Cost stickiness in R&D-intensive firms and its effect on the informativeness of earnings

By

WALAA SAMIR GHAZY

M.S., Al-Azhar University, Egypt, 2005

PhD, Al-Azhar University, Egypt, 2013

A thesis submitted to

Auckland University of Technology

in fulfilment of the requirements for the degree of

Doctor of Philosophy (PhD)

2023

Faculty of Business, Economics and Law

Department of Accounting

Abstract

Innovation in new products and processes has become increasingly important for companies to achieve and maintain their competitive advantage in the current rapidly changing environment. This thesis aims to investigate cost stickiness behaviour in research and development (R&D) firms[1] and examine the determinants and consequences of this behaviour. The thesis includes three related empirical studies on cost stickiness in R&D firms. The first study uses the evolutionary theory of the firm to investigate whether R&D intensity is a determinant of cost stickiness. The evolutionary theory of the firm integrates the implications of innovative activity characteristics, notably features of entrepreneurial and experiential behaviour, for resource allocation decisions. According to this theory, the firm is an adaptive entity that develops and adapts its competencies and processes to the changes in its environment. The results reveal a statistically significant positive association between R&D intensity and cost stickiness. Further analysis confirms that the positive association between R&D intensity and cost stickiness prevails only in R&D-intensive firms. These results support the propositions of the evolutionary theory of the firm that innovative firms tend to retain the allocated resources when demand falls to preserve the firm's organisational memory and to reduce interorganisational conflict between the members of the firm. Simultaneously, managers of these firms redirect the existing resources towards searching for an alternative routine to cope with the adverse market conditions, which increases cost stickiness.

[1] In this research, I am using R&D firms to indicate firms engaged in research and development activities, and I am using R&D-intensive firms and innovative firms interchangeably to indicate firms with high R&D intensity.

The second study extends the prior research and examines the relationship between cost stickiness and earnings informativeness in R&D firms. The study also investigates whether R&D intensity moderates the association between cost stickiness and the earnings-returns relationship. The results suggest that the adverse effect of cost stickiness on earnings informativeness reported in the literature is not applicable to R&D firms. The study also shows that higher R&D intensity attenuates the previously reported negative impact of cost stickiness on earnings informativeness. Finally, I find that cost stickiness is positively associated with earning informativeness only in R&D-intensive firms. These results suggest that accounting earnings signal relevant information when firms with sticky costs invest their resources in R&D activities.

The third study examines the role of uncertainty in shaping cost behaviour during the COVID-19 crisis and whether the government's intervention policy mitigates it. It also evaluates whether R&D-intensive firms respond differently to uncertainty and show a different level of cost stickiness in their financial statements during the crisis. The results show that cost stickiness declines with the severity of the COVID-19 crisis, indicating that managers reduce the committed resources and lay off their employees when demand decreases to avoid retaining them at a loss. However, it is hard for managers to accommodate the growth in demand by increasing their resources due to input scarcity and supply chain disruptions during the COVID-19 pandemic. The results also indicate that the government income support was insufficient to attenuate workplace closure's negative impact on firms' cost stickiness. However, the significant adverse impact of the COVID-19 crisis on cost stickiness is not observed in R&D-intensive firms, indicating that firms that invested in R&D and technology during the crisis were able to retain their resources and redirect them towards the recovery process.

In sum, cost stickiness behaviour observed in the financial statements of R&D-intensive firms is driven by the capabilities' retention triggers and has other consequences on earnings properties than those observed in non-R&D firms. Cost stickiness is a natural result of how managers in R&D-intensive firms make their operating decisions and allocate resources during hard times. Even in the case of an unprecedented crisis such as the COVID-19 pandemic, managers of innovative firms preserve the firm's resources and capabilities to retain their competitive advantage and reinvest them in the recovery process.

Table of Contents

List of Tables

List of Figures

Attestation of Authorship

I hereby declare that this submission is my work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which, to a substantial extent has been submitted for the award of any degree or diploma of a university or other institution of higher learning.

Signature:

Name: Walaa Samir Ghazy

Date: 28/11/2022

Acknowledgements

I would like to thank the following people, without whom I would not have made it through my PhD journey.

First and foremost, I am extremely grateful to my primary supervisor, Prof. Asheq Rahman, for his invaluable advice, continuous support, and patience during my PhD study. I also want to thank him for being my role model and the teacher I aspire to be. His immense knowledge and plentiful experience have encouraged me continuously in my academic research and daily life. I am also grateful to my secondary supervisors Dr Humayun Kabir and Dr Tom Scott for their insightful comments and suggestions, especially in the empirical part of my research. Their insight and knowledge of the subject matter steered me through this research.

I would like to thank all the staff in the Accounting Department at AUT, especially Dr Anil Narayan, the head of the Accounting Department. It is their kindness and help that have made my study and life in New Zealand a wonderful experience. Thanks also goes to all the staff of the postgraduate office in the Business School at AUT, especially Dr Eathar Abdul-Ghani, for their help and encouragement from day 1 and through every step of the PhD program.

I also want to acknowledge the funding I received from the Accounting Department at AUT through the Graduate Teaching Assistant Award that supported me throughout my PhD program period and also gave me the opportunity to gain valuable teaching experience at the institution. I would also like to extend my sincere thanks to the organizers and participants of the conferences where I presented my work such as the AFAANZ Doctoral Symposium (2020), the AFAANZ Annual Meeting (2020), the ARA Annual Meeting (2021), the QARN Annual Meeting (2019 and 2021) and the AAA

Management Accounting Section (2021). The feedback I received during these conferences opened my eyes to new ideas and redirected my research when needed.

My biggest thanks goes to my family and friends for all the support they have shown me throughout this research process. I want to thank my husband, Moustafa, for being the motivator to come to New Zealand and start this journey. He was always there for me, providing me with all the love, help and support that I needed to carry on. I also want to thank my beautiful two kids, Ahmed and Khadija, without whom I would have stopped these studies a long time ago. I also want to thank my brother, Mohammed, for taking care of our mother in Egypt while I'm in NZ doing my PhD. Finally, I want to thank my friends and chosen sisters Mehnaz and Negin for being with me every step of the way as we all reached this final stage of our PhDs.

Dedication

To the soul of my father, Samir Ghazy.

“I wish you were here with me now”

Chapter 1 Introduction

1.1 Motivation, research questions and the main findings

In the last twenty years, accounting researchers have been interested in examining how costs behave in response to changes in market conditions. Anderson et al. (2003), in their seminal paper, found that managerial intervention in the resource adjustment process results in asymmetric behaviour of costs in response to changes in activity levels. Costs increase more when activity levels rise than they decrease for equivalent sales fall; in other words, costs are sticky (Anderson et al., 2003).

Adjustment costs and demand uncertainty are the cornerstones of the theory of cost stickiness that explains this behaviour as a reflection of the efficient managerial response towards changes in market conditions (Anderson et al., 2003; Banker et al., 2013). When demand declines, managers trade off the anticipated costs of carrying unutilised resources against the expected adjustment costs of retrenching and ramping up if demand is restored. The higher the adjustment costs relative to the costs of maintaining unutilised resources, the more managers will retain committed resources, resulting in higher cost stickiness. By contrast, managers must acquire the resources necessary to accommodate the increased sales volume when demand increases (Anderson et al., 2003; Banker et al., 2013). Additionally, prior literature confirms that demand uncertainty motivates managers to purposefully delay reductions to committed resources until they are more certain about the permanence of the decline in demand, which increases the cost stickiness (Banker & Byzalov, 2014; Lee et al., 2020)

The previous explanation would be suitable for firms working in a static or steadily growing environment where managers can perform those trade offs between alternatives and allocate their resources to the most efficient course of action. However, firms in the modern economy work in a dynamic environment with rapidly evolving technologies, fast-changing consumer preferences, accelerated product cycles and globalised operations and markets (Hidma et al., 2020). Thus, innovation in new products and processes has become increasingly important for companies to achieve and maintain their competitive advantage in this rapidly changing environment (Lome et al., 2016). However, when firms attempt something new, that is, innovating, the extreme uncertainty inherent in the organisational learning process generates severe difficulties in predicting the costs, benefits and time required for their innovative projects or market demand for the products resulting from them (Pavitt, 2005). Thus, the trade-off between the adjustment costs and the costs of retaining the slack resources when demand declines does not represent the resource allocation decisions in innovative firms. Consequently, Banker et al. (2018) called for examining the consequences of the innovative operating process dynamics on cost behaviour. I am responding to this call and extending Anderson et al. (2003) study to the research and development (R&D) context by investigating whether R&D intensity is a determinant of cost stickiness through the following research question:

RQ (1): Does cost stickiness rise with the increases in R&D intensity?

I present the results of examining research question 1 in Chapter 2. The study in this chapter is entitled “The Pursuit of Innovation: Cost Stickiness in R&D-intensive Firms”. In this chapter, I complement the previous cost stickiness literature and respond to the call from Nelson and Winter (1982) to use the evolutionary theory of the firm. The

evolutionary theory provides a theoretical foundation to interpret the accounting practices by adopting the evolutionary perspective to simulate the resource allocation processes in R&D-intensive firms. The evolutionary theory of the firm focuses on the problem of innovation, learning and steady competitive advantage and surveys the firm in light of its own history (Kállay, 2012). The theory integrates the implications of innovative activity characteristics, notably features of entrepreneurial and experiential behaviour, for resource allocation decisions. This theory also recognizes that technological advances are the key driving forces of competition in technologically dynamic industries. Thus, the evolutionary theory incorporates the interaction between market changes driven by the dynamics of this kind of competition and resource allocation in R&D-intensive firms. Additionally, the evolutionary perspective relies on the firms' routine and working procedures to provide a cumulative learning-based view of organisational competencies and capabilities. Organizational routine refers to a set of established and standardized procedures, practices, and patterns of behaviour that are followed by individuals or groups within an organization to achieve specific objectives or goals. Routines are the basic component of organizational behaviour and the repository of organizational capabilities as they provide a framework for employees to follow, promote consistency and predictability, and enhance efficiency, productivity, and quality within the organization. (Nelson & Winter, 1982, 2002).

According to the evolutionary theory of the firm, the firm is an adaptive entity that develops and adapts its competencies and processes to the changes in its environment. Based on this theory, I argue that R&D intensity would increase the level of cost stickiness. When demand increases, firms will increase their output by replicating the same routine because they possess the required resources to apply this routine on a larger scale. However, when demand declines, managers would retain the existing resources and

redirect them towards a search for a modified version of the current routine. The managerial decision to retain the existing resources even if the current practice leads to an unsatisfactory outcome is critical to R&D-intensive firms because the organisational memory may lose a repository of the firm's knowledge if the employees leave the firm, which poses a significant threat to routine continuity. Additionally, the theory considers the firm as a coalition of individuals with diverse interests, such as managers, workers, stockholders, suppliers, customers, lawyers, tax collectors and regulatory agencies. Any initiative to modify the existing routines would be opposed by the organisational members seeking to assure that their interests continue to be recognized and preserved by the agreement they had with the organisation. Therefore, the continuity of routines is critical for firms as they include ways of coping with the occasions of conflict between the organizational members, whether between managers and shareholders, managers and workers, or managers and managers (Nelson & Winter, 1982). Retaining those resources while revenues decline would increase cost stickiness.

I test the previous propositions on a sample of 74,815 firm-quarter observations for 3,086 US public firms engaged in R&D activities over 20 years. The empirical results reveal a significant positive association between R&D intensity and cost stickiness. However, the results of the subsample analysis confirm that the positive association between R&D intensity and cost stickiness prevails only in R&D-intensive firms.

The cost stickiness literature also shows the resulting contemporaneous earnings asymmetry – earnings decrease more when revenues fall than they increase when revenues rise. Weiss (2010) argues that this greater decrease in earnings increases the variability of the earnings distribution when activity levels drop, resulting in less predictable profitability. He finds that cost stickiness negatively affects the

informativeness of earnings in manufacturing firms. However, innovation is playing an increasingly essential role in all sectors of the modern economy. It fundamentally changes the "DNA" of many emerging and existing firms, the various stakeholders in these firms, the capital markets that finance these firms, and the role of accounting information in allocating capital to them (Zimmerman, 2015).

Additionally, cost stickiness observed in the financial statements of R&D firms is driven by the dynamics of the innovative business model. When these firms face a reduction in their product demand, they retain the allocated resources and reinvest them in new technologies and innovations to realign the organisation with its external environment (Gulati et al., 2010; Holland & Katzin, 2019). These decisions can enhance firms' competitive advantage, enabling them to operate in a concentrated market with high entry barriers (Archibugi et al., 2013). Ahmed (1994) and Biddle and Seow (1991) assert that earnings informativeness increases in this non-competitive market structure. Moreover, investing in innovation during the demand reduction periods can reduce the technical and commercial uncertainty related to R&D activity and increase firms' growth options (Ciftci & Cready, 2011; Laitinen, 2000). These implications can enable R&D-intensive firms to sustain their earnings for the medium and long term, enhancing the informativeness of this information (Collins & Kothari, 1989).

Consequently, I am extending Weiss's (2010) study that reported the negative effect of cost stickiness on the informativeness of earnings in non-R&D firms and examining this relationship for a sample of R&D firms. I am also investigating whether R&D intensity moderates the association between cost stickiness and the earnings-returns relationship. To achieve these objectives, I am examining the following two research questions:

RQ (2): Does cost stickiness affect earnings informativeness of R&D firms?

RQ (3): Does R&D intensity attenuate the relationship between cost stickiness and earnings informativeness?

I address the second and third research questions in Chapter 3. The study in this chapter is entitled “Cost Stickiness Behaviour, R&D Intensity and the Informativeness of Earnings”. Based on a sample of 63,280 firm-quarter observations for 3,641 US public firms engaged in R&D activities from 2000 through 2019, the results imply that the previously reported adverse effect of cost stickiness on earnings informativeness is not applicable for R&D firms. This chapter also shows that the higher R&D intensity attenuates the previously reported negative impact of cost stickiness on earnings informativeness. However, I find evidence that the informativeness of earnings increases with cost stickiness only in R&D-intensive firms. These results suggest that accounting earnings signal relevant information when firms with sticky costs invest in R&D activities. These findings indicate that the reported earnings of R&D-intensive firms with sticky costs capture the underlying causes of this cost behaviour. These firms are investing in R&D activities during difficult times to improve their performance and increase their ability to compete.

I also estimate the effect of the extreme uncertainty caused by an economic crisis on firms’ cost behaviour. COVID-19 disruptions represent a suitable context to study how managers adjust the acquired resources when demand fluctuates. COVID-19 lockdowns, workforce restrictions and limited access to inputs reduced firms’ productivity and supply capacity. At the same time, demand slumped or shifted toward new products or services. This simultaneity of shocks to supply and demand makes the COVID-19 recession singular and dangerous (D. Strauss-Kahn, 2020). These shocks were also compounded

by unprecedented uncertainty about the virus, the extent and duration of public policy responses and future outlooks.

The organisational uncertainty levels managers face during the pandemic differ from those of other global crises. Sharif et al. (2020) reported that the US stock markets volatility measures exceed those observed during the December 2008, October 1987 and October 1929 crashes. This extreme level of uncertainty was because COVID-19 is genuinely a global pandemic, interest rates are at historical lows, global financial markets are highly interconnected, and there are spill-over effects throughout supply chains (Ozili & Arun, 2020). Additionally, the COVID-19 shock is exogenous to the economic system. Therefore, the financial tools of the central banks used in economic crises are only temporary measures of reducing uncertainties (M. O. Strauss-Kahn, 2020).

