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How uncertainties impact R&D investments during COVID-19: Analysis in the ICT industry

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Abstract

Title: How uncertainties impact R&D investments during COVID-19: Analysis in the ICT industry

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Key words: R&D Investments, Cash Flow Uncertainty, Market Uncertainty, Market Beta, Dividend Payout Ratio, COVID-19 Pandemic, ICT Industry

Purpose and research question: The aim of this study is to investigate whether two types of uncertainties caused by COVID-19, which are market and cash flow uncertainties, have positive impacts on R&D investment in the ICT industry. We focus on the ICT industry since it plays a crucial role in alleviating the COVID-19 crisis by providing technological solutions worldwide.

Methodology: For the panel data, we use fixed effect model and introduce an interaction term to test the effect of firm size and the impact of COVID-19 induced market uncertainty on R&D investment. Finally, we test the robustness of our results.

Theoretical perspectives: The theoretical perspectives used to develop our hypotheses and contextualize our findings are growth theory, real option theory, information asymmetry, dividend payout policy, and pecking order theory.

Empirical foundation: The study uses a final sample comprising 18,055 firm-year observations, consisting of 5,934 ICT and ICT related firms from 91 countries over the fiscal years of 2018 to 2022.

Conclusions: We provide evidence that there is a significant positive relationship between market uncertainty induced by COVID-19 and R&D investments by high-tech firms. Moreover, our results suggest that the benefits for firms during the global pandemic depend mainly on flexible business strategy and innovation rather than firm size. However, we found a negative relationship between cash flow uncertainty and R&D investment.

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Abbreviations

CAPM	Capital Asset Pricing Model
DJIA	Dow Jones Industrial Average
DPR	Dividend Payout Ratio
DWH	Durbin-Wu-Hausman
EU	European Union
FE	Fixed Effects
FF3	Fama & French Three Factor Model
FF5	Fama & French Five Factor Model
GICS	Global Industry Classification Standard
GLS	Generalized Least Squares
ICT	Information and Communication Technology
IMF	International Monetary Fund
LDC	Least Developed Countries
OCF	Operating Cash Flow ratio
OECD	Organisation for Economic Co-operation
OLS	Ordinary Least Squares
R&D	Research and Development
RE	Random Effects
RQ	Research Question
ROS	Return on Sales
UNCTAD	United Nations Conference on Trade and Development
WEO	World Economic Outlook

1. Introduction

1.1. General background

The outbreak of COVID-19 disease posed new challenges to our lives and routines through social mobility controls, such as quarantines and travel restrictions, that lasted longer than expected. The prolonged containment measures triggered a global crisis with various implications for the economy. The crisis has created numerous economic uncertainties in all aspects of life, with a notable change in how society was forced to conduct daily activities through virtual spaces. The social distancing policies have, consequently, accelerated technology absorption (Castka et al., 2020) and put forward a new role of the digital economy as the global crisis recovery driver (Banga & Velde, 2020). In response to the shift, many companies, especially in the information and communication technology (ICT) sector, have carried out more research and development (R&D) activities to adapt to this situation and benefit from the circumstances through R&D investments.

To fund the investments, companies have choices to source the financing internally, externally, or the mix of both. However, if companies opt for external financing, the economic uncertainties and unstable markets during a pandemic-induced crisis have slowed down investors' investments and led them to adopt a wait-and-see attitude to observe the evolving future dynamics during the pandemic (Bachmann et al., 2013; Watanabe, 2008). Additionally, R&D investments and business innovation in ICT companies are characterized by a lengthy, and high, expenditure cycle of which benefits are not gained immediately and will take some time to transform into corporate profits. Therefore, R&D projects are associated with high external financing costs and high adjustment costs.

Under the on-going uncertainties in the market, a company's ability to innovate is highly dependent on its internal cash flow (Beladi et al., 2021). Nonetheless, the market uncertainties may impact negatively on the company's cash flow as future earnings are questionable. Concurrently, managements are posed with options to invest in R&D projects, paying back the stockholders in dividends, or hold the cash as a cautionary move in times of crises. We expect to see other forms of unpredictable risks to be exacerbated during the pandemic period.

1.2. Purpose and methodology

This study aims to empirically examine the effects of COVID-19-induced market and cash flow uncertainties on R&D investments in ICT and ICT-related companies. Existing research has examined these forms of uncertainties prior to COVID-19, thus we intend to look for any substantial difference caused by the pandemic. Moreover, the limited research on R&D investments during COVID-19 has not focused on the ICT and ICT-related industries, despite their central roles in shaping modern society's behaviors towards technology utilization in daily life. Notably, this industry was only slightly affected by the pandemic compared to other industries (De Vet et al., 2021), which heightens our interest on why ICT and ICT-related companies, contrary to most industries, thrived during this period.

The key empirical approach utilized in this paper is fixed effects (FE) panel regression which enables us to observe the effect of the macro and firm-level variables on the level of R&D investments. We use unbalanced panel data on 5,934 ICT and ICT-related companies available on Bloomberg over the period of 2018-2022. The paper does not use geographical limitation for the samples as the pandemic resulted in an increase of technology usage worldwide and had an immediate impact on the ICT sector's global supply chain. The samples are based in 91 countries.

In line with previous literature, variables for macro and firm-level uncertainties induced by COVID-19 are represented by companies' market *Beta* and dividend payout ratio (*DPR*), respectively. The amount of R&D spending would define companies' innovation capabilities in developing new products and/or services to remain competitive. Thus, we proxy the level of R&D investments by using the ratio of R&D expenditure to operating income. To address the aim of the study, the following research questions will be addressed:

RQ1: *Does market uncertainty induced by COVID-19 pandemic impact positively on R&D investments in ICT and ICT-related companies?*

RQ2: Does cash flow uncertainty induced by COVID-19 pandemic impact positively on R&D investments in ICT and ICT-related companies?

1.3. Main findings

The empirical results in this paper show that market uncertainty during the years observed has a positive effect on R&D investment in the highly competitive ICT and ICT-related sectors, and the effect is more pronounced during the COVID-19 period. Our findings correspond with the growth theory and real options theory which back on our hypothesis. Evidence also suggests that market uncertainty does not provide an additional economic advantage to large companies over small companies. Thus, the additional economic benefit for companies during the global pandemic depends mainly on flexible business strategy and innovation, not on company size.

However, the same effect did not occur on cash flow uncertainty. Following the pecking order theory, companies tend to fund investments using internal cash before seeking external financing, thus the R&D projects are highly dependent on companies' cash flow forecast. From our estimates, we found a negative correlation between dividend payout ratios, as the proxy of cash flow uncertainty, and R&D investments. A high payout ratio leads to a lower R&D investments as managers need to opt for either paying the dividends or use the cash balance for investments. The results are consistent with previous studies and prove that no anomaly occurs in the ICT and ICT-related sectors related to their R&D investments, despite the significant hike in the demands of technology throughout the pandemic.

1.4. Contribution

This study contributes to the existing literature by focusing on the ICT and ICT-related sectors globally to fill the gap and enrich the knowledge on R&D investments impacted by COVID-19. To the best of our knowledge, this is the first empirical paper that tests market and cash flow uncertainties specifically in these sectors. These sectors are important to look at, as the more digitally integrated our lives become, the higher the urgency to advance the technology to cater to society's ever-changing needs. This spike in demands will need to be supported by continuous efforts to innovate and invest in innovative projects during and post pandemic-induced global crisis.

1.5. Outline

The rest of the paper is organized as follows. Section 2 provides an overview of the macroeconomic landscape during the global health pandemic and the surge of ICT utilization caused by COVID-19. Section 3 presents related theoretical and empirical literature. Section 4 describes methodology. Section 5 presents the data and descriptive statistics. Section 6 reports the empirical findings on whether market and cash flow uncertainty caused by COVID-19 affect company's R&D investments, while Section 7 provides limitations of the study. Finally, Section 8 concludes the paper.

2. Macroeconomic overview during the global health pandemic

2.1. Market uncertainty caused by COVID-19

Many countries announced intervention policies to combat COVID-19 outbreak that extended longer than expected. Such restrictions implied a rapid, forceful shift towards working and studying from home which is unlikely to return as it was before. COVID-19 was recognized not only as a health contingency but also a global crisis with several impacts on the global economy which set unprecedented levels of uncertainty to companies in all industries worldwide. In March 2020, the Dow Jones Industrial Average (DJIA) Index recorded a decline of more than 30% in response to the global pandemic. In fact, the impact of COVID-19 on stock markets was more severe than any other pandemic in history, including the Spanish flu of 1918 (Baker et al., 2020). In June 2020, the International Monetary Fund (IMF) announced in the World Economic Outlook (WEO) that the annual growth forecast for the global economy would fall to 4.9% (IMF, 2020). This represents a 1.9% decline from the April 2020 WEO forecast, making COVID-19 the worst recession since the Great Depression of 1929 and much worse than the 2007 global financial crisis (IMF, 2020). The Organisation for Economic Co-operation (OECD) in their 2020 report also projected that many economies could only recover their output levels to those of 2019 as soon as 2022 at the earliest.

Despite the positive intention to mitigate the financial shock, continued restrictive policies have led to unforeseen outcomes that have changed the economy's perception of risk towards more cautious assumptions (Stewart, 2021). These assumptions have led to a conservative approach in businesses by restricting their spending to anticipate long-term uncertainty (Stewart, 2021). At the firm-level, revenue growth and corporate profitability resulting from market uncertainty have led companies to adjust their business strategies, including capital structures, financing, investment activities, and dividend policy, to adapt to COVID-19 constraints (Deev & Plíhal, 2022). Overall, the impacts of COVID-19 pandemic were multidimensional, manifesting itself in government policy responses, company's risk exposures, and investor's risk expectations. He et al. (2020) examined the impact of COVID-19 on stock prices in different sectors and found that the pandemic negatively and more severely affected traditional industries, yet created opportunities for the development of high-technology industries. On the other hand, the prevailing uncertainties in the market are holding back investors' investment, provoking them to adopt a wait-and-see strategy to monitor the unfolding future dynamics during the pandemic (Bachmann et al., 2013; Watanabe, 2008). Due to the above mentioned strategy of investors, the companies face cash flow uncertainty to finance their R&D projects.

2.2. The surge of ICT utilization caused by COVID-19

The emergence of disruptive events has also urged organizations and businesses to accelerate the development and application of ICT capabilities to further facilitate the shift to digitalization driven by COVID-19 restriction policies. Banga & Velde (2020) raised the notion that digitalization is the key to mitigate further economic losses. They further elaborated that countries with digital readiness, more developed broadband infrastructure, and high internet access were able to offset the negative effects of the pandemic despite having more stringent policy responses. In the EU, where digital readiness is relatively high, the digital adoption had increased from 81% to 95% during the first wave of the pandemic (De Vet et al., 2021). In developing and least developed countries (LDC), Banga & Velde (2020)'s report shows that there was a varying degree of adoption levels as the LDC experienced a reduced imports on ICT infrastructures that would support digital transformations due to the restriction policies. However, they found 30% increase in internet traffic globally during lockdowns with the biggest determinant being communication apps, such as Zoom, Skype, and WhatsApp. In 2021, United Nations Conference on Trade and Development (UNCTAD) reported that the number of users of the internet had reached the highest point for the first time during the lockdown period, as 57% of the population in developing countries were connected through the world wide web. This number was up from 44% in 2019 (UNCTAD, 2021). In the LDC, the rate increased from 19 to 27% (UNCTAD, 2021). The same report suggests a proxy of ICT universality and affordability by measuring the proportion of the population covered by a mobile network. It shows that the number had fallen in the beginning of the pandemic in 2020, and then rose to reach 105 subscriptions per 100 inhabitants in 2021, implying a significant increase in internet connectivity throughout the period.

Digitalization occurs in every aspect of life: education, remote work, commerce, health services, public administration, and government services, including e-democracy tools (Banga & Velde, 2020; OECD, 2020; UNCTAD, 2021). The existence of education apps, such as Google Classroom and Canvas, and other supporting apps, such as Microsoft Teams, enable students to be engaged with their teachers and classmates during distance learning. Remote work gained significant attention during the pandemic as the extent on which types of jobs were able to be conducted remotely was an important factor in measuring the economic impact of COVID-19 restriction policies and dictating the economy's resilience (OECD, 2021). For instance, from Banga & Velde (2020)'s survey, 30% of the Kenya Association of Manufacturers members increased their digital and online capacities to cope with the crisis, and more than 20% of the manufacturing firms surveyed in Russian Federation, Jordan, Morocco, Zimbabwe, and Zambia have started and intensified their online business activities since the start of the pandemic. It also resulted in a surge of online-buying behaviour, where on average 24% of the world's population shopped online (Banga & Velde, 2020). In OECD countries, the increase topped at 5.2% which was the highest since 2005 (OECD, 2021).

