “called for countries to take urgent and aggressive action”. |
| 2020-04-04 | WHO reported that over 1 million cases of COVID-19 had been confirmed worldwide. |

Fig. A.1. Share of critical industrial groups by sector. This figure depicts that some sectors, such as accommodation and food services, had no industrial groups considered essential during the COVID-19 pandemic. On the other hand, sectors such as utilities had all their industrial groups regarded as critical.
Fig. A.2. Share of critical industrial groups versus telework propensity of sectors. This figure illustrates that within the sectors with none or a handful of industrial groups identified as critical while some have a high propensity for telework (e.g. information), others have only a minor share of the workforce able to work from home (e.g. arts, entertainment and recreation).

Fig. A.3. Evolution of the percentage of sample countries employing each of the four scales of business closure provided by the OxCGRT workplace closing indicator. This figure reveals that between late March and early June, the share of countries implementing scales 2 or 3 is always above 80%, indicating significant constraints on firms’ business related to non-essential products/services.
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