Moreover, the impact of the COVID-19 pandemic is more severe than previous outbreaks and pandemics, such as the Spanish Flu in 1918 and Ebola in 2014 (Baker et al., 2020). The absence of a similar historical event means that managers have little clarity about the effects of the pandemic on output, demand, employability and earnings both in the short and long term (Sharif et al., 2020). This extreme level of uncertainty – defined in terms of novelty, magnitude, duration, and the rapid pace of change – calls for examining the role of uncertainty in shaping cost behaviour and whether the government's intervention policy during the crisis mitigates the impact. I also extend the analysis by evaluating whether innovative firms respond differently to uncertainty and show a different level of cost stickiness in their financial statements. Based on the above arguments, the following research questions are examined:

RQ(4): Does the extreme uncertainty of the COVID-19 crisis affect cost stickiness?

RQ(5): Does government income support attenuate the effect of the extreme uncertainty of the COVID-19 crisis on cost stickiness?

RQ(6): Does R&D intensity attenuate the effect of the extreme uncertainty of the COVID-19 crisis on cost stickiness?

Research questions 4,5 and 6 are addressed in Chapter 4, entitled "COVID-19 Uncertainty and Cost Stickiness". Based on a sample consisting of 1,615 firm-quarter observations for 938 firms whose headquarters are located in the USA from the first quarter of 2020 to the last quarter of 2021, the results show that cost stickiness declines with the severity of the COVID-19 crisis, indicating that managers remove their resources and lay off their employees when demand decreases to avoid retaining them at a loss, especially when they have negative expectations about the recovery of the economic activity. However, it is hard for managers to accommodate the growth in demand by increasing their resources due to input scarcity and supply chain disruptions during the COVID-19 crisis. The results also indicate that the US government income support was insufficient to attenuate workplace closure's negative effect on firms' cost stickiness. However, the significant adverse impact of the COVID-19 crisis on cost stickiness is not observed in R&D-intensive firms, indicating that firms invested in R&D and technology during the crisis were able to retain their resources and redirect them towards the recovery process.

In sum, the thesis reports that a better understanding of cost stickiness requires careful analysis of the business model and the specific characteristics of the resource allocation process of the research settings. In R&D-intensive firms, cost stickiness is a sign of the managerial decision to preserve the firm's capabilities and competencies during hard times and reinvest them in new technologies and R&D activities to realign the organisation with its external environment. The results also indicate that the consequences

of cost stickiness on earnings properties differ according to the properties of the investigation context.

Figure 1.1. depicts an overview of the research setting and questions to be addressed in this thesis.

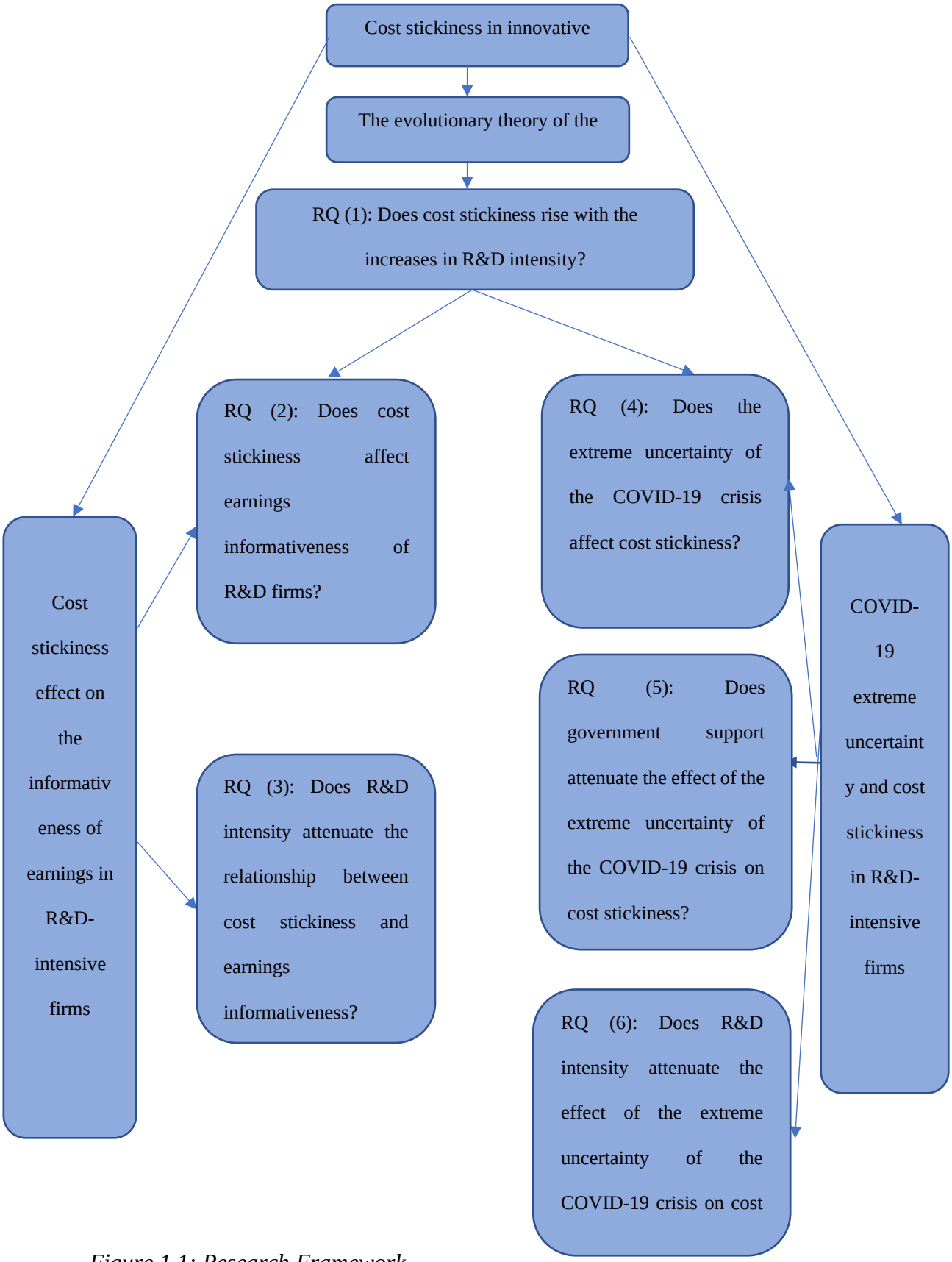

Figure 1.1: Research Framework

1.2 Contribution

This thesis contributes to the growing body of literature on cost stickiness by proposing the evolutionary theory of the firm as a relevant theoretical explanation of cost stickiness behaviour in innovative firms. The prior literature on cost stickiness depends on the optimal resource allocation model to explain this asymmetric cost behaviour. While this model has aided our understanding of cost behaviour, it is built on concepts that capture some dimensions of the modern economy, notably short-term and static ones. But in the real world, such a stationary state would never (or only occasionally) be reached because contemporary businesses, especially R&D-intensive firms, work in a dynamic environment constantly disrupted by innovation (Schumpeter, 2005). Therefore, I adopt the evolutionary perspective that considers the effect of firms' continuous adaptation to fast technological advances and market forces changes on the resource allocation behaviour in R&D-intensive firms. The evolutionary theory also incorporates information and insights from different sources to explain the firm's capabilities and behaviour such as management theory and practices, psychology, biology, organisational theory and business history.

The findings of this thesis also show that a complete understanding of cost stickiness requires careful analysis of the business model of the research settings. This study indicates that the observed cost behaviour in the financial statements of R&D-intensive firms reflects the dynamics of the innovative business model. Engaging in R&D activities reinforces the asymmetric cost behaviour because managers of innovative firms would preserve the firm's capabilities and competencies during hard times and reinvest them in new technologies and R&D activities to realign the organisation with its external

environment. These findings should also be taken into account by investors and analysts while evaluating the performance of R&D-intensive firms. Cost stickiness is a sign of effective and efficient managerial decisions that are consistent with the business model employed in innovative firms.

This study also contributes to the extensive literature on earnings informativeness by identifying cost stickiness as an economic determinant of the earnings-returns relationship. These results support the argument that stickier cost behaviour reduces the predictive power of realised earnings in low R&D-intensive firms. However, the informativeness of earnings increases with the increased levels of cost stickiness in high R&D-intensive firms. In addition, the results contribute to the literature that focuses on investigating the implications of this asymmetric cost behaviour (Banker & Chen, 2006; He et al., 2020; Homburg et al., 2018; Weiss, 2010). These findings show that higher R&D intensity attenuates the negative effect of cost stickiness on the informativeness of earnings information previously documented in the literature.

Additionally, the findings of this study contribute to the literature focusing on identifying the determinants of the cost behaviour (Anderson et al., 2003; Banker et al., 2014; Lee et al., 2020). This research extends this literature by examining the effect of COVID-19 extreme uncertainty on this behaviour. The results show that managerial response to COVID-19 uncertainty reduces cost stickiness. The severe demand shock caused by the pandemic and its containment measures drives managers to remove their committed resources. Simultaneously, they could not accommodate the increase in demand due to the effect of the crisis on productivity and supply chains. These results indicate that the impact of uncertainty on cost stickiness depends on the level of uncertainty and its root cause. The results also imply that investors would benefit from considering cost stickiness

information when making investment decisions. Integrating the extreme levels of uncertainty caused by the COVID-19 pandemic into models that predict cost stickiness may help in predicting these firms' financial performance.

Finally, these results are relevant to the growing literature assessing the economic consequences of COVID-19 (Altig et al., 2020; Koren & Pető, 2020). This study extends this literature by providing first-hand evidence of the impact of the COVID-19 extreme uncertainty on cost behaviour as a reflection of the managerial operating decisions towards the crisis and the associated governmental response. The results indicate that governmental income support was insufficient to preserve firms' productive capital and, more importantly, workers' skills. The results also show that firms must be innovative in response to the enormous disruption caused by COVID-19.

1.3 Organisation of the thesis

The remainder of this thesis is as follows. Chapter 2 articulates the investigation of the relationship between the intensity of R&D activities and cost stickiness behaviour in innovative firms. Chapter 3 examines the impact of cost stickiness on the informativeness of earnings in R&D firms and whether R&D intensity attenuates this effect. Chapter 4 illustrates the investigation of the impact of COVID-19 extreme uncertainty on cost stickiness behaviour for firms with low and high R&D intensity levels and whether the governmental response to the crisis attenuates this effect. Chapter 5 summarises the thesis and concludes with the aggregate findings and implications of the three research papers. The limitations and suggestions for future research are also presented.

Chapter 2 The Pursuit of Innovation: Cost Stickiness in R&D-intensive Firms

Abstract

In this chapter, I use the evolutionary theory of the firm to investigate the effect of R&D intensity on cost stickiness behaviour in innovative firms. I predict that engaging in R&D activities fosters cost stickiness because it is critical for R&D-intensive firms to retain the existing resources when demand declines to preserve the firm's organisational memory and avoid any disruption to the current agreement between the organisation and its members. Simultaneously, managers of R&D-intensive firms reinvest the retained resources in recovery and future growth options. Consistent with this prediction, I find that R&D intensity is associated with increased cost stickiness. Further analysis also provides evidence that cost stickiness rises with higher R&D intensity only in R&D-intensive firms. These results enrich the understanding of investors and analysts of the relationship between managerial operating decisions and cost behaviour in innovative firms.

2.1 Introduction

Firms in the modern economy work in a dynamic environment with rapidly evolving technologies, fast-changing consumer preferences, accelerated product cycles and globalised operations and markets (Hidma et al., 2020). Thus, innovation in new products and processes has become increasingly important for companies to achieve and maintain their competitive advantage in this rapidly changing environment (Lome et al., 2016). Innovative firms are more knowledge-based, have more intangible assets, rely on their employees' human capital, confront increased competition, and face the uncertainty inherent in the underlying continuous learning process (Lundvall, 2016). Thus, R&D-intensive firms must adapt their operational structure and resource allocation patterns to match the unique characteristics of the innovation process (O'Sullivan, 2000). At the same time, it is documented that managerial resource allocation decisions are reflected in the financial statements as sticky costs behaviour (Anderson et al., 2003). Therefore, Banker et al. (2018) called for investigating the effect of the dynamics of R&D-intensive firms on their cost behaviour. I am responding to this call by using the evolutionary theory of the firm to provide a theoretically sound explanation for the association between R&D intensity and cost stickiness in innovative firms. The evolutionary perspective is relevant to studying cost behaviour in R&D-intensive firms as it focuses on the processes that link changes in firms' decision rules to the changing market conditions in industries marked by high rates of innovation.

The prior cost stickiness literature interprets cost stickiness behaviour as a direct consequence of the optimal resources' commitment decisions with adjustment costs. Managers rationally decide to bear the costs of operating with unutilised resources to avoid incurring the higher adjustment costs associated with cutting slack resources and

replacing them if demand is restored (Anderson et al., 2003; Banker et al., 2013). However, economists argue that we should recognise that firms working in technologically dynamic industries use their resources less than optimally and consider those utilisation decisions by adopting different theoretical assumptions to explain the managerial operating behaviour (Nelson & Winter, 2002).

In this research, I complement the cost stickiness literature by adopting the evolutionary theory of the firm to simulate the resource allocation process in R&D-intensive firms. The evolutionary theory by Nelson and Winter (1982) integrates the implications of innovative activity characteristics, notably features of entrepreneurial and experiential behaviour, for resource allocation decisions. This theory also recognizes that technological advances are the key driving forces of competition in technologically dynamic industries. Thus, the theory incorporates the interaction between market changes driven by the dynamics of this kind of competition and resource allocation in R&D-intensive firms. Additionally, the evolutionary perspective relies on firms' routine and working procedures to provide a cumulative learning-based view of organisational competencies and capabilities (Nelson & Winter, 1982, 2002).

Although Nelson and Winter (1982) called for using the evolutionary theory of the firm as a theoretical representation of accounting practices, accounting scholars have not responded to this call until now (August 2023). However, strategic management researchers used the evolutionary viewpoint as a theoretical foundation for understanding the firms' adaptation and change. For example, Flier et al. (2003) used the evolutionary perspective to investigate the effect of the interaction between environmental selection, institutional effects and managerial intentionality on the strategic renewal behaviour of British, Dutch and French financial incumbents. Abatecola (2012) used the organizational

evolutionary perspective to explain the overall dynamics of corporate crises' paths. Fortune and Mitchell (2012) used evolutionary multilevel analysis to investigate how managerial and functional organizational capabilities affect whether struggling firms exit by acquisition or dissolution. Using a comparative historical method and drawing on evidence from five countries over a 60-year period, Murmann (2013) inquires how precisely evolutionary processes work in shaping the evolution of industries and important features of their environments. Teece (2019) developed a framework of firms' capabilities to explain how firms innovate and change to maintain evolutionary fitness. His basic argument is that firms differentiate themselves through learning, entrepreneurship, innovation, and astute decision-making.