Digital tools have been crucial to alleviate the spread of the virus and manage the health crisis. Some countries developed tracking apps to monitor citizens' mobility, communicate information and precautionary measures transparently, and provide access to health authorities related to isolation and emergency events (OECD, 2021). Telemedicine and e-prescription services emerged as a way out in times where going to a hospital to seek medical services becomes a risky decision. Public services and administration have also been digitally revamped, which cover multiple ease of access ranging from tax payments through mobile money payment to online debating and voting (OECD, 2021). In the Netherlands, it is permissible to have digital decision-making through digital meeting; similar adjustment is applied in Spain, where the governing bodies are now allowed to run remote sessions through telematic means (OECD, 2021). Hence, the ICT industry holds a crucial role in easing COVID-19 crisis by providing high-tech products and services that enable activities to be conducted across the globe.

3. Theoretical framework

3.1. Theoretical background related to market uncertainty and R&D investments

3.1.1. Growth theory

The traditional growth theory considers the presence of an aggregate production function whose existence and properties are connected to the assumption of optimal resource allocation. It leads to a concept of investment as the commitment of current resources in the expectation of future growth in returns (Fisher, 1906; Samuelson, 1961). Investment in tangible assets is the most transparent illustration of investment as a source of economic growth (Jorgenson & Stiroh, 1999). This form of investment creates transferable intellectual property rights, such through direct sales or licensing agreements, with returns that can be internalized (Jorgenson & Stiroh, 1999). The increase in intellectual assets contributes to the growth of income the same way as tangible assets.

Additionally, the new growth theory focuses more on the importance of entrepreneurship, knowledge, innovation and technology. It also challenges the exogenous growth view of neoclassical economics, according to which economic progress is determined by external, uncontrollable forces. The theory mentioned that innovation and new technologies do not simply emerge by chance (Kim & Sanders, 2002). Rather, it depends on how many people look for new innovations or technologies and how intensively they look for them. The inflow of new investment into R&D for economic growth was resulting in the high level of intellectual energy that fuelled rapid progress. In new growth theory, human capital is a key input to research and innovation activity. Both R&D investments and productivity are crucial sources of economic growth for assessing the explanatory power of new growth theory.

3.1.2. Real options theory

Real options theory describes how to make investment decisions when the future is uncertain. Abel & Eberly (1996), Abel et al. (1996), Dixit & Pindyck (1994), and Pindyck (1990) concluded that firms invest less when they face high uncertainty. This is because an increase in uncertainty leads firms to wait for a higher value of their options rather than making irreversible and costly investments immediately. Leiblein (2003) stated two assumptions for real option theory. Firstly, it is possible to develop estimates of the potential value associated with different options to abandon, postpone, or increase investments along a given investment path. This assumption implies a concept of uncertainty closer to Knight (1921)'s concept of risk, where probabilities of possible outcomes are available to guide decisions, rather than to uncertainty, where information is too imprecise to be adequately summarized in probabilities. Afterward, real options theory has been used to produce a series of forecasts of an investment's potential values that offer option-holders a range of opportunities to improve performance. Schwartz (2013) further indicated the opportunities as expansion into attractive markets or technologies and the risk of loss by postponing investments, abandoning activities, and growing or curtailing activities. The theory of real options dictates that there may be considerable risks involved in committing oneself rashly. In these situations, the option to wait for new information that might affect the attractiveness or timing of the investment is of value (Schwartz, 2013). Furthermore, the real options theory also analyzes the value of management flexibility to adjust and revise future decisions to take advantage of favorable future investment opportunities (Scherpereel, 2008). Scherpereel (2008) argued that taking benefit from adverse market developments is critical to long-term corporate success in an uncertain and changing market.

The second assumption of Leiblein (2003) is that real options approach management decisions through growth options. He also stated that growth options give the firm the right to expand or to develop a related product or technology. These growth options are particularly valuable in high-tech industries where weak appropriation rules and intergenerational knowledge spillovers are often considered important (Leiblein, 2003). Additionally, real options are valuable because agents who own them are better able to take advantage of volatile environments (Leiblein, 2003). Moreover, it simplifies the real option model to a two-factor model, namely interaction effects and competitor reactions, to focus on the basic factors that affect the variance of the return on capital (Kim & Sanders, 2002). The real options theory extended the point of view of options from financial markets, of which previously based on tradable contracts with specific terms, to real assets, both tangible and intangible. The underlying real assets of a real option include R&D investments, patents, real estate, natural resources, production facilities, and strategic acquisitions (Scherpereel, 2008).

3.2. Theoretical background related to cash flow uncertainty and R&D investments

3.2.1. Information asymmetry & dividend payout policy

Information asymmetry between management as insiders and stockholders as outsiders becomes the main setting in Bhattacharya (1979) and John & Williams (1985) studies which found that, in such an environment, cash dividend becomes the signal of expected cash flow. Stockholders primarily observe the priced-in market value and confide in the expectation, as their investment horizons are shorter compared to the anticipated perpetual stream of cash flow generated by the companies' assets (Bhattacharya, 1979). The signals coming from dividends announcements would dictate companies' ability and commitment in meeting the expectation. Despite the major influence in shaping stockholders' expectation on future earnings prospects, Miller & Rock (1985) concluded that the dividend announcements only provide limited information on current earnings and have low predictive power for future earnings. The announcement only fills the gap of priorly unobserved information concerning companies' earnings, and triggers a tendency for companies to pay out more dividends to run up the stock price (Li & Zhao, 2008; Miller & Rock, 1985), specifically when the stockholders demand current cash (John & Williams, 1985) or the company is based in a country with weak stockholder-protection law (La Porta et al., 2000). Consequently, the reduction of cash balance due to dividend payment forced companies to reduce investment allocation, and hence signalling that higher dividend payout equals to lower investment level (Miller & Rock, 1985).

Dividend payments reduce the agency cost by restricting managements in utilizing the internal cash flow to benefit themselves (La Porta et al., 2000; Moh'd et al., 1995; Morris, 1987) and by mitigating information asymmetry (Hail et al., 2014). The lower the information asymmetry, the more precise and transparent the common information is to stockholders. Stockholders can rely on the information to reduce adverse selections, enhance better monitoring (Hail et al., 2014), and get higher dividend payout ratios (Li & Zhao, 2008). Yet, in the presence of informational shock, such as newly mandated disclosures in regard to IFRS adoption in mid 2000s, companies are found to be less likely to pay dividends, more likely to reduce the frequency of dividend payments, even stop completely, and cut back on the information content of the dividends (Hail et al., 2014). This finding is notably opposing Lintner (1956)'s theory that proposed dividends as sticky; that companies have target dividend payout ratios and managements avoid changing the dividend payments and policies due to its potential impact on publicity and financial press. Dividend patterns reflect publicized earnings of which a change in the pattern in a negative direction implies a decline in earnings and cash flow position. Stockholders would only accept the dividend cuts when prudent decisions are made under the circumstance of consistent substantial fall in earnings (Lintner, 1956).

Cash disbursements in the form of dividends fulfil the demand of wealth distribution to stockholders (Moh'd et al., 1995), especially the minority ones, as cash accumulated in retained earnings will be less likely to be distributed back to stockholders (La Porta et al., 2000). Rozeff (1982) argued that if the past and future growth is rapid, management tends to allocate the fund to reinvest rather than to distribute the cash through dividends as this source of funding is cheaper and, thus, preferable. The dividend payout ratio is determined by the investment financing scheme where the choice to finance heavily internally or externally would negatively impact each other. Higher investment opportunities and growth rates will lead to lower dividend payout (Rozeff, 1982).

In terms of investment policies related to dividends, La Porta et al. (2000) elaborated on the differences in the policies based on the type of stockholder protection law imposed in different countries: common or civil law. Investors in a legally highly protective country, being mostly imposing a common law, will accept low dividend payouts and higher reinvestment rates since the reinvestments would pay off in higher dividends in the future. The strong law enforcements give high assurance on stockholders' power to execute their rights compared to a relatively weaker, less legally protective country. In this scenario, dividends provide a substitutive role for stockholders' legal protection aspect, as shown by higher payout ratio demands from stockholders in weaker protection countries (La Porta et al., 2000). Consequently, companies would fulfil the demand to maintain their reputation, regardless of the investment opportunities (La Porta et al., 2000). It is also found that higher protection countries tend to have more developed capital markets, and vice versa.

3.2.2. Pecking order theory

The pecking order theory states that in a hierarchy of project funding, companies prefer internal over external funds, followed by debt and then equity (Myers, 1984). Companies opt for issuing debt to equity in a deficit circumstance and repaying their debt obligations before buying back their equity in a surplus circumstance, although in the latter there is more room for companies to choose either to repay the debt or buy back shares (Myers, 2001). According to Myers (1984)'s theory, internal funds have no information asymmetry or listing costs and are therefore preferred over external financing. Equity is only issued when the existing limits on debt capacity are exhausted. According to Myers (2001), companies will issue the safest security first, i.e. debt, before equity. When internally generated cash flow exceeds capital investment, the excess is used to repay debt rather than repurchase or return equity.

Managers of large companies usually prefer internal to external financing (Donaldson, 1961). Myers (1984) and Myers & Majluf (1984) introduced the pecking order into a theoretical model and suggested that companies favor internal over expensive external funds due to the presence of information asymmetries on the latter. Overvalued companies issue more equity, while undervalued companies resort to cash when it is available and then use the option of debt (Dong et al., 2012). Moreover, the pecking order is determined by information costs, and large companies tend to have lower information costs. The theory is thought to work better for companies with high information asymmetry, such as small companies. However, Frank & Goyal (2003), De Jong & Verwijmeren (2010), Lemmon & Zender (2010), and Cotei & Farhat (2009) suggested that large companies are more likely to follow the pecking order theory than small companies. Komera & Lukose (2014) found that the pecking order theory does not describe companies with high information asymmetry costs, but may be more appropriate for companies without debt capacity constraints.

3.3. Empirical literature review

3.3.1. R&D investments in ICT industry

Companies' R&D investment is determined by three factors, namely financial, physical, and intangible resources, with the latter emerging as the most pivotal factor (Del Canto & Gonzalez, 1999; Lai et al., 2015). Canarella & Miller (2018) supported this notion that intellectual capital as intangible assets endure the characteristics of R&D intensive industries. The high-tech industry penetrates the market and benefits from economic growth through its investment in R&D, i.e. the development of intellectual property through innovation and technology. In addition, the ICT industry plays a crucial role in alleviating the COVID-19 crisis by providing technological solutions around the world. Overall, this is in line with the new growth theory.

Abel & Eberly (1996), Abel et al. (1996), Dixit & Pindyck (1994), and Pindyck (1990) mentioned that, in real options theory, companies invest less when they face high uncertainty. Therefore, high uncertainty discourages investment, while low uncertainty increases companies' willingness to invest. Accordingly, the relationship between uncertainty and investment should be negative. However, based on Leiblein (2003)'s assumptions, real options theory was used to make a series of predictions on the potential value of investments, offering opportunities to option-holders to improve performance by expanding into attractive markets or technologies.

On the other hand, management makes decisions through growth options, where investments are encouraged under imperfect competition (Kulatilaka & Perotti, 1998). An initial investment is seen as acquiring opportunities for growth compared to other competitors, which gives the company a competitive advantage. Additionally, Van Vo & Le (2017) stated that firms are under greater pressure to survive under a competitive market and have more incentive to increase their competitive advantage. Moreover, the value of the option to wait can easily erode. Thus, the market uncertainty has greater impacts on R&D investments in a competitive market.

During the global pandemic, all industries are forced to change their business strategy to adapt to the new economy. On facing a new equilibrium of demand, the ICT industry, specifically, is taking advantage of the volatile market by developing new innovations and technologies that are consistent with COVID-19 mobility restrictions and the tech-heavy attributes that follow the policies. In such markets, the high technology industry usually recognizes that early investment, especially in R&D, is associated with a greater capacity for future expansion.

3.3.2. R&D investments and cash flow uncertainty

Canarella & Miller (2018) provided evidence that intellectual capital bears the characteristics of R&D intensive industries. The drawback of this concept is that the knowledge base is excessively complex to be used as collateral, resulting in an increased difficulty in securing external financing and high reliance on internal funds (Bloch, 2005; Qu, 2020) as commonly postulated in Myers' (1984) pecking order theory. Eng & Shackell (2001) also indicated that institutional investors such as banks, insurance, and investment companies restrict their investments in companies with high R&D expenditures due to the high risk associated with it. They further argued that the benefits of such investments are likely to be materialized only over the long run and have immediate effect in reducing near-term earnings.

However, Bloch (2005) and Eng & Shackell (2001) found that significant information asymmetry persists in R&D projects, whereby the future values of the investments are not fully reflected in the corresponding stock prices. Companies reserve more information regarding the projects and are restrained from disclosing them due to strategic considerations which further limit companies' access to external funding. By not having access to external funding, companies depend on internal cash to finance their investments. Beladi et al. (2021) and Qu (2020) argued that companies with higher levels of cash flow uncertainty tend to make more conservative and prudent investment choices, and thus inhibit innovation. On the contrary, Pham et al. (2018) observed that companies possessing high levels of liquid assets to mitigate cash flow uncertainties tend to be more innovative and generate higher numbers of patents, albeit the impact is less pronounced for larger companies.

A company's cash flow forecasts can be signalled from its dividend announcements as concluded by Bhattacharya (1979) and John & Williams (1985). They discussed that in the presence of information asymmetry, the market price of a stock has accounted for the expected cash flow and profitability. Owing to its signalling function, Bradley et al. (1998) and Brook et al. (1998) showed that the market penalizes a company's stock price three days after a dividend cut announcement as market participants would expect declining future cash flow and profitability as the underlying cause. Accordingly, dividend policy is used to signal the expected level and the volatility of cash flow and future earnings (Brook et al., 1998), where higher uncertainty would lead to lower dividends payout ratios as managers' confidence toward sustained dividend payment diminished (Bradley et al., 1998; Chay & Suh, 2009).

3.4. Hypothesis development

3.4.1 Market uncertainty and R&D investment

Segal et al. (2015) classified uncertainty as "good" and "bad" market volatility components based on its influence on innovations on macroeconomic growth. The study found that good uncertainty risk positively predicts future economic growth, including investment, R&D, market earnings, and equity beta. Van Vo & Le (2017) argued that R&D investment has a positive relationship with market uncertainty, according to the theory of strategic growth options, as competition being the leading driver of the relationship. They confirmed, therefore, that uncertainty enhances the positive effect on R&D investment, mainly when the company is part of a competitive industry or its market power is low.

On the one hand, some studies based on real option theory have verified the negative relationship between uncertainty and investment overall (Jung & Kwak, 2018). These studies show that companies are less likely to invest when uncertainty increases, or it would be economically disadvantageous (Kang et al., 2014). Uncertainty in the market leads to higher financing costs and financial bottlenecks for companies. Therefore, it is quite possible that companies scale back their R&D investments when they are faced with financial constraints (Lin et al., 2021). In addition, Barrero et al. (2017) and Khan et al. (2020) also discovered that in the presence of uncertainty in the short and long-term, the growth of R&D expenditures is considerably decelerated as it may have adverse effects on innovation and productivity, owing to the challenges in scaling down the R&D activities at a later stage. In addition, the inherent strategic growth that R&D brings is also responsible for the positive impact of uncertainty on R&D investment, creating a first-mover advantage for a leading company, such as Zoom Video Communications, Inc. As the use of technology significantly minimise the impact of the COVID-19 pandemic, the demand for digital access, equipment, life-saving devices, and tools has increased at an unprecedented rate (Banga & Velde, 2020; Chandra et al., 2022; OECD, 2020; UNCTAD, 2021).

We suspect technological advancement resulting from R&D investments in the ICT industry as a crucial aspect for conducting activities during COVID-19. Technology companies experienced rapid growth in the market due to their business innovations and are in a better competitive position during the global pandemic. According to the points discussed above, the market uncertainty triggered by COVID-19 prompts a rapid improvement in R&D investment in ICT-related companies, while R&D investment in other sectors may decreased during the higher market uncertainty. Therefore, we expect the impact of market uncertainty on R&D investment to be more pronounced for companies in the more competitive industry. Consistent with our prediction, we assume that the positive relationship between market uncertainty and R&D investment is significantly stronger for companies in the ICT and ICT-related sectors as these sectors are more inherently competitive.

Thus, we hypothesise our first prediction as follow:

H1: COVID-19-induced market uncertainty has a positive relationship with R&D investments in ICT and ICT-related companies.

3.4.2 Impacts of firm size on R&D investments and market uncertainty

Reflecting on Jung & Kwak (2018)'s findings, we assume there is a moderating effect of company size on the relationship between market uncertainty and R&D investments. It is widely known that R&D activities are an important driver of business productivity and economic growth, and these results can provide evidence to promote R&D activities to benefit from the pandemic-induced unstable economy (Jung & Kwak 2018). However, the absorptive capacity of high-tech companies might be an increasing function of company size, such that large high-tech companies with high innovation capacity have higher absorptive capacity (Jung & Kwak, 2018). From Jung & Kwak (2018)'s study, companies with high absorptive capacity can easily and quickly mimic the results of their competitors' innovations, which may increase the incentive to postpone R&D investments under market uncertainty as competitors might employ the same strategy. Therefore, if the size of companies with high innovation capacity exceeds a certain level, it can be predicted that market uncertainty is a factor that hold back R&D investments, which is aligned with real option theory supported by Abel & Eberly (1996), Abel et al. (1996), Dixit & Pindyck (1994), and Pindyck (1990).

On the other hand, uncertainty leads to investments under imperfect competition based on the growth options (Kulatilaka & Perotti, 1998). When competition is strong, companies have greater pressure to survive and higher incentive to benefit from their competitive advantage (Van Vo & Le, 2017). Moreover, Van Vo & Le (2017) mentioned that in a highly competitive landscape, the value of the option to wait can easily erode and the impact of uncertainty on R&D investments is, therefore, greater. To benefit from the competition, Bonaccorsi (1992) and Calof (1993) assumed that larger companies are in more favorable positions as they have more resources, such as financial and technological means, to achieve economies of scale compared to smaller companies.

An interaction between company size, market uncertainty induced by COVID-19. and R&D investments, therefore, is presented in our second hypothesis:

H2: COVID-19-induced market uncertainty has a positive relationship with R&D investments in the larger ICT and ICT-related companies.

3.4.3. Cash flow uncertainty and R&D

Beladi et al. (2021) showed that cash flow uncertainty, as a predominant form of financial constraint, has a negative impact on R&D investment decisions, confirming the pecking order theory and the findings of Bloch (2005) and Qu (2020) on cash flow being the primary source of funding for innovation projects. As innovation projects are kept confidential to maintain strategic advantage, it limits the ability of companies to seek external financing and thus may heavily rely on internal funding (Bloch, 2005; Eng & Shackell, 2001). Hence, future cash flow projections become a main concern for companies to ensure sufficient balance of cash is secured to fund the entirety of the projects. When the market movements become unpredictable due to the unforeseen global crisis induced by COVID-19, the company's future earnings tend to go in the same direction. With an unclear future prospects, investing in R&D projects turns into a high-risk option that is unlikely to be considered.

A company's future cash flow and profitability can be signalled from its dividend policies (Bhattacharya, 1979; Bradley et al., 1998; Brook et al., 1998; John & Williams, 1985). Bradley et al. (1998) proposed that when managers anticipate uncertain future cash flow, they tend to give out more dividends to guarantee the stockholders that they will not engage in non-value maximizing investments. On the other hand, Chay & Suh (2009) and Fairchild (2010) found the opposite and showed that companies with more value-creating investment opportunities choose to undertake the investment and opt for paying lower dividends. Fairchild (2010) further suggested that managers can mitigate bad news in the market coming from the dividend cut by communicating the reasons behind the decisions to stockholders, especially when strong growth opportunities are present. Without a proper clarification, the dividend cut would signal a declining current earnings and affect stockholders' beliefs on the prospects of the company. Hence, to offset the impact, the company would consequently maintain or increase the dividend payout and pass up the good projects instead.

Limited source of funding forces companies to select a mutually exclusive option of distributing cash as dividends or investing in R&D projects. Following the arguments above, as well as Miller & Rock (1985)'s and Rozeff (1982)'s findings, we presume that companies with higher dividend payment ratios will have lower R&D investments. However, as explained in previous sections, an anomaly happened to the ICT companies during the global pandemic where the crisis generated higher demands and greater future prospects for the industry as the world became more digitized and tech-dependent. R&D investments in technology are expected to intensify in the upcoming years to offer innovative products and services to gain more users and expand market shares. Consequently, this growth opportunity adds more interest to stockholders on betting a superior future performance in this specific industry and hoping for higher dividend yields. Therefore, contrary to previous studies, we predict a positive relationship between dividend payout ratios and R&D investments. With a confidently high future performance, thus a more certain cash flow prospect, ICT companies are anticipated to have both higher dividends payout ratio and R&D investments.

We formulate our third hypothesis as follows:

H3: Dividend payment ratio, as the proxy of COVID-19-induced cash flow uncertainty, impacts positively towards R&D investments in ICT and ICT-related companies.

4. Methodology

The relationship between R&D investments and market uncertainty (*H1*) will be examined using panel regression in two different models as follow:

$$RDI_{i,t} = \beta_0 + \beta_1 Beta_{i,t} + \beta_2 CF_{i,t} + \beta_3 DPR_{i,t} + \beta_4 TotalAssets_{i,t} + \beta_5 ROS_{i,t} + \beta_6 Lev_{i,t} + \beta_7 Profit_{i,t} + \beta_8 TobinsQ_{i,t} + s_i + y_t + a_{i,t} + u_{i,t} \quad \textbf{(1a)}$$

$$RDI_{i,t} = \beta_0 + \beta_1 Beta_{i,t} + \beta_2 COVID_{i,t} + \beta_3 BetaxCOVID_{i,t} + \beta_4 CF_{i,t} + \beta_5 DPR_{i,t} + \beta_6 TotalAssets_{i,t} + \beta_7 ROS_{i,t} + \beta_8 Lev_{i,t} + \beta_9 Profit_{i,t} + \beta_{10} TobinsQ_{i,t} + s_i + y_t + a_{i,t} + u_{i,t} \quad \textbf{(1b)}$$

Model (1a) will be used as the main model where $RDI_{i,t}$ stands for R&D investments for firm *i* at time *t* which is measured by the ratio of R&D expenditures to operating income; $Beta_{i,t}$ as proxy for market uncertainty which is derived from weekly market data for the past two years adjusted using the assumption that the beta moves toward the market average (0.666 * raw beta + 0.333 * 1.0); $CF_{i,t}$ stands for cash flow, proxied by the ratio of net change in cash to total assets; $DPR_{i,t}$ stands for dividend payment ratio which is measured by dividend paid divided by total assets; $TotalAssets_{i,t}$ is company's total assets in logged value as proxy of firm size; $ROS_{i,t}$ stands for return on sales, measured by net income divided by total sales; $Lev_{i,t}$ denotes leverage, calculated by total debt divided by total assets; $Profit_{i,t}$ is company's net income in logged value; $TobinsQ_{i,t}$ is the ratio of market value to total assets; s_i is the dummy variable for sub-industry where firm *i* is classified into, to control for industry-effect; y_t is the dummy variable for fiscal year *t* to control for time-effect; and $a_{i,t}$ represents the unobservable variables.

Model (1b) is a complementary model to see the impact of COVID-19 by setting up a dummy variable of $COVID_{i,t}$, denoting one for samples in the fiscal year 2020-2022 and zero for fiscal year 2018-2019. We interact this variable to the main explanatory variable $Beta_{i,t}$ to form $BetaxCOVID_{i,t}$. This interaction variable enables us to gain insights on whether or not there is any influence of COVID-19-induced market uncertainty to R&D investments.