After more than 40 years, I am responding to Nelson and Winter (1982) call and applying the evolutionary theory of the firm in the accounting discipline as a theoretical framework to interpret the cost stickiness phenomenon. Based on the evolutionary theory, I argue that R&D intensity in innovative firms would increase the level of cost stickiness. When demand increases, firms will increase their output by replicating the same routine because they possess the required resources to apply this routine on a larger scale. However, when demand declines, managers would retain the existing resources and redirect them towards searching for a modified version of the current routine, which will eventually be adopted if it satisfies the criteria set by the firm. The managerial decision to retain the existing resources even if the current practice leads to an unsatisfactory outcome is critical to R&D-intensive firms because the organisational memory may lose the storage point of the firm's knowledge if the employees leave the firm, which poses a significant threat to routine continuity. Additionally, any initiative to modify the existing routines would be opposed by the organisational members seeking to ensure that their interests continue to be recognized and preserved by the agreement they had with the organisation (Nelson &

Winter, 1982). Retaining those resources while revenues decline would be reflected in the financial statements as an increased cost stickiness.

I test the previous proposition on a sample of 74,815 firm-quarter observations for 3,086 US public firms engaged in R&D activities over 20 years. The empirical results reveal a significant positive association between R&D intensity and cost stickiness. Further analysis also suggests that the hypothesised positive association between R&D intensity and cost stickiness prevails only in R&D-intensive firms.

The results of this study and their implications contribute to the growing body of literature on cost stickiness by proposing the evolutionary theory of the firm as a relevant theoretical explanation of cost stickiness behaviour in innovative firms. This perspective considers the effect of firms' continuous adaptation to fast technological advances and market force changes on resource allocation behaviour. The evolutionary theory also incorporates information and insights from different sources to explain firms' capabilities and behaviour, such as management theory and practices, psychology, biology, organisational theory and business history.

The results also show that a complete understanding of cost stickiness requires careful analysis of the business model of the research settings. This study indicates that the observed cost behaviour in the financial statements of R&D-intensive firms reflects the dynamics of the innovative business model. Engaging in R&D activities reinforces the asymmetric cost behaviour because managers of innovative firms would preserve their capabilities and competencies during hard times and reinvest them in new technologies and R&D activities to realign the organisation with its external environment. These findings should also be considered by investors and analysts while evaluating the performance of R&D-intensive firms. Cost stickiness is a sign of effective and efficient

managerial decisions that are consistent with the business model employed in innovative firms.

The following section reviews the related literature and the theoretical framework. The third section illustrates the hypotheses' development. The fourth section describes the research design. Section 5 presents the main results of the simultaneous equations system, followed, in the final section, by the conclusion of this research.

2.2 Literature review and theoretical framework

Cost stickiness is rooted in asymmetric cost behaviour – costs increase more when sales grow than they decline when sales fall (Anderson et al., 2003). Prior research suggests that the key to understanding sticky cost behaviour is to view many costs arising from managers' deliberate resource commitment decisions and speculate that adjustment costs play a central role in these decisions. When demand declines, managers trade off the anticipated costs of carrying unutilised resources against the expected adjustment costs of retrenching and ramping up if demand is restored. The higher the adjustment costs relative to the costs of maintaining unutilised resources, the more managers will retain committed resources, resulting in higher cost stickiness. By contrast, managers must acquire the resources necessary to accommodate the increased sales volume when demand increases (Anderson et al., 2003; Banker et al., 2013).

Prior literature also confirms that demand uncertainty motivates managers to purposefully delay reductions to committed resources until they are more certain about the permanence of the decline in demand, which increases cost stickiness. Consequently, Anderson et al. (2003) find that cost stickiness reverses in the subsequent period when uncertainty is resolved. They also find that cost stickiness falls with the aggregation of the estimated

period. Based on this argument, Lee et al. (2020) find that the stickiness of operating and R&D costs increases in election periods due to increased political uncertainty.

The previous arguments are based on the optimal resources allocation model that depends on comparing the costs of different alternatives and choosing the option that achieves the ultimate goal of minimising firms' costs. For example, optimal manager decisions regarding labour resources trade off the adjustment costs associated with hiring or firing a marginal worker with the net present value of cash flows that this worker is expected to generate during their tenure with the firm (Bentolila & Bertola, 1990). Accordingly, the degree of cost stickiness will be higher when the firing costs for labour (or downward adjustment costs more generally) are higher.

While the optimal decision model has aided our understanding of cost behaviour, it is built on concepts that capture some dimensions of the modern economy working in a state of equilibrium, notably short-term and static ones. But in the real world, such a stationary state would never (or only occasionally) be reached because contemporary businesses, especially R&D-intensive firms, work in a dynamically changing disequilibrium environment constantly disrupted by innovation (Schumpeter, 2005). Innovation fundamentally changes the "DNA" of many emerging and existing firms; it is the disruptive enabler of new products, services, business models and operating structures and a catalyst for creating opportunities for new players to evolve within the markets (PwC, 2020; Zimmerman, 2015).

The innovative business model always aims to transform the technological and market conditions it faces at a given time to generate higher-quality, lower-cost products and thus differentiate the firm from its competitors (Lazonick, 2002). Therefore, managers in innovative firms do not passively respond to changes in market conditions by only

considering them as signals for modifying their productivity level. Alternatively, they recognise demand reduction as a driver for developing the capabilities that would transform their cost structure and enhance their competitive advantage. Additionally, the extreme uncertainty associated with attempting something new, that is, innovation, has consequences that would extend beyond the difficulty of predicting the permanence of the demand reduction status. The uncertainty associated with the organisational learning process generates severe challenges in predicting the costs, benefits and time required for their innovative projects or even the market demand for the products resulting from them (Pavitt, 2005). Thus, the trade-off between the adjustment costs and the costs of retaining the slack resources when demand declines does not represent the resource allocation decisions in innovative firms.

The cost stickiness literature recognized the importance of interpreting this cost behaviour through a different theoretical lens to enhance our interpretation of this phenomenon. Prior research used the firms' strategic orientation to explain the asymmetric cost behaviour. Venieris et al. (2015) used the resource-based view (RBV) of strategy (Martín-de-Castro et al., 2011) as a theoretical lens to investigate the effect of the firms' level of organizational capital on selling, general and administrative (SG&A) cost stickiness. They find that firms with high levels of organizational capital have higher SG&A cost stickiness during demand decline periods. This is because a high level of organisational capital increases adjustment costs and drives managers to shape more optimistic expectations regarding whether future sales growth will absorb the slack of unutilised resources.

Ballas et al. (2020) and Wu and Wilson (2022) used Miles and Snow's strategic typology (1978) to investigate the effect of the firms' strategic choices on the asymmetric cost

behaviour of SG&A expenses. The results show that firms classified as prospectors exhibit higher SG&A cost stickiness than firms with a different strategic orientation that operate within the same sector. These results are justified as a prospector is expected to exhibit higher levels of strategic resources whose development is associated with the previous period's SG&A expenses, and the presence of these costs increases the current level of adjustment costs. Additionally, this strategy orientation shapes managerial expectations for increased uncertainty of future sales revenues.

Although this stream of literature opens the discussion around the importance of considering high-level managerial decisions while explaining cost behaviour, this explanation is still within the building blocks of the traditional neoclassical economic theory. The strategic view is built on optimizing actors aiming to achieve equilibrium by applying strategies that have proven effective in achieving stability. Moreover, strategic processes are not built on a theoretical basis that can guide organisational adaptation to environmental changes. For example, Volberda and Lewin (2003) illustrate that RBV is a firm-level theory that focuses on providing the theoretical foundation for explaining firm heterogeneity. Therefore, this theory is not concerned with the interactions between the firm and the external environment. Additionally, strategic management processes do not consider the variety of strategies applied by innovative firms while adapting to environmental changes, as the focus of this perspective is always on applying a singular course of action. Simon (1993) demonstrates that this approach might be understood in industries where firms live in a stable environment. However, in industries whose products have a short life and whose firms live by innovation, strategy planning needs to be organised and institutionalised as a continuing responsibility. The time when a company is enjoying its most recent success is the time when it needs to be planning its next initiatives. If they did not, they would not survive long.

The evolutionary theory of the firm proposes an alternative model that simulates the resource allocation process in R&D-intensive firms (Nelson, 2020; Nelson & Winter, 1982). According to this theory, firms are viewed as coalitions of decision-makers with different interests that have incomplete access to information and limited ability to absorb it. Therefore, they make business decisions based on acceptable working procedures and decision rules (or routines) that yield satisfactory results rather than exhaustively comparing all possible alternatives to choose the best option.

Routines provide the focal point for a learning-based approach to explaining firms' responses to market changes. They represent a set of established and standardized procedures, practices, and patterns of behavior that are followed by individuals or groups within an organization to achieve specific objectives or goals. The routinization of a firm's activities represents the organisational memory that stores the employees' operational skills and knowledge. These skills entail the ability of each organisational member to perform the required tasks and also to receive, interpret and appropriately respond to the messages received from other members and from the environment in a manner that is specific to the organisational context. Thus, the productive capabilities of the firm are reflected in the knowledge stored in the memories of the collection of its individual members. As a result, one of the propositions of the evolutionary theory is that the knowledge an organisation possesses is reducible to the knowledge of its individual members, which will be meaningful and effective only if it is exercised within the organisational context (Nelson & Winter, 1982).

The theory also considers the routinized systems of internal control as part of the organisational context that defines the contracts that individual members make with the organisation. It also includes mechanisms to cope with the occasions of conflict between

the organizational members, whether between managers and shareholders, managers and workers, or managers and managers. Applying those mechanisms would make the inter-organisational conflict follow predictable paths and stay within predictable bounds that are consistent with the ongoing routine. Therefore, the second proposition of the evolutionary theory is that routine operation involves a comprehensive truce that is critical in keeping inter-organisational conflict between the organisational members from being expressed in a highly disruptive manner (Nelson & Winter, 1982).

Based on the previous propositions, the theory confirms that the control process of the organisational system would resist any changes to the prevailing routine to avoid the loss of any part of the organisational memory that stores the employees' operational skills and knowledge. Moreover, the existing routine would also persist to avoid any disruption to the current agreement between the organisation and its members. The conscious intervention of top management in the functioning of the current operations is triggered when the existing routines are ineffective or when managers have reasons to believe that to remain or become competitive, they have to improve their performance (Nelson, 2020; Nelson & Winter, 1982). This deliberation could result in the firm trying practices it had used successfully in other contexts, in applying new technologies and methods used by firms in the industry, or it could result in innovation – the trial of something that had not been used before. Evolutionary economists saw the continuing presence of these potentially creative aspects of organisational behaviour as the source of continuing variety and continuing economic evolution (Nelson, 2020).

Accordingly, the evolutionary theory of the firm asserts the asymmetric behaviour of costs in innovative firms; in other words, costs are sticky in R&D-intensive firms. When demand increases, firms will increase their output by replicating the same routine because

they possess the required resources to apply it on a larger scale. The existing practice serves as a template for the firm already successful in a given activity to be successful with a new capacity of the same sort. However, when demand declines, managers would retain the existing resources and redirect them towards a search for a modified version of the current routine, which will eventually be adopted if it satisfies the criteria set by the firm (Nelson & Winter, 1982).

The managerial decision to retain the existing resources even if the current routine leads to an unsatisfactory outcome is critical to R&D-intensive firms because the organisational memory may lose the information stored in the memory of its individuals if one of the employees leaves the firm. In some cases, the memory of a single organisational member may be the only storage point of knowledge that is both distinctive and of great importance to the organisation. The loss of an employee with such essential idiosyncratic knowledge poses a significant threat to the continuity of organisational routine (Nelson & Winter, 1982). Additionally, any initiative to modify the existing routines would be opposed by the defensive alertness of the organisational members seeking to ensure that their interests continue to be recognized and preserved by the agreement they had with the organisation. At the same time, the firm will redirect its resources to a search for a modified version of the current practices in two ways: developing a new routine from scratch (innovation) or adopting an existing routine from elsewhere (imitation). In both cases, there are search costs, R&D expenses being the most typical example, and these costs rise with the difficulty of the search. The probability of finding a better routine will, in any case, strongly depend on how much the firm spends on R&D and other search costs (Fagerberg, 2003).

The evolutionary theory of the firm explains the economic change by linking the firms' adaptation to the changes in the external environment. Therefore, the theory focuses only on innovative firms that have adaptive and learning capabilities and are able to interact and mutually influence each other. Those firms can develop new routines and capabilities that give the firm the needed competitive advantages through innovation and knowledge creation. Additionally, this theory is not concerned with studying the adaptation and renewal of individual firms. Therefore, this theory or its empirical research does not study or offer insights about outlier firms or non-innovative firms that successfully adapt and change as their original industry population co-evolves into new organisational forms (Volberda & Lewin, 2003).

From the previous evolutionary assumptions, I argue that cost stickiness occurs in innovative firms for a different reason than what was asserted in the prior literature. The search for a better way of conducting innovative activities motivates managers to retain their resources instead of removing them when faced with challenging market conditions.

2.3 Hypotheses development

One of the most significant achievements of evolutionary economics is applying the systems perspective to the study of innovation. An innovation system – as a network – consists of the various actors and the practices they induce that support and orient efforts towards innovation (Nelson, 2020). Innovative firms encourage their employees to establish patterns of interaction within the organisation that would enable them to mobilise a firm's knowledge base when confronting new challenges. Such organising does not stop at the gate of the firm but extends to relations with other organisations such as suppliers, customers and competitors (Lam, 2005). Applying the systematic perspective to innovation causes costs to be sticky when demand fluctuates due to the

strong complementarities between the components of innovation systems. If one critical element is lacking, this may block or slow down the growth of the entire system (Fagerberg et al., 2005).

The principal reason for this cooperative behaviour of innovative firms is that every innovation consists of a new combination of existing ideas, capabilities, skills, and resources (Edwards-Schachter, 2018; Schumpeter, 2005). The greater the variety of these factors within a given system, the greater the scope for them to be combined in different ways, producing innovations that will be more complex and sophisticated. Therefore, organisations broaden their networks to be exposed to more varied activities, experiences, and collaborators (Hagedoorn, 2002). Such access creates an environment whereby innovation occurs at the boundaries between mindsets, not within the provincial territory of one knowledge and skill base (Leonard-Barton, 1995). Thus, it is documented that relationships at the firm level depend on the ongoing interpersonal ties between the network members. Those relationships would be severely harmed if the key participants were to depart (Powell & Grodal, 2005). These unique attachments between the resources employed in innovative systems would prevent managers from removing their resources when demand declines.

Managers are also motivated to retain the resources even if the products' demand is declining because cultivating the current capacity of R&D-intensive firms is critical for absorbing external knowledge – so-called "absorptive capacity" (Cohen & Levinthal, 1990). In other words, innovative firms learn and benefit from the knowledge developed by other firms by acquiring the capacity required to exploit that knowledge (e.g., retaining scientists who will follow other firms' activities) (Lev & Sougiannis, 1996). Thus, the innovation process is cumulative when learning cannot be done all at once; what can be

learned is crucially affected by what is already known (Powell & Grodal, 2005). Organisations accumulate know-how and tacit knowledge during their development, and the resulting organisational routines and skills become core competence that is difficult to change (Lam, 2005).