In *H2*, we would like to investigate how innovation capacity moderates the impact of market uncertainty caused by the global pandemic on R&D investment as a function of company size. To observe the relationship, we generate a dummy variable labeled $Large_{i,t}$ which equals one if total assets of the company are above the mean value, and zero otherwise. We also generate an interaction variable $BetaxLarge_{i,t}$ to capture the moderating effect of firm size to market uncertainty. This approach allows us to examine how the relation between market uncertainty caused by COVID-19 and R&D investments of ICT companies varies according to the different levels of size. Hence, our model after adding the interaction term to the main model (1a) is as below:

$$RDI_{i,t} = \beta_0 + \beta_1 Beta_{i,t} + \beta_2 Large_{i,t} + \beta_3 BetaxLarge_{i,t} + \beta_4 CF_{i,t} + \beta_5 DPR_{i,t} + \beta_6 TotalAssets_{i,t} + \beta_7 ROS_{i,t} + \beta_8 Lev_{i,t} + \beta_9 Profit_{i,t} + \beta_{10} TobinsQ_{i,t} + s_i + y_t + a_{i,t} + u_{i,t} \quad \mathbf{(2)}$$

As for *H3*, the relationship between R&D investments and cash flow uncertainty will be examined using two different models as follow:

$$RDI_{i,t} = \beta_0 + \beta_1 DPR_{i,t} + \beta_2 TotalAssets_{i,t} + \beta_3 TobinsQ_{i,t} + \beta_4 Lev_{i,t} + \beta_5 Profit_{i,t} + \beta_6 PositiveCF_{i,t} + \beta_7 StockYield_{i,t} + \beta_8 CashHolding_{i,t} + s_i + y_t + a_{i,t} + u_{i,t} \quad \mathbf{(3a)}$$

$$RDI_{i,t} = \beta_0 + \beta_1 DPR_{i,t} + \beta_2 COVID_{i,t} + \beta_3 DPRxCOVID_{i,t} + \beta_4 TotalAssets_{i,t} + \beta_5 TobinsQ_{i,t} + \beta_6 Lev_{i,t} + \beta_7 Profit_{i,t} + \beta_8 PositiveCF_{i,t} + \beta_9 StockYield_{i,t} + \beta_{10} CashHolding_{i,t} + s_i + y_t + a_{i,t} + u_{i,t} \quad \mathbf{(3b)}$$

Similar to *H1*, model (3a) is the main model for *H3* and (3b) is the supplementary model to see the influence of COVID-19 on cash flow uncertainties proxied by $DPR_{i,t}$. Adding to the previous list of variables, $DPRxCOVID_{i,t}$ is the interaction variable of $COVID_{i,t}$ and main explanatory variable $DPR_{i,t}$; $PositiveCF_{i,t}$ is dummy variable denoting one for positive cash balance and zero otherwise; $StockYield_{i,t}$ is the log value of reinvestment rate; and $CashHolding_{i,t}$ is the ratio of cash and cash equivalent to total assets. All variable definitions are summarized in Table 1 in the Appendix.

4.1. Panel regression, Fixed Effect and Random Effect models

Although there are many different methodological approaches to test empirical analysis, various approaches need to be considered and discussed in order to find the most appropriate method for this study. We used a panel dataset that allows us to test different methodological approaches to analyze the impact of market and cash flow uncertainty on R&D investments in the ICT and ICT-related sectors. Previous studies by Van Vo & Le (2017) have used both pooled ordinary least squares (OLS) regressions and fixed effects models (FE) to analyze the relationship between R&D investments and market volatility. In addition, Beladi et al. (2021) also used fixed effects models (FE) to investigate the relationship between cash flow uncertainty and R&D investments.

This study plans to test both fixed effect (FE) and random effect (RE) regression models and assess the appropriateness of the methods using the Hausman test. We prefer FE/RE for our panel data rather than pooled OLS since we mainly run the same sample companies across the 5-year period, thus we want to further control the different companies' effects and time effects. To account for the fact that the sample population may be distributed differently in different periods, it is possible to include annual dummy variables so that the intercept can differ across periods (Wooldridge, 2010).

In all models formulated in previous section, i indicates the unit of data, t is the time period, β is the coefficient, x is the effect of the estimator, $a_{i,t}$ is the unobserved effect or fixed effect that is time-invariant, and $u_{i,t}$ is the idiosyncratic error term that changes over time and affects the dependent variable $y_{i,t}$. For the pooled OLS to provide a consistent estimator for β_1, the unobserved effect $a_{i,t}$ must be uncorrelated with $x_{i,t}$. Thus, pooled OLS may be inefficient and likely to have heterogeneity bias if there is any unobserved heterogeneity that affects the dependent variable (Wooldridge, 2010).

For this reason, this study uses the FE/RE models to analyze the impact of variables that vary over time. In the FE model, the unobserved variable, $a_{i,t}$ does not change over time, thus it allows to minimize the threat of endogeneity problems. Moreover, it allows for arbitrary correlation between $x_{i,t}$ and $a_{i,t}$, but requires a strict exogeneity assumption with respect to $u_{i,t}$, which is $\mathrm{Cov}(x_{i,t}, u_{i,t})=0$. Although $u_{i,t}$ might exhibit serial correlation, which is a problem of heteroscedasticity, we can apply cluster robust inference in the model FE. Moreover, the FE model enables the use of a full set of year dummies and many explanatory variables.

On the other hand, the theory of RE model suggests that unobserved variables are uncorrelated with the explanatory variables in all periods. Unlike FE model, RE model allows $a_{i,t}$ in error term and accounts for the serial correlation over time via generalized least squares (GLS) procedure. Additionally, the RE estimation allows time-constant explanatory variables in the model. Thus, the RE model is also a suitable model for this study because it takes out $a_{i,t}$ and adds a time-constant control. We will also treat the issue of heteroskedasticity by clustering the company for robust standard errors. In order to assist in choosing between the FE and RE models, we will conduct a Hausman test.

4.2. Robustness tests

To verify robustness, we gather additional data to measure alternative proxies for the main explanatory variables and then run the models using those substitutes. The alternative proxy for *H1* and *H2*'s main explanatory variable *Beta* is *Volatility* which measures the risk of share price movement, calculated from the standard deviation of daily logarithmic historical price changes from January 1st to December 31st of each fiscal year. The alternative proxy for *H3*'s main explanatory variable *DPR* is operating cash flow ratio (*OCF*) which is calculated by operating cash flow divided by total assets, modified from Beladi et al. (2021). The results of robustness tests will be elaborated in conjunction to the results of the main models.

Statistical Tests

4.3 Heteroskedasticity

We conduct test to check the presence of heteroskedasticity, which indicates that there is not a constant variance between the error term and the explanatory variables. The homoscedasticity assumption is rational for linear regression models. To check whether our regression meets this assumption, we use the White test. The results of the White test can be found in Table 9. The null and alternative hypotheses are:

H_0: *homoscedasticity*

H_a: *unrestricted heteroskedasticity*

Based on the results of the White test of *H1* and *H3* in Table 9, we reject the null hypothesis of constant variance (heteroskedasticity) at the 1% significance level since the p-values for both hypotheses are 0.000. This means that we find evidence against homoscedasticity, i.e. the variance is constant and our data does not show heteroscedasticity. We can therefore draw statistical inferences without worrying about the correlation between the main explanatory variable and the error term. To correct for heteroskedasticity problems, we also create dummy variables for year and industry. In addition, a cluster variance estimator is used to obtain a robust estimate of the variance of the coefficients.

4.4. Test for endogeneity

Endogeneity is defined as a condition in which the independent variable, also predictor or explanatory variable, is associated with the error term of a model (Sibande et al., 2017; Hamilton & Nickerson, 2003; Semadeni et al., 2014). Additionally, endogeneity leads to biased and inconsistent parameter estimates that make reliable inferences virtually impossible. In our model, we use the FE model which can potentially control for unobservable heterogeneity under the assumption of strict exogeneity. However, this assumption of strict exogeneity can be violated as R&D investments can be affected by COVID-19 induced market uncertainty from *H1* and cash flow uncertainty from *H3*.

However, the nature of market uncertainty itself is more exogenous, as economic prosperity is thought to be determined primarily by external, independent factors, as opposed to internal, interdependent factors. On the other hand, cash flow uncertainty may have more endogeneity issues. Therefore, we would like to test whether the independent variables of market uncertainty from *H1* and *H2*, and cash flow uncertainty from *H3* are endogenous or exogenous. The following models will be used to estimate each main explanatory variable and predict the corresponding residuals:

$$Beta_{i,t} = \beta_0 + \beta_1 RDI_{i,t} + \beta_2 CF_{i,t} + \beta_3 DPR_{i,t} + \beta_4 TotalAssets_{i,t} + \beta_5 ROS_{i,t} + \beta_6 Lev_{i,t} + \beta_7 Profit_{i,t} + \beta_8 TobinsQ_{i,t} + u_{i,t} \quad \textbf{(5)}$$

$$DPR_{i,t} = \beta_0 + \beta_1 RDI_{i,t} + \beta_2 TotalAssets_{i,t} + \beta_3 TobinsQ_{i,t} + \beta_4 Lev_{i,t} + \beta_5 Profit_{i,t} + \beta_6 PositiveCF_{i,t} + \beta_7 StockYield_{i,t} + \beta_8 CashHolding_{i,t} + u_{i,t} \quad \textbf{(6)}$$

In our main models, the dependent variable is *RDI*. To test the endogeneity/exogeneity of market and cash flow uncertainty, in model (5) and (6) above we employ the main explanatory variables as the dependent variables. We will use the Durbin-Wu-Hausman (DWH) (Durbin, 1954; Hausman, 1978; Wu, 1973) to detect endogeneity in the OLS regression. The null and alternative hypotheses are:

H_0:exogenous

H_a: endogenous

The test results are presented in Table 11 and 12. The p-value from both test results are greater than 0.05 thus we failed to reject H_0. Hence, we can confirm that the coefficient estimates in the OLS and FE panel specification estimates are free of endogeneity bias.

5. Data and descriptive statistics

5.1. Data and variables

The unbalanced panel data for this study are obtained from Bloomberg over the period of fiscal year 2018-2022 to observe any variations prior (2018-2019) and during (2020-2022) the pandemic. Panel A of Table 2 shows the selected sectors, industries, and sub-industries observed in this study based on the Global Industry Classification Standard (GICS). The aim of this study is to assess the ICT sector, yet we include other sectors that complement and heavily rely on the utilization of ICT during the pandemic, which are Communication Services and Consumer Discretionary with specific sub-industry of Broadline Retail. The relevance of these other sectors is considered after reviewing that big tech companies, such as Google (Alphabet, Inc.) and Facebook (Meta Platforms, Inc.), are being classified as Communication Services instead of ICT. E-commerce giants, such as Amazon (Amazon.com, Inc.) and Alibaba (Alibaba Group Holding), are classified under newly formed sub-industry classification of Broadline Retail which was previously known as Internet & Direct Marketing Retail (sub-industry code 25502020). The new classification was implemented effectively after the closing of 17 March 2023 (MSCI, 2023). As we acknowledge that COVID-19-induced digital transformation has impacted many aspects of life, by including these related sectors we expect that the estimates would give more comprehensive insights. The majority of the samples are ICT companies that constitute 60% of the firm-year observations, followed by 36% from the Communication Services, and 4% from Consumer Discretionary.

We collected the panel data for companies all over the globe that fall into the chosen GICS industries. Panel B of Table 2 shows the distribution of the firms' home countries. The top 5 countries where each comprises more than 1,000 firm-year observations are Japan (19%), China (17%), Taiwan (15%), United States (8%), and South Korea (7%). There are 17 countries which have firm-year observations between 100 and 1,000 that comprises 26% of the samples. The rest of the countries have less than 100 firm-year observations ranging from 1 to 99 and comprise 7% of the samples.

Panel C of Table 2 shows the yearly distribution of the observations. The fiscal year of 2018 has the most observations which constitutes 26% of the samples. Fiscal years of 2019-2021 are distributed fairly equally across the samples, whereas the year 2022 has the least amount of firm-year observations and only constitutes 11% of the samples. We drop companies in the fiscal year of 2022 which have incomplete data for variables that are required in the models used in this study.

The instruments in this study are modified from Van Vo & Le (2017) for *H1* and *H2*; and Beladi et al. (2021) for *H3*. Table 1 summarized the variables used where the dependent variable for all hypotheses is R&D Investment (*RDI*). *RDI* is calculated from R&D expenditures divided by total sales, where higher values suggest a more intense R&D budget allocation. The term "R&D Investment" is interchangeable with "R&D Intensity" that is employed in a similar study (Jung & Kwak, 2018; Morbey, 1988). The main explanatory variables are *Beta* or systematic risk as the proxy of market uncertainty for each fiscal year and *DPR* or dividend payout ratio as the proxy of cash flow uncertainty. The market volatility captures uncertainty raised from exogenous factors, such as the economic cycle, changes in customer preferences, demographics, or institutional factors. The market *Beta* collected from Bloomberg is an adjusted beta derived from the past two years of weekly data with an assumption that the beta moves toward the market average. *DPR* is used for cash flow uncertainty due to the signaling effect of dividend on future cash flow (Bhattacharya, 1979; Brook et al., 1998; John & Williams 1985). *DPR* is calculated as the dividend paid in the fiscal year divided by total assets.

We employ several control variables, namely *TotalAssets* in logged value as the proxy of firm size; *CF* or cash flow ratio, calculated as net changes in cash divided by total assets which observes as the ready source of liquidity and, thus, a healthy balance allows the company to exploit investment opportunities; *ROS* or return on sales, proxied by net income divided by net total sales; *Lev* or leverage, proxied by total debt divided by total assets to observe the impact of capital structure to *RDI*; *Profit*, measured by the logged value of net income for each fiscal years; *Tobin'sQ*, proxied by the logged value of company's market value divided by total assets; *StockYield*, which shows investment opportunities proxied by the logged value of reinvestment ratio; *CashHolding*, which is the total of cash and cash equivalents divided by total assets; and a dummy variable of *PositiveCF* where the value of one is given if the cash balance is positive and zero otherwise, to test the impact of positive cash balances on *RDI*. In addition, we generate dummy variables to control for different sub-industries and time-effects within the samples.

We also use interaction variables to see the influence of different moderating variables on *RDI*. The dummy variable of *COVID* is generated to see the impact of COVID-19 which was started in early 2020. Value of one is given for samples in the fiscal year of 2020-2022 and zero for fiscal year 2018-2019. We interact *COVID* with main explanatory variables of *Beta* and *DPR*. Another dummy variable, *Large*, is used for *H2* to see the impact of a company's innovative capacity, proxied by company's size, to *RDI*. Value of one is given for samples which have total assets above the mean, and zero otherwise. We interact *Large* with *Beta*.

We eliminate observations with missing values in any of the chosen variables. Further, we winsorize all variables at the 1^{st} and 99^{th} percentiles. Our final samples comprises 18,055 firm-year observations, consisting of 5,934 companies from 91 countries.

5.2. Descriptive statistics

Table 3 reports the summary statistics of all variables used in this empirical analysis. The dependent variable of *RDI* shows a range of -29.932 to 4.642. The average of -1.309 suggests companies in general have allocated more than 100% of their operating income for R&D investments. For the main explanatory variables, *Beta* ranges from 0.010 to 1.877 with an average of 0.897 and median of 0.906 which imply that the companies in the samples tend to have a high market uncertainty. A value of *Beta* that is close to 1 indicates that the company's stock movements are more likely to mirror the volatility of the market. Notably, due to the winsorized values, none of the samples observed has negative *Beta* and thus none of the observations has stock movement against the market. *DPR* ranges from 0.000 to -0.266 which implies that some companies did not pay any dividends. An average of -0.023 shows that the companies in the sample paid dividends up to 2.3% of its total assets.

For control variables, the size of the companies vary widely. The average company size, proxied by *TotalAssets*, is US$2,345.467 million. The smallest size is US$1.761 million, while the largest is US$67,443.330 million. The dummy variable *Large* shows that 13.7% of the samples are considered big-size as they have total assets above the average. Average *CF* is 0.016 which signifies that overall the companies in the samples have positive net cash changes. Average *ROS* is -0.047 which implies that on average the companies experienced loss during the observed period. *Lev* on average is 0.158 which suggests that companies did not engage in a relatively high debt capital structure. Average *Profit* is US$106.409 million with a wide gap between highest and lowest values which are US$3,646.840 million and -US$339.000 million, respectively. *Tobin'sQ* on average is 0.099, *Stock Yield* is 1.301, and *CashHolding* is 0.222 with the smallest amount of cash balance is 0.3% of its total assets. Based on the dummy variable of *PositiveCF*, 57% of the samples have positive cash balance. *COVID* shows that 53.4% of the samples go through the pandemic period.

5.3. Correlation Analysis

Table 4 presents the pairwise correlation matrix for all variables used in the main models in this empirical study. Most variables have values of less than 0.5 which indicates that the variables are independent to each other. However, it is shown that *Profit* has a high correlation with *TotalAssets* with a magnitude of 0.747. It suggests a strong linear relationship between company size and its profitability. Nonetheless, our models will still use both control variables as they will provide two separate insights.

6. Empirical analysis

After running the Hausman for all hypotheses, the p-value results based on Table 10 are equal to zero which implies that we reject the null hypothesis of RE being consistent. Thus, the FE model will be the more suitable option for estimating the models.

6.1. Market uncertainty and R&D investments

Model (1a) of Table 5 shows the regression results for *H1* using the FE model with clustered robust standard errors. According to the results from Table 5, *Beta* has a moderately statistically significant correlation with a confidence level of 5% and a positive sign, thus verifying *H1*. This result is consistent with the findings of Van Vo & Le (2017) that a 1% increase in market uncertainty would lead to a 0.2% increase in *RDI*. This result confirms that, according to growth option theory, there is a positive relationship between investments and market uncertainty. The results imply that high-tech companies tend to invest more in R&D when they face high market uncertainty. As the ICT industry plays a crucial role in alleviating the COVID-19 crisis by providing high-tech products and services, the competition among companies within the industry becomes higher in order to be the market leader and reap the most benefit from the circumstance. Therefore, our results stand with the findings of Van Van Vo & Le (2017) that companies under greater pressure to survive in a competitive market have a greater incentive to increase their competitive advantage by investing in R&D. Our results are consistent with the growth theory, which states that firms seek to invest in R&D investment to achieve economic growth by evaluating the explanatory power of the new growth theory. Our results also confirm Leiblein (2003)'s second assumption from real options theory which states that firms choose to expand or develop their products or services through R&D investment in order to benefit from a volatile environment.

To observe the moderating effect of COVID-19 on *RDI*, the results from model (1b) show that the COVID-19 is moderately statistically significant at 5% confidence level and has a negative correlation with *RDI*. This explains that the global crisis induced by the pandemic brought various impacts for companies in all industries worldwide, including ICT and ICT-related sectors. However, the estimate for *BetaxCOVID* in column (1b) is not statistically significant to confirm that COVID-19 have specific influence on *RDI*. It may be supported by the fact that the companies in these sectors are relatively more prepared in facing the rapid digital transformations triggered by the pandemic compared to other sectors (Banga & Velde, 2020; De Vet et al., 2021). Additionally, these companies benefit from the competitive advantage by providing and developing new digital solutions that adapts to the pandemic situation (Leiblein, 2003). The inherent strategic growth that R&D brings to high-tech firms is the positive outcome of the market uncertainty caused by COVID-19.

Other findings that emerge from the regression results is that *CF*, *DPR*, *TotalAssets*, and *TobinsQ* have a highly statistically significant effect on *RDI* at 1% with a negative correlation. *DPR* will be elaborated more thoroughly in Section 6.3, while *CF*, proxied by net change in cash divided by total assets, shows that higher net change in cash leads to lower investments in R&D projects. Moreover, the higher the *TotalAssets* and *TobinsQ* of technology companies, the lower the *RDI*. This is consistent with the findings of Jung & Kwak (2018) that companies with high absorptive capacity can easily and quickly mimic the results of their competitors' innovations, which may increase the incentive to defer R&D investment under market uncertainty as the competitors might employ the same strategy. However, *ROS*, *Lev* and *Profit* have a highly statistically significant effect on *RDI* at 1% with a positive correlation. This result is consistent with the new growth theory of Kim & Sanders (2002), which stated that new investment in R&D activities to promote economic growth leads to a high level of intellectual energy as the growth driver with the expectation of future increases in returns.

Table 6 shows the results of estimating *H1* and *H3* when we use alternative proxy for *Beta* to test robustness of our models. We replace market beta with stock price volatility, which measures the risk of stock price movements, calculated from the standard deviation of daily log historical stock price changes as used in Van Vo & Le (2017), and refer to it as *Volatility*. We intend to substitute *Beta* since the results can vary due to variations in estimation, as it is an extensive and complicated process. However, the results report that there is no significant impact of *Volatility* on *RDI*. The possible underlying reason for the insignificant results is that the higher the volatility of the stock price, according to Leiblein (2003)'s first assumption on real option theory, the greater the value of being able to defer an investment to await future investment opportunities. Thus, changing the independent variables in different proxies causes our main assumptions to go in a different direction and is less suitable for determining the impact compared to the main proxy.

6.2. The moderating effect of company size on market uncertainty and R&D investments

Model (2) from Table 5 shows the result of the main model (1a) after introducing the interaction variable *BetaxLarge* from *H2* to observe the moderating effect of firm size on *RDI* by *Beta*. The estimates show no statistical significance for the interaction variable, implying that it is independent of company size. This insignificance suggests that *H3* is rejected and it supports the findings of Jung & Kwak (2018) regarding the absorptive and mimicry capacity of their rivals' innovations as mentioned in section 6.1. Moreover, our results are also consistent with the real options theory supported by Abel & Eberly (1996), Abel et al. (1996), Dixit & Pindyck (1994), and Pindyck (1990), which states that market uncertainty is a factor that restrains R&D investment. This is because an increase in uncertainty leads large companies to wait for a higher value of their options rather than making irreversible and costly investments immediately. The insignificance may be due to the fact that market uncertainty has the same impact on R&D investment during the COVID-19 period and does not provide large companies with any additional economic advantage over small ones. Our findings assume that the additional economic benefits for companies during the global pandemic depend mainly on flexible business strategy and innovation, not on company size.

6.3. Cash flow uncertainty and R&D investments

Table 7 presents the estimates for *H3* using the FE model with clustered robust standard errors. Based on the results of the main model (3a), it is shown that *DPR* has a highly significant negative impact on *RDI* at 1% confidence level. The estimates report that when there is an increase in *DPR* by 1%, there will be a decrease in *RDI* by 2.7%. This finding is consistent with previous literature which stated higher dividend payment ratios signal managers' anticipation towards uncertain future cash flow (Bradley et al., 1998), and thus refraining managers from investing in R&D projects (Beladi et al., 2021; Qu, 2020). Similarly, the supplementary model (3b) also suggests a negative effect of *DPR* to *RDI* at 1% confidence level with an identical magnitude, implying the same conclusion after taking into account the COVID-19 pandemic period. The samples in the pandemic period on its own, reflected by dummy variable *COVID*, show a fairly statistically significant negative effect at 5% confidence level which signifies that the pandemic has a discouraging effect on *RDI*, although in a lower magnitude than the full period of 2018-2022. However, we did not find any statistically significant result from the interaction variable *DPRxCOVID* to successfully observe any influence of the pandemic on the changes in *DPR*.

The opposing results from both models have proven that our *H3* that predicts *DPR* to have a positive effect on *RDI* is rejected. We anticipated that during the pandemic crisis, ICT companies would gain benefit from the digital transformation (Banga & Velde, 2020; UNCTAD, 2021) by investing on more innovative projects (Chay & Suh, 2009; Fairchild, 2010). We also expected that the current tech-dependence shift in most of daily life activities would lead to positive market expectation on the growth of ICT and ICT-related sectors and stable future cash flows that would manifested into higher dividend payments by the companies (Bhattacharya, 1979; John & Williams (1985); Bradley et al., 1998; Brook et al., 1998). Despite the fact that the ICT and ICT related companies have benefited from the pandemic as proven by the results in *H1*, it is assumed that the financial restriction of having to fund the R&D projects mainly with internal cash may still become the reason why *RDI* is lower when *DPR* is higher which supports the findings of Bloch (2005), Eng & Shackell (2001), and Qu (2020). Financial constraint would limit managers' flexibilities in utilizing the cash. They need to appropriately allocate it into cash dividends, R&D projects, or hold it as idle cash as precautionary measure.

The control variables show a highly significant negative relationship at 1% of *TotalAssets*, *TobinsQ*, and *PositiveCF*; and positive relationship of *Lev* and *Profit* on *RDI*. *TotalAssets* and *TobinsQ* indicate that the higher their values are, the lower companies would invest in R&D projects which is consistent with the results in *H1* and Jung & Kwak (2018)'s study. *PositiveCF* expresses a positive balance of cash, which the results report to have a negative impact on *RDI*. This finding is in line with Brown & Peterson (2011) who discovered that there is a negative link between maintaining cash balance and R&D, especially during the bubble period market crash. However, our results do not find any significance on *CashHolding*. The results for *Lev* and *Profit* are consistent with those of *H1*.