Additionally, innovative firms are characterised by decision-making in the entrepreneurial mode, with more significant opportunities for employees' initiatives and decision-making freedom. Thus, punishing short-term failures with low reward and termination may adversely affect innovation (Hitt et al., 1996). Manso (2011) shows that the optimal contract to motivate innovation not only exhibits tolerance for short-term failure but also rewards it to create incentives for successful innovation in the long term. Spotify, for example, started an initiative called "fail wall", which is a whiteboard with Post-it notes that publicly celebrates project failures and serves as the starting point for the engineering teams' investigations to examine what has been learned and how to prevent similar failures in the future (Anthony et al., 2019).

Manso (2011) also points out that managerial entrenchment is one of the optimal contracts that motivate innovation since such a practice gives managers job security by protecting or rewarding them after a poor short-term performance. Acharya et al. (2014) emphasise the importance of job security for employees at all levels to motivate innovation. One major global bank, ING, has developed a set of internal processes called PIE: P for protecting, meaning that employees who leave their jobs to work on a "squad"[2] project can return to those jobs if the initiative fails; I for independence, meaning that squad

[2] Squad is a team, but it differs from most big-companies teams in being empowered to solve key problems quickly, as an entrepreneur would (Furr & Shipilov, 2019).

members have their own resources and can make their own decisions; and E for encouragement, meaning that if the squad is successful, its work will be widely celebrated in the company (Furr & Shipilov, 2019).

Based on the previous insights, economists recognise that innovation depends on an experiential and interpretative decision-making process as the uncertainty inherent in the learning process unfolds over time. So, managers must control resources to allocate them based on their evaluation of the problems and possibilities of alternative learning strategies. They also require control to keep resources committed to the innovative approach until the learning process has generated higher-quality, lower-cost products that enable the investment strategy to reap returns. The withdrawal of some of the learners or physical resources from the learning process before it is complete may endanger the success of the entire undertaking (O'Sullivan, 2000; O'Sullivan, 2004).

In sum, the systematic perspective of innovation illustrates that removing unused resources as a response to the market mechanisms would destroy the cooperative and accumulative learning process, increasing cost stickiness in R&D-intensive firms. Additionally, applying the internal control mechanisms that serve to threaten sanctions, including dismissal, for behaviour that deviates from the organisational requirements would be detrimental to the required innovative and experiential behaviour, which also raises cost stickiness in these firms. As a result, when demand increases in R&D-intensive firms, managers will allocate more operating resources to accommodate the demand increases. However, when demand declines, it would be destructive to cut those resources because part of a firm's knowledge base and innovative capabilities would disappear if they reduce those resources. Retaining those resources while sales revenues are declining would lower the correlation between costs and revenues, reflected in the financial

statements as an increased level of cost stickiness. Consequently, I expect R&D intensity to be a determinant of cost stickiness, which leads to the following hypothesis:

H1: The level of cost stickiness increases with the firm's R&D intensity.

2.4 Research design and sample

2.4.1 Variables measurements

The R&D intensity measure

I follow Chan et al. (2001) and Eberhart et al. (2008) and use the ratio of R&D expenses to sales revenues (RD_{iq}) to measure the intensity of R&D activities of firm *i* in quarter *q*. On the Compustat database, R&D expenses cover all costs incurred, including salaries and departmental expenses related to developing new products or services during the fiscal quarter. I also create an indicator variable, *INV*, which represents high R&D-intensive firms. Following Ciftci et al. (2011), I use the industry-adjusted R&D expenses to sales ratio as a benchmark to classify firms into high and low R&D-intensive firms. The benchmark is the weighted average R&D expenses to sales ratio of all firms in the four-digit SIC industry group, where the weights are sales. Firms whose R&D intensity exceeds the benchmark are classified as high R&D-intensive firms (*INV* =1), and the rest as low R&D-intensive firms (*INV* =0).

The cross-sectional measure of cost stickiness

To test the research hypothesis, I follow the extensive literature on cost stickiness (Chen et al., 2012; Venieris et al., 2015) and use the standard methodology for measuring cost stickiness through the cross-sectional model developed by Anderson et al. (2003). This model is suitable for investigating the determinants of cost stickiness as it compares changes in costs and simultaneous changes in sales to proxy for asymmetric cost behaviour. Equation (1) represents the basic model:

$$ln\left(\frac{OC_{i,t}}{OC_{i,t-1}}\right) = \beta_0 + \beta_1 ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_2 Dec\_Dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \varepsilon_{i,t} \quad (1)$$

Subscripts *i (t)* reflect firm (time) indices, respectively. *OC* denotes operating costs that equal sales revenues minus income from operations. The rationale for focusing on measuring the effect of R&D intensity on the stickiness of operating costs stems from the main argument of this research that managers would redirect their resources to support the R&D activities during hard times. Therefore, I am investigating this reallocation of resources from one cost item to another and its effect on the behaviour of the aggregated cost items, such as operating costs. To distinguish between periods with a positive and negative change in activity; the indicator *Dec_Dum* is integrated as an interaction term with the change in sales. It equals 1 if sales of firm *i* decrease between fiscal years *t-1* and *t*, and 0 otherwise.

Applying ratios and log specifications enhances the comparability across firms and moderates the potential heteroscedasticity (Anderson et al., 2003). Log specifications also enable a more straightforward interpretation of coefficients as percentage changes in costs when sales increase by 1%. In comparison, the sum of β_1 and β_2 represents the average cost decline for a 1% decrease in sales. Cost stickiness implies that β_1 is significantly positive and β_2 is significantly negative, meaning that costs fall to a lesser extent for a 1% sales decrease than they rise for an equivalent sales increase (i.e., $\beta_1 + \beta_2 < \beta_1$).

2.4.2 Data and samples

The initial sample comprises 13,848 firms based on 456,140 firm-quarter observations from quarter industrial files for public firms in the North America Compustat database that located their headquarters in the USA over 20 years (from the first quarter of 2002 to the last quarter of 2021 last quarter). Table 2.1 describes the construction of this sample.

Following prior literature (Kama & Weiss, 2013; Zhong, 2018), I exclude financial institutions and public utilities firms (four-digit SIC codes 6000-6999 and 4900-4999) as these two industries are highly regulated, and I also remove duplicate observations. Moreover, I discard invalid observations that have missing or negative values of sales revenues or operating costs in the current year or the previous year (Anderson et al., 2003; Venieris et al., 2015). To remove the effects of mergers, acquisitions and divestitures, I eliminate those firm quarters in which the revenue changes by more than 50% from one year to the next; I also delete all firms with sales and total assets lower than $5 million (Subramaniam & Weidenmier, 2016; Venieris et al., 2015). Additionally, I follow the prior literature and exclude observations with sales and costs changing in the opposite direction (Anderson & Lanen, 2009; Chen et al., 2012). Finally, I drop observations with missing data on R&D intensity measure and control variables. The final sample size consists of 74,815 firm-quarter observations for 3,086 firms. All continuous variables are winsorised to the 1st and 99th percentile to reduce the influence of extreme outliers.

Table 2-1:Sample Selection Procedures

Initial Sample: Firm-quarter observations in Compustat NA for USA public firms over the period 2002-2021.	456,140
Excluding financial and utility firms and duplicate observations.	329,979
Drop observations with missing or negative sales revenues or operating costs in the current year or in the previous year	255,102
Eliminate mergers and small firms	188,563
Drop observations with sales and costs change in the opposite direction	164,862
Final Sample: Drop observations with missing data on R&D intensity measure and control variables.	74,815

This table presents the sample firms' selection procedures.

Table 2.2 shows the sample distribution by industry, where industry classification is based on the two-digit SIC code. The business services industry accounts for the most significant portion of the sample (16.54%), followed by the electronics and other electrical equipment industry (13.77%), followed by the instruments and related products industry (11.93%), chemical and allied products (10.33%) and industrial and commercial machinery and computer equipment (8.66%), respectively. As expected, the sample firms work in industries intensively involved in research activities according to the classification of R&D-intensive industries in many recognized taxonomies (Galindo-Rueda & Verger, 2016; Hill, 2020).

Table 2-2: Sample Distribution

SIC code	Industry	Number of obs.	Percentage of sample	Cumulative percentage
73	Business Services	12,378	16.54	16.54
36	Electronics & Other Electrical Equipment	10,301	13.77	30.31
38	Instruments & Related Products	8,927	11.93	42.24
28	Chemical & Allied Products	7,727	10.33	52.57
35	Industrial and Commercial Machinery & Computer Equipment	6,481	8.66	61.23
58	Eating &Drinking Places	2,709	3.62	64.85
59	Miscellaneous Retail	2,470	3.30	68.15
80	Health Services	2,423	3.24	71.39
56	Apparel & Accessory Stores	2,344	3.13	74.52
-	Other	19,055	25.48	100.00
	Total	74,815	100.00	

This table reports the sample distribution by industry. respectively

2.4.3 Research model

To estimate the hypothesized effect of R&D intensity on cost stickiness, I extend the basic model of cost stickiness and add the R&D intensity measure (*RD*) as a three-way interaction term and a stand-alone variable to this model. To test the research hypothesis,

I add the control variables recognised by prior literature to influence the degree of cost stickiness. I control the asset and employee intensity as measures for the adjustment costs. Following previous research, I used the natural log form of employee intensity *EMP_INT* and asset intensity *AST_INT* to control their effect on cost stickiness (Anderson et al., 2003). To capture the impact of anticipations of future sales on the degree of cost stickiness, I include an indicator variable *SUCC_DEC* that equals 1 if sales decrease in two consecutive years and 0 otherwise. I also control for the managerial empire-building incentives by adding free cash flows *FCF* to the model based on the results of Chen et al. (2012). The definition of these variables is provided in the Appendix. To control for firms' differences over time and industries, I include the year, quarter and industry indicator variables (one-digit SIC code) and correct the standard errors for the firm clustering effects.

$$ln\left(\frac{OC_{i,t}}{OC_{i,t-1}}\right) = \beta_0 + \beta_1 ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_2\, Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_3\, Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times RD_{i,t} + \beta_4\, RD_{i,t} + \mathcal{E}_2 \quad (2)$$

$$\begin{aligned} ln\left(\frac{OC_{i,t}}{OC_{i,t-1}}\right) = {} & \beta_0 + \beta_1 ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_2\, Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \\ & + \beta_3\, Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times RD_{i,t} \\ & + \beta_4\, Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times ln(Emp_{int\,i,t}) \\ & + \beta_5\, Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times ln(Ast_{int\,i,t}) \\ & + \beta_6\, Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times Succ_{dec\,i,t} \\ & + \beta_7\, Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times Fcf_{i,t} + \beta_8\, RD_{i,t} + \beta_9\, ln(Emp_{int\,i,t}) \\ & + \beta_{10}\, ln(Ast_{int\,i,t}) + \beta_{11}\, Succ\_dec + \beta_{12}\, Fcf_{i,t} + \mathcal{E}_2 \end{aligned} \quad (3)$$

2.5 Empirical results

2.5.1 Descriptive statistics

Table 2.3 provides descriptive statistics on the main variables used in the analysis. The average firm spends 9.6% (median = 5.0%) on R&D expenditures scaled by sales revenues. The sample firms have $1,101 million in average quarter sales revenues (median = $130.319 million) and $977 million in average operating costs (median = $120.436 million in operating costs. On average, the sample firms use 22 thousand (median = 16 thousand) employees and $5,140 million (median = $4,261 million) of assets to support every million dollars in sales revenues. On average, free cash flow accounts for 0.9% of total assets (median = 1.6%) for the sample firms. Finally, 35.2% of the sample firms experienced two consecutive years of sales reduction in the past two years.

Table 2-3:Descriptive Statistics

(N = 74,815 firm-quarter observations)

VARIABLES	Mean	Standard deviation	P1	P25	Median	P75	P99
OC	977.003	4552.304	5.535	33.444	120.436	471.677	16181.000
SALES	1101.459	4990.573	5.509	32.979	130.319	535.027	18,246.000
Dec_dum	0.303	0.459	0	0	0	1	1
RD	0.096	0.144	0	0.001	0.050	0.134	0.978
INV	0.373	0.484	0	0	0	1	1
EMP_INT	0.022	0.021	0.002	0.010	0.016	0.024	0.114
AST_INT	5.140	3.835	0.960	2.759	4.261	6.272	23.929
FCF	0.009	0.061	-0.212	-0.010	0.016	0.038	0.186
SUCC_DEC	0.352	0.478	0	0	0	1	1

This table presents descriptive statistics for all the variables in the different regression models. All variables are defined in the Appendix.

Table 2.4 reports Spearman and Pearson correlations between the main variables used in the main models. Most of the correlations are significant but small in magnitude, suggesting that multicollinearity is not a concern in the estimation of the research model. Additionally, continuous variables used in the interaction terms are mean-centred before they are included in the analysis to mitigate multicollinearity and to facilitate the interpretation of the main effects (Aiken & West, 1991; Chen et al., 2012). The only strong correlation exists between sales revenues and operating costs. This significant relationship is expected and acceptable, and the question I am asking in this study is to what extent this association exists while sales revenues increase or decrease.

Table 2-4:Correlation Matrices

(N = 68,482 firm-quarter observations)							
	OC	*SALES*	*RD*	*EMP_INT*	*AST_INT*	*SUCC_DEC*	*FCF*
OC		0.994***	-0.310***	-0.161***	-0.077***	-0.103***	0.1094***
SALES	0.995***		-0.325***	-0.176***	-0.084***	-0.114***	0.127***
RD	-0.073***	-0.071***		-0.218***	0.555***	0.012***	-0.065***
EMP_INT	-0.079***	-0.084***	-0.138***		-0.073***	0.059***	-0.044***
AST_INT	-0.056***	-0.049***	0.521***	-0.055***		-0.002	-0.091***
SUCC_DEC	-0.037***	-0.040***	0.030***	0.040***	0.027***		-0.085***
FCF	0.011***	0.012***	-0.157***	-0.023***	-0.098***	-0.060***	

1. This table reports cross-sectional correlation coefficients for the period 1989-2018.
2. Each matrix provides Spearman (Pearson)correlations above (below) the diagonal, respectively.
3. ***, **, * indicate two-sided significance at the 0.01,0.05 and 0.1 levels, respectively.
4. All variables are defined in the Appendix.

2.5.2 Multivariate results

This section presents the results for examining the association between cost stickiness level and R&D intensity. In model (1) presented in the first column of Table 2.5, I estimate the asymmetric adjustment of operating costs at the firm level with the changes in sales revenues. Because the value *Dec_Dum* is 1 when sales revenues decrease, the sum of the coefficients ($\beta_1+\beta_2$) measures the percentage decrease in operating costs with

a 1% decrease in sales revenues. A significantly positive coefficient β_1 and a significantly negative coefficient β_2 would be consistent with the cost stickiness hypothesis. The results of the basic model of Anderson et al. (2003) shown in column (1) of Table 2.5 show that the estimated value of β_1 is 0.860 (t = 159.19). This indicates that operating costs increase by 0.86% per 1% increase in sales revenues. The estimated value of β_2 is -0.110 (t = -11.52). The combined value of $\beta_1+\beta_2 = 0.750$ indicates that the operating costs decrease by about 0.75% per 1% decrease in sales revenues. These results indicate that the sample firms are subject to cost stickiness.