Table 8 shows our robustness results using an alternative proxy of *OCF* for *DPR*. This proxy is modified from Beladi et al. (2021) to identify positive operating cash flow as a projection of low cash flow uncertainty. We did not encounter any statistical significance to imply that changes in operating cash flow would have any impact on *RDI*. We found that *DPR* is more appropriate to signify cash flow uncertainty as elaborated in Bhattacharya (1979)'s and John & Williams (1985)'s studies.

7. Limitations

Although we have made a number of improvements to our basic models to check the validity and robustness of our results, our regression analysis may still have some shortcomings. First, the main explanatory variable used in *H1* for market uncertainty caused by COVID-19 is market beta, which reflects the sum of raw beta and inflation. This proxy may not be the best indicator of market uncertainty as there are many other methods to calculate the systematic risk of the market, such as the Capital Asset Pricing Model (CAPM), the beta bottom-up approach, the Fama & French Three Factor Model (FF3), and the Fama & French Five Factor Model (FF5). Moreover, estimating beta is a comprehensive and complicated process. Beta results may vary due to variations in estimation.

Second, referring to Kulatilaka & Perotti (1998), real options theory is based on two specific assumptions, namely that a firm has a monopoly on an investment opportunity and that its actions do not affect prices or market structure. These assumptions can be useful when product markets are less competitive or monopolistic, such as in the commodity industry. Due to these limitations of real options theory, the current literature in this study has relaxed these assumptions to examine the impact of uncertainty on a company's investment decision.

Lastly, our study could only complement previous findings, specifically in the ICT and ICT-related sectors, without exploring causal relationship that it may have. Adding qualitative measurements to seek causal relationship, such as managers' tendencies in choosing cash disbursement outlets in times of crisis, could enrich our insights on management choices in regard to R&D investments funded by internal cash. This qualitative approach can provide a more comprehensive view on cash flow uncertainty and its indirect influence on agency issues related to cash allocation.

8. Conclusion

From previous studies by Van Vo & Le (2017) and Beladi et al. (2021) on the impact of uncertainty on R&D investment, we develop this study with the aim of observing the impact of market and cash flow uncertainty caused by the COVID-19 global health pandemic on the R&D investment of companies in the ICT and ICT-related sector. We further intend to exhibit the notion of ICT companies' ability to develop new products and services that would provide a competitive advantage in the changing digital landscape after the global pandemic. R&D activities are a source of innovation that leads to productivity and economic growth. Therefore, we amplify the literature on growth options which is one of the distinguishing factors that R&D investment has over other types of investment by a company. The presence of a growth option is a key factor that distinguishes the impact of market uncertainty on R&D investment from other types of investment.

Based on our results, we found a positive correlation between market uncertainty and R&D investment of ICT companies with a reasonably significant result at 5% confidence level. We also tested for moderating impact of size, proxied by total assets, to see whether companies' size could influence management decisions on the R&D investment during market uncertainty caused by COVID-19. Our findings show that there is no evidence that company size has a moderating effect towards R&D investment through market uncertainty. The research results present that increasing innovation capacity is a factor that promotes R&D investment regardless of company size, and that size is more likely to be a factor that hinders R&D investment in companies with high innovation capacity. Additionally, large companies with high absorptive capacity can easily and quickly mimic the results of their competitors' innovations, which may increase the incentive to defer R&D investment under market uncertainty as competitors would employ the similar strategy. An interesting fact from our regression result from *H1* is that *ROS*, *Profit*, and *Lev* are more important than size in maximizing the value of growth options associated with R&D activities.

The results from the moderating effect of COVID-19 on R&D investment show that COVID-19 has a negative impact on ICT and ICT-related firms and on all industries worldwide. However, high-tech companies play an important role in reducing the impact of COVID-19 by developing technological capabilities, products, and services through their R&D activities. Moreover, by intensifying their R&D efforts, high-tech companies can efficiently penetrate the market and benefit from economic growth, especially when they are under greater pressure to survive in a competitive market and have a greater incentive to expand their competitive advantage. Thus, our *H1* results prove that market uncertainty induced by COVID-19 favors R&D investments of ICT companies, which belong in a highly competitive sector, and offset the negative impacts of the pandemic.

Additionally, we also seek to observe the impact of cash flow uncertainty induced by COVID-19 on R&D investments. We use dividend payment ratio as the proxy for cash flow uncertainty due to its signalling effect on company's future cash flows and earnings prospects. Our results are aligned with the findings of previous research that show dividend payment ratio correlates negatively with R&D investment. On the contrary, this verdict opposes our initial prediction of having a positive relationship between dividend payments and R&D investment. Reflecting upon the increasing demand of technology due to rapid digital transformation induced by COVID-19, we expected a linear effect on payout ratio, as a signal of stable future cash flow, and R&D investments, as an effort to gain benefit of the new circumstance. The results reject our hypothesis and stand consistent with previous studies which have not covered ICT and ICT-related sectors specifically.

The unexpected outcome can be explained by the pecking order theory. Companies prefer to rely on internal funding to finance investments as it is cheaper and more accessible than external funding. Consequently, limited internal cash balance becomes the underlying attribute that resulted in a negative relationship between dividends payment and R&D investments. Managers need to allocate company's cash to either pay dividends or invest in innovative projects, triggering a potential agency issue. In relation to agency cost, stockholders would expect higher dividends to ensure managers not to use the cash to invest in negative-value projects.

To the best of our knowledge, this is the first empirical paper that tests market uncertainty caused by COVID-19 to investigate the relationship between uncertainties impacting R&D investments during COVID-19 in the ICT and ICT-related industries. Consistent with the theories, we prove that market uncertainty and high competition are the main drivers of the positive relationship between uncertainty and R&D investment of technology companies. Furthermore, we did not find any anomaly concerning internal funding for R&D investments in the ICT and ICT-related sectors despite the significant increase of technology usages during the observed periods.

Appendix

Table 1. Variable definitions

Variables	Definition
Dependent:	
RDI	R&D expenditures divided by operating income
Main explanatory:	
Beta	Weekly market data for the past two years adjusted using the assumption that the beta moves toward the market average (0.666 * raw beta + 0.333 * 1.0)
DPR	Dividend paid divided by total assets
Control:	
TotalAssets	Total assets of the company, in logged value
CF	Net changes in cash divided by total assets
ROS	Net income divided by total sales
Lev	Total debt divided by total assets
Profit	Net income for the year, in logged value
Tobin'sQ	Market value divided by total assets, in logged value
StockYield	Reinvestment rate, in logged value
CashHolding	Total of cash and cash equivalents divided by total assets
Dummy:	
PositiveCF	Value of 1 is assigned if the company has a positive cash balance, and 0 otherwise
COVID	Value of 1 is assigned for samples in fiscal year 2020-2022, and 0 for fiscal year 2018-2019
Large	Value of 1 is assigned for samples with total assets higher than the mean value, and 0 otherwise
Interaction:	
BetaxCOVID	Variables generated to see the influence of COVID-19 on market uncertainty
BetaxLarge	Variable generated to see the influence of company's size on market uncertainty
DPRxCOVID	Variable generated to see the influence of COVID-19 on cash flow uncertainty
Alternative proxies:	
Volatility	Standard deviation of daily logarithmic historical price changes from January 1st to December 31st of each fiscal year
OCF	Operating cash flow divided by total assets

Table 2. Sample distribution

Panel A: Sectoral distribution				
GICS Sector	**GICS Industry**	**GICS Sub-industry**	**Number of Samples**	**Proportion**
ICT	Electronic Equipment, Instruments & Components	Electronic Components	1,665	9%
ICT	Electronic Equipment, Instruments & Components	Electronic Equipment & Instruments	1,348	7%
ICT	Semiconductors & Semiconductor Equipment	Semiconductors	1,333	7%
ICT	IT Services	IT Consulting & Other Services	1,288	7%
ICT	Software & Services	Application Software	1,158	6%
ICT	Communications Equipment	Communications Equipment	899	5%
ICT	Semiconductors & Semiconductor Equipment	Semiconductor Equipment	822	5%
ICT	Technology Hardware, Storage & Peripherals	Technology Hardware, Storage & Peripherals	694	4%
ICT	Electronic Equipment, Instruments & Components	Technology Distributors	707	4%
ICT	Software	Systems Software	426	2%
ICT	Electronic Equipment, Instruments & Components	Electronic Manufacturing Services	270	1%
ICT	IT Services	Internet Services & Infrastructure	158	1%
Subtotal ICT			**10,768**	**60%**

GICS Sector	GICS Industry	GICS Sub-industry	Number of Samples	Proportion
Communication Services	Media	Advertising	1,060	6%
Communication Services	Entertainment	Movies & Entertainment	993	5%
Communication Services	Interactive Media & Services	Interactive Media & Services	899	5%
Communication Services	Entertainment	Interactive Home Entertainment	864	5%
Communication Services	Media	Publishing	717	4%
Communication Services	Diversified Telecommunication Services	Integrated Telecommunication Services	662	4%
Communication Services	Media	Broadcasting	474	3%
Communication Services	Wireless Telecommunication Services	Wireless Telecommunication Services	372	2%
Communication Services	Diversified Telecommunication Services	Alternative Carriers	261	1%
Communication Services	Media	Cable & Satellite	193	1%
Subtotal Communication Services			**6,495**	**36%**
Consumer Discretionary	Broadline Retail	Broadline Retail	792	4%
Grand Total			**18,055**	**100%**

Panel B: Country distribution		
Country	Number of Samples	Proportion
Japan	3,439	19%
China	3,115	17%
Taiwan	2,782	15%
United States	1,361	8%
South Korea	1,256	7%
India	563	3%
Hong Kong	555	3%
United Kingdom	456	3%
Australia	383	2%
Sweden	348	2%
Germany	308	2%
Thailand	271	2%
Malaysia	266	1%
Canada	265	1%
France	232	1%
Indonesia	207	1%
Singapore	193	1%
Israel	172	1%
Italy	148	1%
Poland	137	1%
Vietnam	120	1%
Finland	115	1%
Others	1,363	8%
Total	18,055	100%

Panel C: Yearly distribution		
Year	Number of Samples	Proportion
2018	4,735	26%
2019	3,684	20%
2020	3,660	20%
2021	3,902	22%
2022	2,074	11%
Total	18,055	100%

Table 3. Summary Statistics

Variables	Mean	Median	Standard Deviation	Max	Min
Dependent:					
RDI	-1.309	0.000	4.300	4.642	-29.932
Main explanatory:					
Beta	0.897	0.906	0.352	1.877	0.010
DPR	-0.023	-0.009	0.040	0.000	-0.266
Control:					
TotalAssets (in mio USD)	2,345.467	210.518	8,507.424	67,443.330	1.761
CF	0.016	0.008	0.112	0.469	-0.362
ROS	-0.047	0.053	0.628	0.600	-4.936
Lev	0.158	0.111	0.159	0.637	0.000
Profit (in mio USD)	106.409	6.562	460.209	3,646.840	-339.000
TobinsQ	0.099	0.047	0.927	2.478	-2.560
StockYield	1.301	1.416	1.261	4.203	-1.723
CashHolding	0.222	0.173	0.183	0.815	0.003
PositiveCF	0.570	1.000	0.495	1.000	0.000
COVID	0.534	1.000	0.499	1.000	0.000
Large	0.137	1.000	0.344	1.000	0.000

The table reports descriptive statistics on 18,055 firm-year observations representing 5,934 individual firms from 91 countries over the period 2018-2022. ***RDI*** is calculated by R&D expenditures divided by operating income. ***Beta*** is derived from the past two years of weekly data, adjusted using the assumption that the beta moves toward the market average (0.666 * raw beta + 0.333 * 1.0). ***DPR*** is dividend paid divided by total assets. ***TotalAssets*** represents the size of the company in million USD. ***CF*** is calculated by using net changes in cash divided by total assets. ***ROS*** is net income divided by total sales. ***Lev*** is total debt divided by total assets. ***Profit*** is the net income for the year, shown in million USD. ***TobinsQ*** is the logged value of market value divided by total assets. ***StockYield*** is the logged value of reinvestment ratio. ***CashHolding*** is the total of cash and cash equivalents divided by total assets. ***PositiveCF*** is a dummy variable that represents a positive cash balance if valued as 1 and 0 otherwise. ***COVID*** is a dummy variable that represents a period of COVID-19 pandemic (2020-2022) if valued as 1 and 0 for pre-pandemic (2018-2019). ***Large*** is a dummy variable that represents company sizes that are above the mean if valued as 1 and 0 otherwise.

Table 4. Correlation

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) RDI	1.000										
(2) Beta	-0.088	1.000									
(3) DPR	-0.072	0.017	1.000								
(4) CF	-0.021	0.044	0.053	1.000							
(5) TotalAssets	-0.087	0.252	-0.002	-0.027	1.000						
(6) ROS	-0.035	0.073	-0.141	0.033	0.230	1.000					
(7) Leverage	-0.031	0.040	0.127	-0.060	0.311	-0.006	1.000				
(8) Profit	-0.014	0.209	-0.181	0.037	0.747	0.277	0.065	1.000			
(9) TobinsQ	-0.077	0.143	-0.156	0.117	-0.022	-0.013	-0.012	0.154	1.000		
(10) StockYield	0.010	0.120	-0.065	0.178	0.131	0.284	-0.058	0.508	0.230	1.000	
(11) CashHolding	0.017	0.031	-0.062	0.363	-0.306	-0.038	-0.370	-0.136	0.101	0.076	1.000

The table reports pairwise correlation results on 18,055 firm-year observations representing 5,934 individual firms from 91 countries over the period 2018-2022. ***RDI*** is calculated by R&D expenditures divided by operating income. ***Beta*** is derived from the past two years of weekly data, adjusted using the assumption that the beta moves toward the market average (0.666 * raw beta + 0.333 * 1.0). ***DPR*** is dividend paid divided by total assets. ***TotalAssets*** represents the size of the company in million USD. ***CF*** is calculated by using net changes in cash divided by total assets. ***ROS*** is net income divided by total sales. ***Lev*** is total debt divided by total assets. ***Profit*** is the net income for the year, shown in million USD. ***TobinsQ*** is the logged value of market value divided by total assets. ***StockYield*** is the logged value of reinvestment ratio. ***CashHolding*** is the total of cash and cash equivalents divided by total assets.

Table 5. Regression results *H1* & *H2*

Models	(1a)	(1b)	(2)
Variables	**RDI**	**RDI**	**RDI**
Beta	0.244**	0.245**	0.252**
	(0.117)	(0.117)	(0.118)
COVID		-0.136**	
		(0.058)	
BetaxCOVID		0.000	
		(0.000)	
Large			-0.362
			(0.361)
BetaxLarge			-0.000*
			(0.000)
CF	-0.675***	-0.672***	-0.677***
	(0.236)	(0.237)	(0.236)
DPR	-2.600***	-2.621***	-2.583***
	(0.883)	(0.886)	(0.882)
TotalAssets	-0.587***	-0.586***	-0.563***
	(0.146)	(0.146)	(0.144)
ROS	0.158***	0.157***	0.157***
	(0.059)	(0.059)	(0.059)
Lev	1.854***	1.866***	1.852***
	(0.462)	(0.463)	(0.462)
Profit	0.144***	0.144***	0.144***
	(0.038)	(0.038)	(0.037)
TobinsQ	-0.481***	-0.482***	-0.481***
	(0.070)	(0.070)	(0.070)
Constant	0.670	0.732	0.586
	(0.788)	(0.789)	(0.780)
Observations		18,055	
Number of Company		5,934	
Sub-industry Controls		Yes	
Year Controls		Yes	
Standard Errors		Clustered robust	
R-squared	0.129	0.130	0.130

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The table reports regression estimates on 18,055 firm-year observations representing 5,934 individual firms from 91 countries over the period 2018-2022.
RDI is calculated by R&D expenditures divided by operating income.
Beta is derived from the past two years of weekly data, adjusted using the assumption that the beta moves toward the market average (0.666 * raw beta + 0.333 * 1.0).
COVID is a dummy variable that represents a period of COVID-19 pandemic (2020-2022) if valued as 1 and 0 for pre-pandemic (2018-2019).
BetaxCOVID is interaction variable to observe the influence of COVID-19 period to market uncertainty.
Large is a dummy variable that represents company sizes that are aboved the mean if valued as 1 and 0 otherwise.
BetaxLarge is interaction variable to observe the size effect of the companies to market uncertainty.
DPR is dividend paid divided by total assets.
TotalAssets represents the size of the company in logged value.
CF is calculated by using net changes in cash divided by total assets.
ROS is net income divided by total sales.
Lev is total debt divided by total assets.
Profit is the net income for the year, in logged values.
TobinsQ is the logged value of market value divided by total assets.

Table 6. Robustness test results *H1* & *H2*

Model	(1a)	(1b)	(2)
Variables	**RDI**	**RDI**	**RDI**
Volatility	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)
CF	-0.720***	-0.718***	-0.722***
	(0.239)	(0.239)	(0.239)
DPR	-2.643***	-2.664***	-2.631***
	(0.882)	(0.885)	(0.881)
TotalAssets	-0.551***	-0.549***	-0.527***
	(0.145)	(0.145)	(0.143)
ROS	0.157***	0.153***	0.157***
	(0.059)	(0.060)	(0.059)
Lev	1.821***	1.825***	1.821***
	(0.462)	(0.463)	(0.462)
Profit	0.145***	0.146***	0.146***
	(0.038)	(0.038)	(0.038)
Tobin'sQ	-0.482***	-0.482***	-0.480***
	(0.070)	(0.070)	(0.070)
COVID		-0.166**	
		(0.068)	
VolxCOVID		0.001	
		(0.001)	
Large			-0.477
			(0.367)
VolxLarge			0.002
			(0.003)
Constant	0.582	0.659	0.514
	(0.804)	(0.805)	(0.796)
Observations		18,055	
Number of Company		5,934	
Sub-industry Controls		Yes	
Year Controls		Yes	
Standard Errors		Clustered robust	
R-squared	0.129	0.130	0.129

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The table reports regression estimates for robustness tests on 18,055 firm-year observations representing 5,934 individual firms from 91 countries over the period 2018-2022.
RDI is calculated by R&D expenditures divided by operating income.
Volatility is the alternative proxy for the main variable *Beta,* calculated from the standard deviation of daily logarithmic historical price changes from January 1st to December 31st of each fiscal year.
DPR is dividend paid divided by total assets.
TotalAssets represents the size of the company in logged value.
CF is calculated by using net changes in cash divided by total assets.
ROS is net income divided by total sales.
Lev is total debt divided by total assets.
Profit is the net income for the year, in logged values.
TobinsQ is the logged value of market value divided by total assets.
COVID is a dummy variable that represents a period of COVID-19 pandemic (2020-2022) if valued as 1 and 0 for pre-pandemic (2018-2019).
VolxCOVID is an interaction variable to observe the influence of COVID-19 period to market uncertainty using the alternative proxy.
Large is a dummy variable that represents company sizes that are above the mean if valued as 1 and 0 otherwise.
VolxLarge is an interaction variable to observe the size effect of the companies to market uncertainty using the alternative proxy.

Table 7. Regression results *H3*

Models	(3a)	(3b)
Variables	**RDI**	**RDI**
DPR	-2.707***	-2.698***
	(0.887)	(0.902)
COVID		-0.136**
		(0.058)
DPRxCOVID		-0.004
		(0.003)
TotalAssets	-0.555***	-0.554***
	(0.144)	(0.144)
Tobin'sQ	-0.479***	-0.479***
	(0.070)	(0.070)
Lev	1.832***	1.842***
	(0.463)	(0.464)
Profit	0.148***	0.149***
	(0.042)	(0.042)
PositiveCF	-0.170***	-0.169**
	(0.066)	(0.066)
StockYield	0.013	0.012
	(0.038)	(0.038)
CashHolding	0.096	0.094
	(0.408)	(0.408)
Constant	0.748	0.811
	(0.800)	(0.801)
Observations	18,055	
Number of Company	5,934	
Sub-industry Controls	Yes	
Year Controls	Yes	
Standard Errors	Clustered robust	
R-squared	0.129	0.130

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The table reports regression estimates on 18,055 firm-year observations representing 5,934 individual firms from 91 countries over the period 2018-2022.
RDI is calculated by R&D expenditures divided by operating income.
DPR is dividend paid divided by total assets.
COVID is a dummy variable that represents a period of COVID-19 pandemic (2020-2022) if valued as 1 and 0 for pre-pandemic (2018-2019).
DPRxCOVID is an interaction variable to observe the influence of COVID-19 period to cash flow uncertainty.
TotalAssets represents the size of the company in logged value.
TobinsQ is the logged value of market value divided by total assets.
Lev is total debt divided by total assets.
Profit is the net income for the year, in logged values.
PositiveCF is a dummy variable valued as 1 for positive cash balance and 0 otherwise.
StockYield is the log value of reinvestment rate.
CashHolding is the ratio of cash and cash equivalent to total assets.

Table 8. Robustness tests results *H3*

Model	(3a)	(3b)
Variables	**RDI**	**RDI**
OCF	0.231	0.122
	(0.391)	(0.405)
TotalAssets	-0.581***	-0.582***
	(0.146)	(0.147)
Tobin'sQ	-0.475***	-0.475***
	(0.070)	(0.070)
Lev	1.828***	1.841***
	(0.470)	(0.470)
Profit	0.156***	0.157***
	(0.041)	(0.041)
PositiveCF	-0.186***	-0.184***
	(0.067)	(0.067)
StockYield	0.003	0.003
	(0.038)	(0.038)
CashHolding	0.091	0.09
	(0.415)	(0.414)
COVID		-0.146**
		(0.063)
OCFxCOVID		0.177
		(0.242)
Constant	0.948	1.033
	(0.809)	(0.812)
Observations	18,055	
Number of Company	5,934	
Sub-industry Controls	Yes	
Year Controls	Yes	
Standard Errors	Clustered robust	
R-squared	0.129	0.129

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The table reports regression estimates for robustness tests on 18,055 firm-year observations representing 5,934 individual firms from 91 countries over the period 2018-2022.
RDI is calculated by R&D expenditures divided by operating income.
OCF is the alternative proxy for main variable *DPR*, calculated as operating cash flow divided by total assets.
TotalAssets represents the size of the company in logged value.
TobinsQ is the logged value of market value divided by total assets.
Lev is total debt divided by total assets.
Profit is the net income for the year, in logged values.
PositiveCF is dummy variable valued as 1 for positive cash balance and 0 otherwise.
StockYield is the log value of reinvestment rate.
CashHolding is the ratio of cash and cash equivalent to total assets.
COVID is a dummy variable that represents a period of COVID-19 pandemic (2020-2022) if valued as 1 and 0 for pre-pandemic (2018-2019).
OCFxCOVID is interaction variable to observe the influence of COVID-19 period to cash flow uncertainty.

Table 9. Heteroskedasticity results for *H1* and *H3*

White's test for *H1*
H_0: Homoskedasticity
H_a: Unrestricted heteroskedasticity

chi2(44) = 695.26
Prob > chi2 = 0.0000
Cameron & Trivedi's decomposition of IM-test

chi2	df	p
695.260	44	0.000
603.460	8	0.000
300.990	1	0.000
1599.72	53	0.000

White's test for *H3*
H0: Homoskedasticity
Ha: Unrestricted heteroskedasticity

chi2(43) = 677.02
Prob > chi2 = 0.0000
Cameron & Trivedi's decomposition of IM-test

chi2	df	p
677.020	43	0.000
602.380	8	0.000
302.070	1	0.000
1581.46	52	0.000

Table 10. Hausman (1978) specification test

Hausman (1978) specification test for H1

	Coef.
Chi-square test value	273.381
P-value	0

Hausman (1978) specification test for H2

	Coef.
Chi-square test value	258.61
P-value	0

Table 11. Durbin–Wu–Hausman test for *H1*

hsng_res	=	0
F (1, 18045)	=	0.21
Prob > F	=	0.6439

Table 12. Durbin–Wu–Hausman test for *H3*

hsng_res1	=	0
F (1, 18045)	=	1.13
Prob > F	=	0.2874

References

Abel, A.B. and Eberly, J.C., 1996. Optimal investment with costly reversibility. *The Review of Economic Studies*, *63*(4), pp.581-593.

Abel, A.B., Dixit, A.K., Eberly, J.C. and Pindyck, R.S., 1996. Options, the value of capital, and investment. *The quarterly Journal of economics*, *111*(3), pp.753-777.