Hypothesis 1 predicts that the intensity of R&D activities is positively associated with the degree of cost stickiness. To test this hypothesis, I added the R&D intensity measure (*RD*) as a three-way interaction term and a stand-alone variable to the basic model. A negative coefficient of the *RD* interaction term would indicate a greater cost stickiness. The results of examining model (2) are presented in the second column of Table 2.5. Similar to the estimated results of model (1), I find that β_1 is 0.848 (t = 161.66), indicating that operating costs increase by 0.85% per 1% increase in sales revenues. The estimated value of β_2 is -0.043 (t = -5.40). The combined value of $\beta_1+\beta_2 = 0.805$ indicates that the operating costs decrease by about 0.81% per 1% decrease in sales revenues. These results suggest that the operating costs are still subject to cost stickiness after adding the R&D intensity measure to the model. The coefficient of the RD interaction term is significantly negative -0.394 (t = -14.23), indicating a positive effect of R&D intensity on the firm's cost stickiness level. These results are consistent with the first hypothesis (H1) that the level of cost stickiness increases with the firm's R&D intensity. The results also support the systematic perspective of firms' innovation that the efficient use of the firms' capabilities motivates managers in firms engaged in R&D activities to retain their resources during

downturns to maintain the firm's competitive advantage and value creation processes, which will increase the cost stickiness level.

In the third column of Table 2.5, I capture the effect of adding the control variables to the model. The results of model (3) show that β_1 is still significantly positive at 0.868 (t = 144.55),), indicating that operating costs increase by 0.87% per 1% increase in sales revenues. The estimated value of β_2 is negative at -0.068 (t = -6.98). The combined value of $\beta_1+\beta_2$ = 0.800 indicates that the operating costs decrease by about 0.80% per 1% decrease in sales revenues. These results suggest that the operating costs remain sticky after adding the control variables to the model. The coefficient of the *RD* interaction term is significantly negative [-0.305 (t = -9.42)], suggesting that cost stickiness increases with the increased levels of R&D intensity, which supports the first hypothesis (H1).

The coefficients of the control variables are mainly consistent with the results of the prior research. The significantly negative coefficients of *Emp_int* and *Ast_int* [-0.010 (t = -1.72) and -0.039 (t = - 4.92)] suggest a greater degree of cost stickiness in firms that require relatively more assets and employees to support their operations. The coefficient of Succ_dec is significantly positive [0.061 (t = 6.76)], indicating lower cost stickiness in firms experiencing adverse demand shocks in two consecutive years. However, unlike Chen et al. (2012), I find a significantly positive coefficient of *FCF* [0.375 (t = 5.30)], suggesting a lower degree of cost stickiness in R&D-intensive firms that acquire relatively more free cash flows. I conjecture that this inconsistency is due to the difference in the samples used in the two studies.

Table 2.2-5: Regression Results

Model	**Expected sign**	**(1)**	**(2)**	**(3)**
Intercept		0.028	0.026	0.041
		(11.79)***	(12.43)***	(17.94)***
$ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right)$	+	0.860	0.848	0.868
		(159.19)***	(161.66)***	(144.55)***
$Dec\_Dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right)$	-	-0.110	-0.043	-0.068
		(-11.52)***	(-5.40)***	(-6.98)***
$Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times RD_{i,t}$	-		-0.394	-0.305
			(-14.23)***	(-9.42)***
$Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times ln(Emp_{int_{i,t}})$	-			-0.010
				(-1.72)*
$Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times ln(Ast_{int_{i,t}})$	-			-0.039
				(-4.92)***
$Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times Succ_{dec_{i,t}}$	+			0.061
				(6.76)***
$Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times Fcf_{i,t}$	-			0.375
				(5.30)***
$RD_{i,t}$			0.040	0.038
			(4.49)***	(3.99)***
$ln(Emp_{int_{i,t}})$				0.002
				(2.17)**
Ln AST_INT				0.002
				(1.83)*
SUCC_DEC				-0.008
				(-6.80)***
FCF				-0.008
				(-0.97)
Controls		No	No	Yes
Fixed Effects		Year-quarter, Industry	Year-quarter, Industry	Year-quarter, Industry
N		74,815	74,815	74,815
Cluster		Firm	Firm	Firm
R^2		80.42%	81.59%	81.97%

1. This table reports OLS regression results for the full sample based on the following models:
Model (1): $ln\left(\frac{OC_{i,t}}{OC_{i,t-1}}\right) = \beta_0 + \beta_1 ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_2 Dec\_Dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \mathcal{E}_{i,t}$
Model (2): $ln\left(\frac{OC_{i,t}}{OC_{i,t-1}}\right) = \beta_0 + \beta_1 ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_2 Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_3 Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times RD_{i,t} + \beta_4 RD_{i,t} + \mathcal{E}_2$

Model (3): $ln\left(\frac{OC_{i,t}}{OC_{i,t-1}}\right) = \beta_0 + \beta_1 ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_2 Dec_{dum} \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_3 Dec_{dum} \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times RD_{i,t} + . \beta_4 RD_{i,t} + \beta_5 \sum CONTROLS + \beta_6 \sum Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times CONTROLS + \varepsilon$

2. ***, **, * indicate two-sided significance at the 0.01, 0.05 and 0.1 levels, respectively.
3. All variables are defined in the Appendix.

2.5.3 Additional analysis

Subsample analysis

Using models (2) and (3), I examine the association between cost behaviour and R&D intensity in firms with high and low R&D intensity levels. I divide the sample firms into these two groups using the R&D intensity indicator (*INV*). Column (1) in Table 2.6 presents the results from estimating model (2) in high R&D-intensive firms. Similar to the estimated results of model (2) in the whole sample, I find that β_1 is significantly positive at 0.832 (t = 82.46), and the estimated value of β_2 is significantly negative -0.063 (t = -4.19), suggesting that the operating costs in firms with high R&D intensity are sticky. The coefficient of the RD interaction term is significantly negative [-0.316 (t = -9.30)], indicating a positive effect of R&D intensity on the firm's cost stickiness level in high R&D-intensive firms. These results confirm that R&D intensity positively and significantly affects cost stickiness in firms with high R&D intensity.

Additionally, I present the results from estimating model (3) in high R&D-intensive firms in column (2) of Table 2.6. The results show that β_1 is still significantly positive 0.833 (t = 96.04) and β_2 is significantly negative -0.076 (t = -4.12), suggesting that the operating costs in firms with high R&D intensity are still sticky after adding the control variables to the model. The coefficient of the *RD* interaction term is significantly negative [-0.261 (t = -6.23). These results confirm that R&D intensity has a positive and significant effect

on cost stickiness in firms with high R&D intensity after controlling for the variables known in the prior literature to impact the level of cost stickiness significantly.

On the other hand, columns (3) and (4) in Table 2.6 show the results of estimating the two models in firms with low R&D intensity. Column (3) presents the results of estimating model (2) in low R&D-intensive firms. The results show that β_1 is significantly positive at 0.811 (t = 74.56). However, the estimated value of β_2 is negative but insignificant at -0.011 (t = -0.36), suggesting that the operating costs in firms with low R&D intensity are not sticky as there is not any significant difference between cost reactions towards demand increases and decreases. The coefficient of the *RD* interaction term is negative and significant [-0.462 (t = -2.85)], meaning that the low levels of R&D intensity in non-innovative firms is a determinant of this observed cost behaviour. This result is consistent with the assumptions of the revolutionary theory of the firm that only firms working in industries where innovation is significant would retain their resources when facing a reduction in their product's demand and redirect them towards innovation.

The previous findings are also supported in column (4) of Table 2.6, illustrating the results of estimating model (3) in firms with low R&D intensity. The estimated value of β_1 is significantly positive at 0.832 (t = 73.01) but β_2 is insignificantly negative -0.002 (t = -0.10). The coefficient of the *RD* interaction term is negative and significant [-0.356 (t = -2.08), meaning that the low levels of R&D intensity in non-innovative firms is a determinant of this observed cost behaviour. These results confirm that the low levels of R&D intensity in non-innovative firms reduces cost stickiness even after controlling for the variables known in the prior literature to impact the level of cost stickiness significantly.

The results of the subsample analysis confirm that the hypothesised positive association between cost stickiness and R&D intensity prevails only in R&D-intensive firms. These findings are consistent with the propositions of the evolutionary theory of the firm which emphasises the importance of retaining human and social capital during downturns in R&D-intensive firms because the loss of key network members can severely damage relationships that contribute to the creation of the firms' capabilities and competencies. Additionally, the disruptions caused by cutting those resources when demand declines may lead to the loss of the experiential and entrepreneurial spirit required for promoting innovative environment in these firms.

Table 2.2-6: Subsample Analysis

	High R&D intensity		Low R&D intensity	
Variable	(1)	(2)	(3)	(4)
Intercept	0.001	0.021	0.039	0.051
	(0.17)	(4.54) ***	(18.01) ***	(22.35) ***
$ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right)$	0.832	0.833	0.811	0.832
	(82.46) ***	(96.04)***	(74.56) ***	(73.01)***
$Dec\_Dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right)$	-0.063	-0.076	-0.011	-0.002
	(-4.19) ***	(-4.12)	(0.63)	(-0.10)
$Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times RD_{i,t}$	-0.316	-0.261	-0.462	-0.356
	(-9.30)***	(-6.23) ***	(-2.85)***	(-2.08) **
$Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times ln(Emp_{int_{i,t}})$		-0.006		-0.019
		(-0.49)		(-2.73)***
$Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times ln(Ast_{int_{i,t}})$		-0.020		-0.042
		(-1.40)		(-4.23)***
$Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times Succ_{dec_{i,t}}$		0.063		-0.042
		(4.66)***		(-3.83) ***
$Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times Fcf_{i,t}$		0.324		0.418
		(2.79)***		(5.19)***
$RD_{i,t}$	0.056	0.045	0.045	0.033
	(4.77)***	(3.64)***	(2.73)***	(1.66)**
$ln(Emp_{int_{i,t}})$		0.001		0.001
		(0.44)		(1.02)
Ln AST_INT		0.009		0.001
		(3.18) ***		(1.21)
SUCC_DEC		-0.014		-0.006
		(-5.89)***		(-5.28)***
FCF		-0.017		-0.003
		(-0.76)		(-0.45)
Controls	No	Yes	No	Yes
Fixed Effects	Year-quarter, Industry	Year-quarter, Industry	Year-quarter, Industry	Year-quarter, Industry
N	27,893	27,893	46,922	46,922
Cluster	Firm	Firm	Firm	Firm
R^2	76.93%	77.46%	85.60%	86.33%

1. This table reports OLS regression results for high and low R&D-intensive firms based on the following models:

   Model (2): $ln\left(\frac{OC_{i,t}}{OC_{i,t-1}}\right) = \beta_0 + \beta_1 ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_2 Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_3 Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times RD_{i,t} + \beta_4 RD_{i,t} + \mathcal{E}_2$

Model (3): $ln\left(\frac{OC_{i,t}}{OC_{i,t-1}}\right) = \beta_0 + \beta_1 ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_2 Dec_{dum} \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_3 Dec_{dum} \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times RD_{i,t} + . \beta_4 RD_{i,t} + \beta_5 \sum CONTROLS + \beta_6 \sum Dec_{dum} \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times CONTROLS + \varepsilon$

2. ***, **, * indicate two-sided significance at the 0.01, 0.05 and 0.1 levels, respectively.
3. All variables are defined in the Appendix.

Excluding R&D from the operating costs measure

To consider the likelihood of realizing a mechanical relationship between the operating costs and R&D intensity during the analysis, I am re-investigating the association between R&D and cost behaviour of *OC* after excluding R&D costs.

In model (1) presented in the first column of Table 2.7, I estimate the asymmetric adjustment of operating costs at the firm level with the changes in sales revenues. The results of the basic model of Anderson et al. (2003) show that the estimated value of β_1 is 0.871 (t = 157.99). This indicates that operating costs increase by 0.87% per 1% increase in sales revenues. The estimated value of β_2 is -0.083 (t = -9.58). The combined value of $\beta_1 + \beta_2 = 0.787$ indicates that the operating costs decrease by about 0.79% per 1% decrease in sales revenues. These results indicate that the sample firms are still subject to cost stickiness after using a different measure for operating costs.

The results of examining model (2) are presented in the second column of Table 2.7. Similar to the estimated results of model (1), I find that β_1 is 0.866 (t = 157.08), indicating that operating costs increase by 0.87% per 1% increase in sales revenues. The estimated value of β_2 is -0.043 (t = -5.30). The combined value of $\beta_1 + \beta_2 = 0.823$ indicates that the operating costs decrease by about 0.82% per 1% decrease in sales revenues. These results suggest that the operating costs are still subject to cost stickiness after adding the R&D intensity measure to the model. The coefficient of the RD interaction term is significantly negative -0.275 (t = -8.77), indicating a positive effect of R&D intensity on the firm's

cost stickiness level. These results are consistent with the first hypothesis (H1) that the level of cost stickiness increases with the firm's R&D intensity.

In the third column of Table 2.7, I capture the effect of adding the control variables to the model. The results of model (3) show that β_1 is still significantly positive at 0.879 (t = 136.17),), indicating that operating costs increase by 0.88% per 1% increase in sales revenues. The estimated value of β_2 is negative at -0.055 (t = -5.52). The combined value of $\beta_1+\beta_2$ = 0.824 indicates that the operating costs decrease by about 0.82% per 1% decrease in sales revenues. These results suggest that the operating costs remain sticky after adding the control variables to the model. The coefficient of the *RD* interaction term is significantly negative [-0.184 (t = -5.27)], suggesting that cost stickiness increases with the increased levels of R&D intensity, which supports the first hypothesis (H1).

The previous results confirm that the significant effect of R&D intensity on cost stickiness is not driven by the mechanical relationship between operating costs and R&D costs.

Table 2.7 Additional test (R&D Excluded)

Model	**Expected sign**	**(1)**	**(2)**	**(3)**
Intercept		0.028	0.029	0.042
		(11.79)***	(12.93)***	(17.42)***
$ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right)$	+	0.871	0.866	0.879
		(157.99)***	(157.08)***	(136.17)***
$Dec\_Dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right)$	-	-0.083	-0.043	-0.055
		(-9.58)***	(-5.30)***	(-5.52)***
$Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times RD_{i,t}$	-		-0.275	-0.184
			(-8.77)***	(-5.27)***
$Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times ln(Emp_{int_{i,t}})$	-			-0.017
				(-2.64)***
$Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times ln(Ast_{int_{i,t}})$	-			-0.043
				(-5.24)***
$Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times Succ_{dec_{i,t}}$	+			0.059
				(6.49)***
$Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times Fcf_{i,t}$	-			0.440
				(6.52)***
$RD_{i,t}$			0.019	0.011
			(1.87)**	(1.00)
$ln(Emp_{int_{i,t}})$				0.001
				(1.16)
Ln AST_INT				0.004
				(3.83)***
SUCC_DEC				-0.006
				(-5.04)***
FCF				-0.006
				(-0.75)
Controls		No	No	Yes
Fixed Effects		Year-quarter, Industry	Year-quarter, Industry	Year-quarter, Industry
N		68,482	68,482	68,482
Cluster		Firm	Firm	Firm
R^2		80.32%	80.77%	81.15%

1. This table reports OLS regression results based on the following models (R&D costs are excluded from OC):

Model (1): $ln\left(\frac{OC_{i,t}}{OC_{i,t-1}}\right) = \beta_0 + \beta_1 ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_2 Dec\_Dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \mathcal{E}_{i,t}$

Model (2): $ln\left(\frac{OC_{i,t}}{OC_{i,t-1}}\right) = \beta_0 + \beta_1 ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_2 Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) +$
$\beta_3 Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times RD_{i,t} + \beta_4 RD_{i,t} + \mathcal{E}_2$

Model (3): $ln\left(\frac{OC_{i,t}}{OC_{i,t-1}}\right) = \beta_0 + \beta_1 ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_2 Dec_{dum} \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_3 Dec_{dum} \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times RD_{i,t} + . \beta_4 RD_{i,t} + \beta_5 \sum CONTROLS + \beta_6 \sum Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times CONTROLS + \varepsilon$

2. ***, **, * indicate two-sided significance at the 0.01, 0.05 and 0.1 levels, respectively.
3. All variables are defined in the Appendix.

Excluding observations with zero R&D costs from the sample

It was observed that the main sample includes a high volume of observations from firms with zero R&D. Therefore, I'm reinvestigating the effect of R&D intensity on the stickiness of operating costs for the main sample after excluding observations with zero R&D costs.

In model (1) presented in the first column of Table 2.8, I estimate the asymmetric adjustment of operating costs at the firm level with the changes in sales revenues. The results of the basic model of Anderson et al. (2003) show that the estimated value of β_1 is 0.845 (t = 133.34). This indicates that operating costs increase by 0.85% per 1% increase in sales revenues. The estimated value of β_2 is -0.114 (t = -10.36). The combined value of $\beta_1+\beta_2$ = 0.731 indicates that the operating costs decrease by about 0.73% per 1% decrease in sales revenues. These results indicate that the sample firms are still subject to cost stickiness after excluding observations with zero R&D costs.

The results of examining model (2) are presented in the second column of Table 2.8. Similar to the estimated results of model (1), I find that β_1 is 0.829 (t = 134.54), indicating that operating costs increase by 0.83% per 1% increase in sales revenues. The estimated value of β_2 is -0.048 (t = -5.06). The combined value of $\beta_1+\beta_2$ = 0.781 indicates that the operating costs decrease by about 0.78% per 1% decrease in sales revenues. These results suggest that the operating costs are still subject to cost stickiness after adding the R&D intensity measure to the model. The coefficient of the RD interaction term is significantly

negative -0.282 (t = -11.31), indicating a positive effect of R&D intensity on the firm's cost stickiness level. These results are consistent with the first hypothesis (H1) that the level of cost stickiness increases with the firm's R&D intensity.

In the third column of Table 2.8, I capture the effect of adding the control variables to the model. The results of model (3) show that β_1 is still significantly positive at 0.849 (t = 118.16),), indicating that operating costs increase by 0.85% per 1% increase in sales revenues. The estimated value of β_2 is negative at -0.077 (t = -6.81). The combined value of $\beta_1+\beta_2$ = 0.824 indicates that the operating costs decrease by about 0.82% per 1% decrease in sales revenues. These results suggest that the operating costs remain sticky after adding the control variables to the model. The coefficient of the *RD* interaction term is significantly negative [-0.225 (t = -7.54)], suggesting that cost stickiness increases with the increased levels of R&D intensity, which supports the first hypothesis (H1).

The previous results confirm that the significant effect of R&D intensity on cost stickiness is not driven by the high volume of observations with zero R&D costs.

Table 2.8 Regression Analysis (excluding observations with zero R&D costs)

Model	Expected sign	(1)	(2)	(3)
Intercept		0.018 (6.52)***	0.019 (6.97)***	0.036 (12.38)***
$ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right)$	+	0.845 (133.34)***	0.829 (134.54)***	0.849 (118.16)***
$Dec\_Dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right)$	-	-0.114 (-10.36)***	-0.048 (-5.06)***	-0.077 (-6.81)***
$Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times RD_{i,t}$	-		-0.282 (-11.31)***	-0.225 (-7.54)***
$Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times ln(Emp_{int_{i,t}})$	-			-0.014 (-1.71)**
$Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times ln(Ast_{int_{i,t}})$	-			-0.031 (-3.04)***
$Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times Succ_{dec_{i,t}}$	+			0.069 (6.63)***
$Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times Fcf_{i,t}$	-			0.334 (4.01)***
$RD_{i,t}$			0.048 (5.62)***	0.039 (4.12)***
$ln(Emp_{int_{i,t}})$				-0.001 (-0.36)
Ln AST_INT				0.008 (4.59)***
SUCC_DEC				-0.009 (-5.91)***
FCF				-0.013 (-0.95)
Controls		No	No	Yes
Fixed Effects		Year-quarter, Industry	Year-quarter, Industry	Year-quarter, Industry
N		56,302	56,302	56,302
Cluster		Firm	Firm	Firm
R^2		78.82%	79.96%	80.41%

Regression Analysis (exclude 0 R&D) 1

1. This table reports OLS regression results for high and low R&D-intensive firms based on the following models:

Model (1): $ln\left(\frac{OC_{i,t}}{OC_{i,t-1}}\right) = \beta_0 + \beta_1 ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_2 Dec\_Dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \varepsilon_{i,t}$

Model (2): $ln\left(\frac{OC_{i,t}}{OC_{i,t-1}}\right) = \beta_0 + \beta_1 ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_2 Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_3 Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times RD_{i,t} + \beta_4 RD_{i,t} + \mathcal{E}_2$

Model (3): $ln\left(\frac{OC_{i,t}}{OC_{i,t-1}}\right) = \beta_0 + \beta_1 ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_2 Dec_{dum} \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) + \beta_3 Dec_{dum} \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times RD_{i,t} + . \beta_4 RD_{i,t} + \beta_5 \sum CONTROLS + \beta_6 \sum Dec\_dum \times ln\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times CONTROLS + \varepsilon$

2. ***, **, * indicate two-sided significance at the 0.01, 0.05 and 0.1 levels, respectively.
3. All variables are defined in the Appendix.

2.6 Conclusion

This study provides an alternative explanation for cost stickiness in R&D-intensive firms. Understanding cost behaviour in these companies requires adopting different theories and perspectives to incorporate innovative resource allocation dynamics. Therefore, I complement prior research and explain this asymmetric cost behaviour based on the evolutionary theory of the firm. I hypothesise that managers of R&D-intensive firms would retain their resources during downturns to avoid the loss of any part of the organisational memory that stores the employees' operational skills and knowledge. Additionally, these resources would also persist to avoid any disruption to the current agreement between the organisation and its members. Simultaneously, managers of R&D-intensive firms would redirect the acquired resources toward the recovery process by investing them in new technologies and R&D activities that realign the organisation with its external environment. These insights suggest a positive association between cost stickiness and R&D intensity.

I investigate this relationship and the results reveal a significant positive association between cost stickiness and R&D intensity. These findings are consistent with the hypothesis that cost stickiness is associated with higher R&D intensity. Further analysis also provides evidence that cost stickiness increases with higher R&D intensity only in

R&D-intensive firms. The results contribute to understanding the resource allocation dynamics in R&D-intensive firms and their consequences on the observed cost behaviour.

I acknowledge the potential limitations of the study related to focusing only on R&D costs as the primary source of innovation in contemporary businesses, overlooking innovation activities based on other sources such as design activities, engineering developments and exploration of markets for new products. Future work can investigate the association between cost stickiness and other direct measures of innovation, such as survey-based indicators. I also recognise that innovation processes are contingent; they differ according to the economic sector, the field of knowledge, the type of innovation, the historical period, and the country concerned. Future research might also determine whether these inferences generalize to samples that cover these different aspects of innovation in the economy. I also acknowledge that the sampling procedures entail the disadvantage of significant data loss as these procedures restrict the sample to observations for which sales and costs change in the same direction. The empirical study of this research is also limited due to the difficulty of measuring the main constructs of the evolutionary theory of the firm such as routines, employees' knowledge and interorganizational conflict and their relationship with cost stickiness in R&D-intensive firms. Future research could examine these relationships if data for the specific constructs are available.

Appendix 2.1: Variables Definitions

Variables	Definition
OC	Sales revenues minus income from operations minus research and development costs (sale - ibq - xrd);
SALES	Sales revenues of the firm (sale);
Dec_dum	An indicator that takes the value of 1 if sales revenues decrease between fiscal years t-1 and t, and 0 otherwise;
RD	Research and development expenses (xrd) divided by sales revenues (sale);
EMP_INT	The number of employees at fiscal year-end divided by total sales revenues (emp /sale);
AST_INT	Total assets divided by total sales revenues (at / sale);
FCF	Cash flow from operating activities minus common and preferred dividends scaled by total assets (oancf – [dvc+ dvp] / at);
SUCC_DEC	An indicator variable that equals 1 if $Sales_{it-4} < Sales_{it-8}$ and 0 otherwise.

Chapter 3 Cost Stickiness Behaviour, R&D Intensity and the Informativeness of Earnings

Abstract

This study examines the relationship between cost stickiness and earnings informativeness in R&D firms. It also investigates whether R&D intensity moderates the association between cost stickiness and the earnings-returns relationship. I predict that accounting earnings of R&D-intensive firms with sticky costs capture the underlying causes of this cost behaviour that managers are reinvesting their resources in new technologies and R&D activities to realign the organisation with its environment. Consistent with this prediction, the results suggest that the adverse effect of cost stickiness on earnings informativeness reported in the literature is not applicable to R&D firms. The study also shows that higher R&D intensity attenuates the previously reported negative impact of cost stickiness on earnings informativeness. Finally, I find that cost stickiness is positively associated with earning informativeness only in R&D-intensive firms. These results suggest that accounting earnings signal relevant information when firms with sticky costs invest their resources in R&D activities.

3.1 Introduction

Innovation is playing an increasingly essential role in all sectors of the modern economy. It drives the ongoing transformation of economies and societies and challenges every aspect of them (OECD, 2017). It is the disruptive enabler of new products, services, business models and operating structures and a catalyst for creating opportunities for new players to evolve within the market (PwC, 2020). Innovation fundamentally changes the "DNA" of many emerging and existing firms, the various stakeholders in these firms, the capital markets that finance these firms, and the role of accounting information in allocating capital to these firms (Zimmerman, 2015). At the same time, the managerial operating decisions that manifest in observed cost stickiness behaviour affect various earnings properties, such as predictability, asymmetric timeliness and persistence (Banker et al., 2016; Weiss, 2010). Extending studies evaluating whether accounting earnings of R&D-intensive firms reflect information used by equity investors (Amir et al., 2007; Chan et al., 2001), I am assessing the informativeness of earnings of these firms when costs behave in a sticky manner.

I predict that the accounting earnings of R&D-intensive firms with sticky costs capture the underlying events of this cost behaviour. Cost stickiness is interpreted as a reflection of the managerial decisions to retain unused resources during periods of sales reduction (Anderson et al., 2003). However, when R&D-intensive firms face a downturn, they invest their resources in new technologies and innovations to realign the organisation with its external environment (Gulati et al., 2010; Holland & Katzin, 2019). These decisions would enhance the firms' competitive advantage, enabling them to operate in a concentrated market. Investing in innovation during demand reduction periods would also reduce the technical and commercial uncertainty related to R&D activity, which reduces

the risks of their R&D investments. R&D investments would also lead to sustained success in responding to the changes in the environment during downturns and increase the firms' growth options. These implications would enable the R&D-intensive firms to sustain their earnings, increasing the predictability and usefulness of this information (Ciftci & Cready, 2011; Collins & Kothari, 1989; Easton & Zmijewski, 1989).

Based on a sample of 63,280 firm-quarter observations for 3,641 US public firms engaged in R&D activities from 2000 through 2019, the results imply that the previously reported adverse effect of cost stickiness on earnings informativeness is not applicable for R&D firms. The study also shows that the higher R&D intensity attenuates the previously reported negative impact of cost stickiness on earnings informativeness. However, I find evidence that the informativeness of earnings increases with cost stickiness only in R&D-intensive firms. These results suggest that accounting earnings reflect information used by equity investors when firms with sticky costs invest in R&D activities. These findings indicate that the reported earnings of R&D-intensive firms with sticky costs capture the underlying causes of this cost behaviour that these firms are investing in R&D activities during difficult times to improve their performance and increase their ability to compete.

This study contributes primarily to two streams of literature. First, it contributes to the extensive literature on earnings informativeness by identifying cost stickiness as an economic determinant of the earnings-returns relationship. These results support the argument that stickier cost behaviour reduces the predictive power of earnings in low R&D-intensive firms. However, the informativeness of earnings increases with the increased levels of cost stickiness in high R&D-intensive firms. Second, the results contribute to the limited literature investigating the implications of this asymmetric cost behaviour (Banker & Chen, 2006; He et al., 2020; Homburg et al., 2018; Weiss, 2010).

These findings show that higher R&D intensity attenuates the negative effect of cost stickiness documented in the literature on the informativeness of earnings information.

More generally, the findings may motivate managers of R&D-intensive firms to disclose more information about the firm's R&D activities and future investment opportunities to enable the investors to incorporate this information into their analysis models. These results may also encourage analysts and investors to use cost stickiness levels as a lens to understand the managerial operating decisions in R&D-intensive firms. Regulators might consider requiring R&D-intensive firms to disclose more information about their operational decisions to enhance the decision-making process of the market participants.

The following section discusses the relevant literature and hypotheses development. The third section describes the research design. Section 4 presents the analysis process results, followed, in the final section, by the conclusion of this research.

3.2 Literature review and hypothesis development

3.2.1 The effect of cost stickiness on the informativeness of earnings for R&D firms

A growing body of literature shows that the empirical behaviour of costs is sticky [see Banker et al. (2018) for a thorough review]. The managerial intervention in the resource adjustment process results in asymmetric behaviour of costs in response to changes in activity levels. When demand increases, managers add the required resources. However, managers deliberately retain the operating resources when demand declines rather than removing them entirely. Therefore, costs increase more when activity levels rise than they decrease for equivalent sales fall (Anderson et al., 2003). Later studies, such as that of Weiss (2010), show the resulting contemporaneous earnings asymmetry – earnings decrease more when revenues fall than they increase when revenues rise. He argues that

this reduction in earnings increases the variability of the earnings distribution when activity levels drop, resulting in less predictable profitability.

Prior research shows that capital markets react to earnings; new information in the earnings announcements leads individual investors to revise their beliefs regarding the firm's value. These differential belief revisions stimulate more trading and stock price changes (Ball & Brown, 1968; Beaver, 1968). However, the association between earnings and returns is contingent on the financial information environment: the precision and the amount of the pre-disclosure information, the private information gathered by individual market participants in conjunction with the content of the earnings announcements itself and the concurrent information released at the same time as the earnings announcements (Bamber, 1987; Barron et al., 2005; Beaver et al., 2020; Kim & Verrecchia, 1991).

The prior literature indicates that cost stickiness is an influential determinant of the firms' financial information environment. Banker and Chen (2006) report that sticky costs lessen the accuracy of earnings forecast models that depend on the financial statements information. Anderson et al. (2007) find that cost stickiness behaviour affects the interpretation of standard financial ratios in fundamental analysis. Banker et al. (2016) show that cost stickiness can be mistaken for conditional conservatism in standard models. Weiss (2010) finds that cost stickiness reduces the accuracy of the analysts' earnings forecasts, reduces the analysts' coverage and reduces the market response to earnings surprises. Moreover, Homburg et al. (2018) find that cost stickiness reduces earnings persistence and quality. The previous findings indicate that the financial information environment for firms with stickier costs provides less useful information for the valuation and prediction of their future earnings.