Bachmann, R., Elstner, S. and Sims, E.R., 2013. Uncertainty and economic activity: Evidence from business survey data. *American Economic Journal: Macroeconomics*, *5*(2), pp.217-249.

Baker, S.R., Bloom, N., Davis, S.J. and Terry, S.J., 2020. *Covid-induced economic uncertainty* (No. w26983). National Bureau of Economic Research.

Banga, K. and te Velde, D.W., 2020. COVID-19 and disruption of the digital economy; evidence from low and middle-income countries. *Digital Pathways at Oxford Paper Series*, *7*.

Barrero, J.M., Bloom, N. and Wright, I., 2017. *Short and long run uncertainty* (No. w23676). National Bureau of Economic Research.

Bhattacharya, S., 1979. Imperfect information, dividend policy, and" the bird in the hand" fallacy. *The bell journal of economics*, pp.259-270.

Beladi, H., Deng, J. and Hu, M., 2021. Cash flow uncertainty, financial constraints and R&D investment. *International Review of Financial Analysis*, *76*, p.101785.

Bloch, C., 2005. R&D investment and internal finance: The cash flow effect. *Economics of Innovation and New Technology*, *14*(3), pp.213-223.

Bradley, M., Capozza, D.R. and Seguin, P.J., 1998. Dividend policy and cash-flow uncertainty. *Real Estate Economics*, *26*(4), pp.555-580.

Brook, Y., Charlton Jr, W.T. and Hendershott, R.J., 1998. Do firms use dividends to signal large future cash flow increases?. *Financial Management*, pp.46-57.

Brown, J.R. and Petersen, B.C., 2011. Cash holdings and R&D smoothing. *Journal of Corporate Finance*, *17*(3), pp.694-709.

Bonaccorsi, A., 1992. On the relationship between firm size and export intensity. *Journal of international business studies*, *23*, pp.605-635.

Calof, J.L., 1993. The mode choice and change decision process and its impact on international performance. *International Business Review*, *2*(1), pp.97-120.

Canarella, G. and Miller, S.M., 2018. The determinants of growth in the US information and communication technology (ICT) industry: A firm-level analysis. *Economic Modelling*, *70*, pp.259-271.

Castka, P., Searcy, C. and Fischer, S., 2020. Technology-enhanced auditing in voluntary sustainability standards: The impact of COVID-19. *Sustainability*, *12*(11), p.4740.

Chandra, M., Kumar, K., Thakur, P., Chattopadhyaya, S., Alam, F. and Kumar, S., 2022. Digital technologies, healthcare and COVID-19: Insights from developing and emerging nations. *Health and Technology*, *12*(2), pp.547-568.

Chay, J.B. and Suh, J., 2009. Payout policy and cash-flow uncertainty. *Journal of Financial Economics*, *93*(1), pp.88-107.

Cotei, C. and Farhat, J.B., 2009. The trade-off theory and the pecking order theory: are they mutually exclusive?. *Available at SSRN 1404576*.

De Jong, A. and Verwijmeren, P., 2010. To have a target debt ratio or not: what difference does it make?. *Applied Financial Economics*, *20*(3), pp.219-226.

De Vet, J.M., Nigohosyan, D., Ferrer, J.N., Gross, A.K., Kuehl, S. and Flickenschild, M., 2021. *Impacts of the COVID-19 pandemic on EU industries* (pp. 1-86). Strasbourg, France: European Parliament.

Deev, O. and Plíhal, T., 2022. How to calm down the markets? The effects of COVID-19 economic policy responses on financial market uncertainty. *Research in International Business and Finance*, *60*, p.101613.

Del Canto, J.G. and Gonzalez, I.S., 1999. A resource-based analysis of the factors determining a firm's R&D activities. *Research Policy*, *28*(8), pp.891-905.

Dixit, A.K. and Pindyck, R.S., 1994. *Investment under uncertainty*. Princeton university press.

Donaldson, G., 2000. *Corporate debt capacity: A study of corporate debt policy and the determination of corporate debt capacity*. Beard Books.

Dong, M., Loncarski, I., Horst, J.T. and Veld, C., 2012. What drives security issuance decisions: Market timing, pecking order, or both?. *Financial Management*, *41*(3), pp.637-663.

Durbin, J., 1954. Errors in variables. *Revue de l'institut International de Statistique*, pp.23-32.

Eng, L.L. and Shackell, M., 2001. The implications of long-term performance plans and institutional ownership for firms' research and development (R&D) investments. *Journal of Accounting, Auditing & Finance*, *16*(2), pp.117-139.

Fairchild, R., 2010. Dividend policy, signalling and free cash flow: an integrated approach. *Managerial Finance*, *36*(5), pp.394-413.

Fisher, I., 1906. *The nature of capital and income*. Macmillan.

Frank, M.Z. and Goyal, V.K., 2003. Testing the pecking order theory of capital structure. *Journal of financial economics*, *67*(2), pp.217-248.

Hail, L., Tahoun, A. and Wang, C., 2014. Dividend payouts and information shocks. *Journal of Accounting Research*, *52*(2), pp.403-456.

Hamilton, B.H. and Nickerson, J.A., 2003. Correcting for endogeneity in strategic management research. *Strategic organization*, *1*(1), pp.51-78.

Hausman, J.A., 1978. Specification tests in econometrics. *Econometrica: Journal of the econometric society*, pp.1251-1271.

He, H. and Harris, L., 2020. The impact of Covid-19 pandemic on corporate social responsibility and marketing philosophy. *Journal of business research*, *116*, pp.176-182.

IMF, 2020. The Great Lockdown: Worst Economic Downturn Since the Great Depression. Available online: https://blogs.imf.org/2020/04/14/the-great-lockdown-worst-economic-downturn-since-the-great-depression/ [Accessed 24 May 2023].

John, K. and Williams, J., 1985. Dividends, dilution, and taxes: A signalling equilibrium. *the Journal of Finance*, *40*(4), pp.1053-1070.

Jorgenson, D.W. and Stiroh, K.J., 1999. Information technology and growth. *American Economic Review*, *89*(2), pp.109-115.

Jung, S. and Kwak, G., 2018. Firm characteristics, uncertainty and research and development (R&D) investment: The role of size and innovation capacity. *Sustainability*, *10*(5), p.1668.

Kang, W., Lee, K. and Ratti, R.A., 2014. Economic policy uncertainty and firm-level investment. *Journal of Macroeconomics*, *39*, pp.42-53.

Khan, M.A., Qin, X., Jebran, K. and Ullah, I., 2020. Uncertainty and R&D investment: Does product market competition matter?. *Research in International Business and Finance*, *52*, p.101167.

Kim, Y.J. and Sanders, G.L., 2002. Strategic actions in information technology investment based on real option theory. *Decision Support Systems*, *33*(1), pp.1-11.

Knight, F.H., 1921. *Risk, uncertainty and profit* (Vol. 31). Houghton Mifflin.

Komera, S. and Lukose PJ, J., 2015. Capital structure choice, information asymmetry, and debt capacity: evidence from India. *Journal of Economics and Finance*, *39*, pp.807-823.

Kulatilaka, N. and Perotti, E.C., 1998. Strategic growth options. *Management Science*, *44*(8), pp.1021-1031.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A. and Vishny, R.W., 2000. Agency problems and dividend policies around the world. *The journal of finance*, *55*(1), pp.1-33.

Lai, Y.L., Lin, F.J. and Lin, Y.H., 2015. Factors affecting firm's R&D investment decisions. *Journal of Business Research*, *68*(4), pp.840-844.

Leiblein, M.J., 2003. The choice of organizational governance form and performance: Predictions from transaction cost, resource-based, and real options theories. *Journal of management*, *29*(6), pp.937-961.

Lemmon, M.L. and Zender, J.F., 2010. Debt capacity and tests of capital structure theories. *Journal of Financial and Quantitative Analysis*, *45*(5), pp.1161-1187.

Li, K. and Zhao, X., 2008. Asymmetric information and dividend policy. *Financial management*, *37*(4), pp.673-694.

Lin, Y., Dong, D. and Wang, J., 2021. The negative impact of uncertainty on R&D investment: international evidence. *Sustainability*, *13*(5), p.2746.

Lintner, J., 1956. Distribution of incomes of corporations among dividends, retained earnings, and taxes. *The American economic review*, *46*(2), pp.97-113.

Miller, M.H. and Rock, K., 1985. Dividend policy under asymmetric information. *The Journal of finance*, *40*(4), pp.1031-1051.

MSCI, 2023. Revision to the global industry classification standard (GICS®) structure effective March, 2023. Available online: https://www.msci.com/documents/1296102/29559863/GICS_Structure_Change_Doc_31_March_2022.pdf/d2437e6d-9ae5-0bad-c758-9e2a5f917a69?t=1648760449996 [Accessed 10 May 2023].

Moh'd, M.A., Perry, L.G. and Rimbey, J.N., 1995. An investigation of the dynamic relationship between agency theory and dividend policy. *Financial Review*, *30*(2), pp.367-385.

Morbey, G.K., 1988. R&D: Its relationship to company performance. *Journal of Product Innovation Management: An international publication of the product development & management association*, *5*(3), pp.191-200.

Morris, R.D., 1987. Signalling, agency theory and accounting policy choice. *Accounting and business Research*, *18*(69), pp.47-56.

Myers, S.C., 2001. Capital structure. *Journal of Economic perspectives*, *15*(2), pp.81-102.

Myers, S.C., 1984. Capital structure puzzle.

Myers, S.C. and Majluf, N.S., 1984. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of financial economics*, *13*(2), pp.187-221.

OECD, 2020. The territorial impact of COVID-19: Managing the crisis across levels of government. Available online: https://read.oecd-ilibrary.org/view/?ref=128_128287-5agkkojaaa&title=The-territorial-impact-of-covid-19-managing-the-crisis-across-levels-of-government [Accessed 10 May 2023].

Pham, L.T.M., Van Vo, L., Le, H.T.T. and Le, D.V., 2018. Asset liquidity and firm innovation. *International review of financial analysis*, *58*, pp.225-234.

Pindyck, R.S., 1990. Irreversibility, uncertainty, and investment.

Qu, J., 2020. Uncertainty of cash flow and corporate innovation. *Modern Economy*, *11*(4), pp.881-893.

Rozeff, M.S., 1982. Growth, beta and agency costs as determinants of dividend payout ratios. *Journal of financial Research*, *5*(3), pp.249-259.

Samuelson, P.A., 1961. The evaluation of 'Social income': Capital formation and wealth. In *The Theory of Capital: Proceedings of a Conference held by the International Economic Association* (pp. 32-57). London: Palgrave Macmillan UK.

Scherpereel, C.M., 2008. The option-creating institution: a real options perspective on economic organization. *Strategic Management Journal*, *29*(5), pp.455-470.

Schwartz, E., 2013. The real options approach to valuation: Challenges and opportunities. *Latin american journal of economics*, *50*(2), pp.163-177.

Segal, G., Shaliastovich, I. and Yaron, A., 2015. Good and bad uncertainty: Macroeconomic and financial market implications. *Journal of Financial Economics*, *117*(2), pp.369-397.

Semadeni, M., Withers, M.C. and Trevis Certo, S., 2014. The perils of endogeneity and instrumental variables in strategy research: Understanding through simulations. *Strategic Management Journal*, *35*(7), pp.1070-1079.

Sibande, L., Bailey, A. and Davidova, S., 2017. The impact of farm input subsidies on maize marketing in Malawi. Food Policy, 69, pp.190-206.

Stewart, D.W., 2021. Uncertainty and risk are multidimensional: Lessons from the COVID-19 pandemic. *Journal of Public Policy & Marketing*, *40*(1), pp.97-98.

Van Vo, L. and Le, H.T.T., 2017. Strategic growth option, uncertainty, and R&D investment. *International Review of Financial Analysis*, *51*, pp.16-24.

Watanabe, M., 2008. Price volatility and investor behavior in an overlapping generations model with information asymmetry. *The Journal of Finance*, *63*(1), pp.229-272.

Wooldridge, J.M., 2010. *Econometric analysis of cross section and panel data*. MIT press.

Wu, S., 1973. Polar and nonpolar interactions in adhesion. *The Journal of Adhesion*, *5*(1), pp.39-55.

UNCTD, 2022. SDG Pulse 2022: UNCTD takes the pulse of the SDGs, pp. 113-119. Available online: https://unctad.org/system/files/official-document/stat2022d1_en.pdf [Accessed 10 May 2023].