In modern economies, firms depend on evolving technologies that substantially alter customer behaviour and demand in many sectors. Additionally, innovation in new products and processes has become increasingly important for companies to achieve and maintain a competitive advantage in this rapidly changing environment (Lome et al., 2016). Therefore, it is essential to investigate the informativeness of earnings of firms with sticky costs by taking a closer look at the degree to which accounting earnings of contemporary businesses, especially those engaged in R&D activities, communicate information about the underlying fundamentals of their businesses in a clear and informative manner. However, the cost stickiness literature did not investigate the effect of this cost behaviour on the informativeness of earnings in firms engaged in R&D activities. In this study, I aim to address this issue and explore its effect and whether R&D intensity attenuates that effect.

R&D firms have more incentives to provide more voluntary disclosures than non-R&D firms. These incentives include rapid growth, the need for external financing, lower profitability tendencies, and greater emphasis on brand-building marketing strategies (Bentley et al., 2013; Bentley-Goode et al., 2019; Rajagopalan, 1997). R&D firms also tend to attract greater coverage by analysts and the business press (Asdemir et al., 2017; Barth, Kasznik, et al., 2001). This improved information environment reduces mispricing, uncertainty about firm value and information asymmetry (Bentley-Goode et al., 2019). Consequently, R&D firms have lower analyst forecast errors due to the greater private information acquisition of individual analysts (Barron et al., 2002). These findings indicate that the financial information environment for R&D firms provides useful information for the valuation and prediction of future earnings, increasing the informativeness of earnings for R&D firms with sticky costs.

However, others argue that there is a deterioration in the usefulness of earnings information in explaining the market value and predicting future returns for R&D firms. These firms are likely to display high volatility in their revenues and cash flows because R&D investments carry higher uncertainty about future benefits than tangible investments (Amir et al., 2007; Kothari et al., 2002). Furthermore, the immediate expensing of R&D investments, irrespective of when their associate benefits materialised, reduces the matching between concurrent revenues and expenses, which reduces the persistence of the earnings (Dichev & Tang, 2008; Srivastava, 2014). Similarly, Roychowdhury and Watts (2007) find that the earnings of R&D firms are unrelated to their market values because those firms are likely to have growth options whose values are not recognised in the financial statements unless purchased.

Based on the previous arguments, R&D firms with sticky costs work in a different information environment that affects earnings explanatory power for stock returns. Thus, this study extends Weiss's research (Weiss, 2010) and examines the association between cost stickiness and earnings informativeness for a sample of R&D firms. I suggest that the cost stickiness level of R&D firms affects the informativeness of earnings for security valuation. However, the direction of this effect is an empirical question; the corresponding hypothesis is stated in the null form.

H1: Cost stickiness does not affect the earnings informativeness of R&D firms.

3.2.2 The moderating effect of R&D intensity on the association between cost stickiness and the informativeness of earnings

Cost stickiness is explained by the deliberate managerial decisions to retain unused resources during periods of weak demand (Anderson et al., 2003). However, when managers of R&D-intensive firms face a downturn, they invest unutilised resources in new technologies and R&D activities that realign the organisation with its external

environment (Gulati et al., 2010; Holland & Katzin, 2019). Presumably, firms invest in R&D activities when demand falls to improve their performance and increase their ability to compete (Frick, 2019; Makkonen et al., 2014). The previous literature finds that investors are fully aware of the performance implications of this strategy, which leads to positive changes in stock prices. Srinivasan et al. (2011) find that when a firm invest in R&D activities during difficult times, investors will infer that the firm has high expectations about its near-term R&D outputs and raise their expectations of its future cash flows, leading to increases in stock returns.

I extend this prior literature and examine whether reported earnings of R&D-intensive firms with sticky costs capture the underlying causes of this cost behaviour, which is part of the information set reflected in stock prices. In other words, I am investigating whether R&D intensity moderates the impact of cost stickiness on earnings informativeness.

The Schumpeterian theoretical framework suggests that economic cycles are the consequences of innovation and that innovative activities and innovative organisations are reshaped by economic crises. In particular, this theory looked at innovation as an event that could revolutionise economic life through the efforts of large, oligopolistic corporations that can perform R&D and innovation as a routine activity by building on their previous competence (Schumpeter, 1943).

Based on these insights, Archibugi et al. (2013) find that firms that would respond to the challenging demand conditions by investing in R&D activities are large and established firms that cannot survive without changing their products and services. The competitive advantage of these firms resides in the generation and upgrading of new knowledge, irrespective of the demand conditions. These firms have the capacity and the resources to set up and maintain internal R&D laboratories. They also have qualified personnel who

interact periodically with universities and public research centres. These technological and organisational capabilities would enable large firms to reduce the risks and costs associated with exploring new technological opportunities during downturns. Ciftci and Cready (2011) find that large firms can diversify away the technical and commercial uncertainty related to R&D activity, which reduces the risks of their R&D investments. Cohen and Klepper (1996) also provide evidence that large firms can spread R&D costs across larger sales bases. This reduction in risks and costs would reduce earnings volatility and increase its persistence, increasing the informativeness of the earnings (Ciftci & Cready, 2011; Collins & Kothari, 1989; Easton & Zmijewski, 1989).

Investing in R&D activities during hard times guarantees that costs and prices are kept competitive and that products are differentiated and improved compared to competitors (Gupta, 2020). This competitive advantage will create a concentrated market structure with high entry barriers and an oligopolistic competition (Archibugi et al., 2013). Ahmed (1994) and Biddle and Seow (1991) assert that earnings informativeness increases in a non-competitive market structure. Moreover, Lev (1983) finds that the impact of favourable events, such as a cost-saving technological change or an introduction of a new product on earnings, might persist in these markets. Greater earnings persistence will lead to more extensive revisions in dividend expectations, and the earnings-return association will be more robust (Collins & Kothari, 1989).

The strategic management literature also recognises that these firms are among the winners during hard times. Laitinen (2000) finds that R&D investments in new product development and marketing are most likely to lead to sustained success in responding to the changes and uncertainty in the environment during downturns. Holland and Katzin (2019) argue that firms that invest in R&D activities during adverse economic situations

grow at a 17% compound annual growth rate (CAGR) during the downturn, compared with 0% among the losers. The winners also grew at an average 13% CAGR in the years after the downturn, while the losers stalled at 1%. Collins and Kothari (1989) and Ahmed (1994) argue that earnings informativeness increases in high-growth firms with options to make future investments at an above-normal rate of return.

Consequently, I suggest that cost stickiness, combined with R&D intensity, positively affects the informativeness of financial information, leading to the following hypothesis.

> *H2: R&D intensity attenuates the association between cost stickiness and earnings informativeness as an explanatory variable of returns.*

3.3 Design of the study

3.3.1 Variables measurements

The R&D intensity measure

I follow Chan et al. (2001) and Eberhart et al. (2008) and use the ratio of R&D expenses to sales revenues (RD_{iq}) to measure the intensity of R&D activities of firm *i* in quarter *q*. On the Compustat database, R&D expenses cover all costs incurred, including salaries and departmental expenses related to developing new products or services during the fiscal quarter. I also create an indicator variable, *INV*, that represents R&D-intensive firms. Following Ciftci et al. (2011), I use the industry-adjusted R&D expenses to sales ratio as a benchmark to classify firms into high and low R&D-intensive firms. The benchmark is the weighted average R&D expenses to sales ratio of all firms in the four-digit SIC industry group, where the weights are sales. Firms whose R&D intensity exceeds the benchmark are classified as high R&D-intensive firms (*INV* =1), and the rest as low R&D-intensive firms (*INV* =0).

The firm-specific measure of cost stickiness

Weiss (2010) has developed a measure of cost stickiness at the firm level. This measure focuses on estimating the difference between the rate of cost decrease for recent quarters with decreasing sales and the corresponding rate of cost increase for recent quarters with increasing sales:

$$STICKY_{i,q} = -\left[ln\left(\frac{\Delta Oprt}{\Delta Sales}\right)_{i,\underline{\tau}} - ln\left(\frac{\Delta Oprt}{\Delta Sales}\right)_{i,\overline{\tau}} \right] with\ \underline{\tau},\ \overline{\tau} \epsilon \{t, \dots, t-3\} \quad (1)$$

$\Delta Sales$ denotes changes in sales revenue between two quarters $\left(Sales_{tq} - Sales_{i,tq-1}\right)$ and $\Delta Oprt$ represents the corresponding change in operating costs $\left(Oprt_{i,tq} - Oprt_{i,tq-1}\right)$. Where operating costs equal sales revenues minus income from operations, $\underline{\tau}$ is the most recent of the last four quarters in fiscal year *t* with a decrease in sales and $\overline{\tau}$ is the most recent of the last four quarters in fiscal year t with an increase in sales.

$Sticky_{i,q}$ compares the slope of a cost function between the two most recent quarters in fiscal year *t*, one with an increase and the other with a decrease in sales. If costs are sticky, meaning that they increase more when activity rises than they decrease when activity falls by an equivalent amount, then the term in square brackets exhibits a negative sign. Following Homburg et al. (2018), I multiply the sticky measure of Weiss (2010) by -1 so that the higher values of $STICKY_{i,q}$ imply more stickiness.

Using this measure entails the disadvantage of a significant data loss. For example, I follow Weiss (2010) and restrict the sample to observations for which sales and costs change in the same direction. Moreover, the measure only identifies firm-year values, which entail quarterly increases and decreases in sales. However, the advantages outweigh these data restrictions. This measure can be used to examine the effects and determinants of cost stickiness. Therefore, this measure is relevant to this study as it

focuses on measuring the consequences of cost stickiness on the informativeness of earnings. Furthermore, it provides a clear reference point of a linear cost function (i.e., *STICKY* = 0) to distinguish between sticky and anti-sticky firms.[3] Based on this, I create the indicator variable (*DUM_STICKY*) that equals 1 if *STICKY* is positive, and 0 otherwise.

Earnings response coefficient (ERC)

This study measures the informativeness of earnings by estimating the ERC using an association study. This methodology would help identifying whether earnings determination process in R&D firms with sticky costs captures in a meaningful and timely fashion the valuation relevant events. Association studies recognize that market agents learn about earnings and valuation-relevant events from many nonaccounting information sources throughout the period. Thus, these studies investigate whether accounting earnings measurements are consistent with the underlying events and information set reflected in stock prices (Collins & Kothari, 1989). Therefore, The ERC is calculated by regressing quarterly abnormal returns on standardized unexpected quarterly earnings over a period of 20 years.

Abnormal returns are calculated by subtracting the expected returns from the firm's actual returns. Expected returns are computed with regression coefficients derived from the market model for 60 months prior to the abnormal return estimation period as follows[4]:

$$R_{im} = \alpha + \beta R_{mm} + \varepsilon_{im} \qquad (2)$$

[3] Costs are termed anti-sticky if they increase less when activity rises than they decrease when activity falls by an equivalent amount.

[4] To mitigate the effect of missing data, I follow Petra, S. (2007). The effects of corporate governance on the informativeness of earnings. Economics of Governance, 8(2), 129-152. https://doi.org/10.1007/s10101-006-0018-8 and excluded firms with less than 28 monthly returns from my dataset.

Where R_{im} is the monthly total return for firm *i* in month *m*. R_{mm} is the monthly total return on the S&P500 index in month *m*. α is the intercept parameter. β is the slope parameter. ε_{im} is the noise term. I calculated the continuously compounded abnormal returns using the following:

$$AR_{im} = \ln(1 + R_{im} - \alpha_i - \beta_i \, . \, R_{mm}) \quad (3)$$

Cumulative abnormal returns are calculated by cumulating the monthly abnormal returns over a 3-month quarterly period as follows:

$$CAR_{iq} = \sum(AR_{im}) \quad (4)$$

Where *m* is *j*-*k* (j = 4, 7, 10, 1) (k = 6, 9, 12, 3). CAR_{iq} is the cumulative abnormal return of firm *i* for quarter *q*. AR_{im} is the monthly continuously compounded abnormal returns of firm *i* in month *m*.

I follow prior literature to compute the standardized unexpected earnings (*SUE*) (Chi & Shanthikumar, 2017). Unexpected earnings are defined as $UE_{iq} = AE_{iq} - AE_{iq-4}$, where AE_{iq} is the announced quarterly earnings per share before discontinued operations and extraordinary items (*EPS*) and AE_{iq-4} is the *EPS* for the prior year's same quarter. *SUE* is defined as UE_{iq} scaled by price per share at the end of quarter *q*.

The ERC is calculated with the following regression model:

$$CAR_{iq} = \alpha + b(SUE_{iq}) + e \quad (5)$$

Where CAR_{iq} is quarterly cumulative abnormal returns of firm *i* in quarter *q* obtained from the abnormal return model above, SUE_{iq} is standardized unexpected quarterly earnings of firm *i* in quarter *q* obtained earlier, and *b* is the ERC.

3.3.2 Data and sample

The initial sample comprises 18,453 firms based on 659,503 firm-quarter observations from quarter industrial files for public firms in the North America Compustat database whose headquarters are located in the USA from the first quarter of 2000 to the last quarter of 2019. Table 3.1 describes the construction of this sample.

Following prior literature (Kama & Weiss, 2013; Zhong, 2018), I exclude financial institutions and public utilities firms (four-digit SIC codes 6000-6999 and 4900-4999) as these two industries are highly regulated and characterised by capital requirements that would affect the statistical measures, and I also remove duplicate observations. Moreover, I discard invalid observations with missing or negative values of either total assets, sales revenues or operating costs (Anderson et al., 2003; Venieris et al., 2015). I also follow Weiss (2010) and exclude observations with sales and costs changing in the opposite direction. In addition, I follow Barth, Beaver, et al. (2001) and exclude observations with sales revenues less than $1 million to avoid potential outliers attributable to very small firms. Then, I drop observations with a missing firm-level cost stickiness measure. Furthermore, I eliminate observations with missing standardized unexpected earnings or cumulative abnormal returns variables. Finally, I drop observations with missing data on the R&D intensity measure and the control variables. The final sample size consists of 63,280 firm-quarter observations for 3,641 firms. All continuous variables are winsorised to the 1st and 99th percentile to reduce the influence of extreme outliers.

Table 3-1:Sample Selection Procedures

Initial Sample: Firm-quarter observations in Compustat NA for USA public firms over 2000-2019.	659,503
Excluding financial and utility firms and duplicate observations.	487,721
Drop observations with missing or negative total assets, sales revenues or operating costs	480,547
Drop observations with sales and costs change in the opposite direction	383,327
Drop observations with sales less than $1 million	333,405
Exclude observations with missing stickiness measure (*STICKY*)	239,299
Exclude observations with missing unexpected earnings and cumulative abnormal returns	175,658
Exclude observations with missing innovation variable	87,163
Final Sample: Drop observations with missing data on control variables.	63,280

This table presents the sample firms' selection procedures.

Table 3.2 shows the sample distribution by industry, where industry classification is based on the two-digit SIC code. The electronics and other electrical equipment industry accounts for the most significant portion of the sample (15.18%), followed by the instruments and related products industry (13.85%), followed by Chemical and Allied Products (11.45%), the business services industry (11.15%) and industrial and commercial machinery and computer equipment (9.56%), respectively. As expected, the sample firms work in industries intensively involved in research activities according to the classification of R&D-intensive industries in many recognized taxonomies (Galindo-Rueda & Verger, 2016; Hill, 2020).

Table 3-2:Sample Distribution

SIC code	Industry	Number of obs.	Percentage of sample	Cumulative percentage
36	Electronics & Other Electrical Equipment	9,608	15.18	15.18
38	Instruments & Related Products	8,767	13.85	29.03
28	Chemical & Allied Products	7,244	11.45	40.48
73	Business Services	7,058	11.15	51.93
35	Industrial and Commercial Machinery & Computer Equipment	6,226	9.84	61.77
56	Apparel & Accessory Stores	2,186	3.45	65.22
59	Miscellaneous Retail	2,094	3.31	68.53
58	Eating &Drinking Places	2,028	3.20	71.73
37	Transportation Equipment	1,902	3.01	74.74
50	Wholesale Trade -Durable Goods	1,892	2.99	77.73
80	Health Services	1,378	2.18	79.91
53	General Merchandise Stores	1,173	1.85	81.76
-	Other	11,724	18.24	100.00
	Total	63,280	100.00	

This table reports the sample distribution by industry, respectively.

3.4 Models

3.4.1 The effect of cost stickiness on the informativeness of earnings

To test the first hypothesis, I estimate ordinary least-squares regression to examine the effect of cost stickiness on earnings informativeness. In this regression, the cumulative abnormal returns (CAR) is the dependent variable; the independent variables include the standardized unexpected earnings SUE, the firm-level cost stickiness measure $STICKY$ and their interaction term as follows:

$$CAR = \alpha + \beta_1 SUE + \beta_2 STICKY + \beta_3 SUE * STICKY + \varepsilon \quad (6)$$

The primary variable of interest is β_3, the coefficient of $SUE * STICKY$, which captures the change in ERCs of the sample firms due to the difference in the cost stickiness level.

Following the literature on the ERCs (Beaver et al., 2020; Biddle & Seow, 1991; Collins & Kothari, 1989; Easton & Zmijewski, 1989; Ferri et al., 2018), I include several control variables, *CONTROLS* and also their interactions with SUE in model (8) (see the Appendix for the detailed definition of the variables). *CONTROLS* include leverage *LEV*, the systematic risk estimated from the market model using 60 monthly firm total returns and the corresponding S&P 500 index total returns before the estimation period *BETA*, the earnings persistence measure *PERS*, the market-to-book ratio at the end of quarter *q* *MTB*, an indicator variable that is equal to 1 for firm-quarters with non-Dec 31 fiscal year-ends and 0 otherwise NON_DEC31 , the number of days after the end of the fiscal quarter that earnings are announced *LAG*, a control variable for the nonlinear relationship NON_LIN and the log of market cap as a proxy for the firm size ln ($SIZE$), a loss indicator *LOSS*. I also include industry fixed effects (using 1-digit SIC industry) and fiscal year and quarter fixed effects and their interactions with SUE to control for differences in investors' reaction to earnings reports in different fiscal years, quarters and across various industries. I also correct the standard errors for the firm clustering effects (Petersen, 2009).

$$CAR = \alpha + \beta_1 SUE + +\beta_2 STICKY + \beta_3\, SUE * STICKY + \beta_4 \sum CONTROLS + \beta_5 \sum SUE * CONTROLS + \varepsilon \quad (7)$$

3.4.2 The moderating effect of innovation

To test the second hypothesis, I examine whether R&D intensity moderates the effect of cost stickiness on earnings informativeness. I expect an interactive relationship between R&D intensity and cost stickiness concerning the informativeness of earnings. Thus, I extend model (6) to include the interaction term between the standardized unexpected

earnings SUE, R&D intensity indicator INV and the firm-level cost stickiness measure $STICKY$ as follows:

$$CAR = \alpha + \beta_1 SUE + \beta_2 STICKY + \beta_3 INV + \beta_4 SUE * STICKY + \beta_5 STICKY * INV + \beta_6 SUE * INV + \beta_7 SUE * STICKY * INV + \varepsilon \quad (8)$$

I also added the control variables and their interactions with DEC_SUE to the previous model as follows:

$$CAR = \alpha + \beta_1 SUE + \beta_2 STICKY + \beta_3 INV + \beta_4 SUE * STICKY + \beta_5 STICKY * INV + \beta_6 SUE * INV + \beta_7 SUE * STICKY * INV + \beta_8 \sum CONTROLS + \beta_9 \sum SUE * CONTROLS + \varepsilon \quad (9)$$

The primary variable of interest in models (8) and (9) is β_7, the coefficient of $SUE * STICKY * INV$, which captures the moderating effect of R&D intensity on the association between cost stickiness and ERC.

3.5 Empirical results

3.5.1 Descriptive statistics

Table 3.3 provides descriptive statistics on the main variables used in the analysis. Firm-level cost stickiness yields a positive mean of 0.050 (median = 0.040). As assumed, the sample, on average, is subject to cost stickiness. Moreover, *DUM_STICKY* indicates that 53% of the sample firms exhibit cost stickiness. The standard deviation of *STICKY* is 1.221, showing considerable variation among the firms' cost behaviour. The mean value of cost stickiness of the sample firms is higher than that reported by Weiss (2010), who noted an average total cost stickiness of (0.017). This difference might be due to the different sampling requirements of each study. Weiss (2010) studied cost stickiness in

manufacturing firms with analysts' forecasts. Meanwhile, this study investigates the cost behaviour of all the US R&D firms.

The average firm spends 12.2% (median = 4.8%) on R&D expenditures scaled by sales revenues. This high value of R&D intensity indicates that the sample firms are R&D-intensive firms, as most of the sample firms operate in innovative industries (as shown in Table 3.2). Additionally, the mean (median) values of the cumulative abnormal returns are 2.739 (2.561), and the sample mean (median) of the standardized unexpected earnings is 0.1% (0.1%).

Table 3-3:Descriptive Statistics

(N = 63,280 firm-quarter observations)

VARIABLES	Mean	Standard deviation	P1	P25	Median	P75	P99
CAR	2.739	2.293	-1.535	0.826	2.561	4.234	8.977
SUE	0.001	0.122	-0.646	-0.009	0.001	0.008	0.648
STICKY	0.050	1.221	-3.954	-0.437	0.040	0.551	3.847
DUM_STICKY	0.534	0.499	0	0	1	1	1
RD	0.122	0.277	0	0.001	0.048	0.129	2.116
INV	0.370	0	0	0	0	1	1
PERS	0.242	0.309	-0.455	0.014	0.211	0.464	0.966
SIZE	6,254.549	33,307.190	1.751	61.6511	373.554	1,979.581	122,564.2
LAG	37.586	17.831	12.000	26.000	34.000	44.000	105.00
LEV	0.486	1.990	-9.118	0	0.190	0.651	11.660
BETA	0.004	0.024	-0.073	-0.006	0.002	0.013	0.088
MTB	2.894	4.896	-16.479	1.203	2.094	3.580	30.408
LOSS	0.325	0.468	0	0	0	1	1
NON_DEC31	0.422	0.494	0	0	0	1	1
NON_LIN	-0.000	0.0676	-0.418	-0.000	0.000	0.000	0.420

This table presents descriptive statistics for all the variables in the different regression models. All variables are defined in the Appendix.

Table 3.4 reports Spearman and Pearson correlations between the main variables used in the main models. Most of the correlations are significant but small in magnitude. As such, collinearity should not be a concern for this study.

Table 3-4:Correlation Matrices

(N = 63,280 firm-quarter observations)

	CAR	*SUE*	*STICKY*	*RD*	*PERS*	*SIZE*	*LAG*
CAR		0.057***	-0.046***	0.036***	-0.003	-0.054***	0.023***
SUE	0.044***		-0.188***	-0.024***	-0.021***	-0.004	0.002
STICKY	-0.048***	-0.093***		0.004	0.006	0.035***	0.011***
RD	0.041***	-0.013	0.013***		0.136***	-0.040***	0.027***
PERS	0.003	-0.022***	0.006	0.045***		0.037***	-0.061***
SIZE	-0.047***	-0.000	-0.001	-0.018***	0.025***		-0.474***
LAG	0.019***	-0.001	0.029***	0.029***	-0.054***	-0.132***	
LEV	-0.014***	-0.010**	0.004	-0.046***	-0.039***	0.025***	-0.025***
BETA	-0.020***	0.001	0.004	0.048***	0.036***	-0.003	-0.039***
MTB	-0.015***	0.005	0.005	0.091***	0.026***	0.102***	-0.086***
LOSS	0.060***	-0.128***	0.065***	0.295***	-0.015***	-0.107***	0.220***
NON_DEC31	-0.013***	-0.007*	0.010**	-0.119***	-0.034***	-0.005	-0.012***
NON_LIN	0.034***	0.943***	-0.056***	-0.002	-0.018***	-0.000	0.002

	LEV	*BETA*	*MTB*	*LOSS*	*Non_DEC31*	*NON_LIN*
CAR	-0.031***	-0.051***	-0.027***	0.048***	-0.014***	0.057***
SUE	-0.017***	0.028***	0.052***	-0.233***	-0.011***	1.000***
STICKY	0.005	-0.005	0.028***	0.072***	0.007*	-0.188***
RD	-0.245***	0.048***	0.147***	0.247***	-0.146***	-0.024***
PERS	-0.092***	0.026***	0.080***	-0.017***	-0.028***	-0.022***
SIZE	0.249***	0.034***	0.458***	-0.380***	-0.047***	-0.004
LAG	-0.044***	-0.058***	-0.217***	0.234***	-0.027***	0.002
LEV		0.001	0.249***	-0.077***	-0.042***	-0.017***
BETA	-0.006		0.060***	-0.047***	-0.011***	0.028***
MTB	0.585***	0.022***		-0.189***	-0.070***	0.052***
LOSS	-0.015***	-0.020***	-0.047*		-0.039***	-0.233***
NON_DEC31	-0.013***	-0.003	-0.048***	-0.039***		-0.011***
NON_LIN	-0.002	-0.004	0.003	-0.077***	-0.005***	

1. This table reports the correlation coefficients for the period 2000-2019.
2. Each matrix provides Spearman (Pearson) correlations above (below) the diagonal, respectively.
3. ***, **, * indicate two-sided significance at the 0.01, 0.05 and 0.1 levels, respectively.
4. All variables are defined in the Appendix.

3.5.2 Multivariate results

The effect of cost stickiness on the informativeness of earnings

Using models (5), (6) and (7), I test the first hypothesis using ordinary least squares (OLS) regression. The results are reported in Table 3.5. The coefficient of *SUE* is positive and significant in all models, which indicates that accounting earnings are informative to their users and reflect information captured in the stock prices of the sample firms.

Column (2) presents results from estimating model (6). The coefficient estimates on the interaction term of *SUE* with the cost stickiness level measure (*STICKY)* is significantly negative (t-stat = -2.10). These results imply that cost stickiness level has a negative effect on ERC, which is consistent with the results reported by Weiss (2010). In other words, higher cost stickiness is associated with less informative quarterly earnings information.

In Column (3), I added the interaction terms of *SUE* with the control variables based on model (7), and the coefficient of the interaction term (*SUE* STICKY)* turns positive but not significant. These results imply that the previously reported adverse effect of cost stickiness on the informativeness of earnings is not applicable to the sample firms, which represent firms engaged in R&D activities.

Table 3-5: Regression Analysis

Variable	Predicted sign	(1)	(2)	(3)	(4)	(5)
Intercept		2.739	2.742	0.977	2.695	0.955
		(300.81)***	(300.16)***	(6.54)***	(234.50)***	(6.43)***
SUE	+	0.829	0.743	1.524	0.741	1.600
		(11.14)***	(9.93)***	(1.75)*	(7.79)***	(1.81)*
STICKY			-0.082	-0.064	-0.076	-0.061
			(-10.96)***	(-8.37)***	(-7.25)***	(-5.61)***
INV					0.125	0.042
					(6.62)***	(1.88)*
SUE × *STICKY*	?		-0.110	0.005	-0.254	-0.156
			(-2.10)**	(0.934)	(-3.69)***	(-1.97)**
SUE× *INV*					0.006	-0.170
					(0.04)	(-0.93)
STICKY × *INV*					-0.014	-0.006
					(-0.93)	(-0.37)
SUE×*STICKY* × *INV*	?				0.348	0.381
					(3.30)***	(3.45)***
SUE × *PERS*	+			-0.436		-0.430
				(-1.50)		(-1.49)
SUE × *BETA*	-			0.420		0.590
				(0.14)		(0.20)
SUE × *LEV*	-			-0.074		-0.076
				(-2.54)***		(-2.59)***
SUE × *MTB*	+			0.020		0.022
				(0.96)		(1.02)
SUE× *ln(SIZE)*	+			-0.041		-0.037
				(-0.91)		(-0.82)
SUE× *NON_LIN*	+			-0.244		-0.258
				(-0.83)		(-0.88)
SUE× *LOSS*	-			-0.742		-0.707
				(-3.82)***		(-3.65)***
SUE× *NON_DEC31*	-			-0.226		-0.215
				(-1.26)		(-1.20)
SUE× *LAG*	-			-0.004		-0.004
				(-0.97)		(-0.95)
CONTROLS		No	No	Yes	No	Yes
Fixed effects × *SUE*		No	No	Year-quarter, Industry	No	Year-quarter, Industry
Nobs	63,280	63,280	63,280	63,280	63,280	63,280
Cluster		No	No	Firm	No	Firm
Adj R^2		0.19%	0.39%	11.98%	0.46%	12.01%

1. This table reports OLS regression results for the following models:

Model (5): $CAR = \alpha + \beta_1 SUE + \varepsilon$

Model (6): $CAR = \alpha + \beta_1 SUE + \beta_2 STICKY + \beta_3 SUE * STICKY + \varepsilon$

Model (7): $CAR = \alpha + \beta_1 SUE + +\beta_2 STICKY + \beta_3 SUE * STICKY + \beta_4 \sum CONTROLS + \beta_5 \sum SUE * CONTROLS + \varepsilon$

Model (8): $CAR = \alpha + \beta_1 SUE + \beta_2 STICKY + \beta_3 INV + \beta_4 SUE * STICKY + \beta_5 STICKY * INV + \beta_6 SUE * INV + \beta_7 SUE * STICKY * INV + \varepsilon$

Model(9): $CAR = \alpha + \beta_1 SUE + \beta_2 STICKY + \beta_3 INV + \beta_4 SUE * STICKY + \beta_5 STICKY * INV + \beta_6 SUE * INV + \beta_7 SUE * STICKY * INV + \beta_8 \sum CONTROLS + \beta_9 \sum SUE * CONTROLS + \varepsilon$

2. ***, **, * indicate two-sided significance at the 0.01, 0.05 and 0.1 levels, respectively.
3. All variables are defined in the Appendix.

The moderating effect of innovation on the impact of cost stickiness on the informativeness of earnings

Using models (8) and (9), I test the second hypothesis (H2) using ordinary least squares (OLS) regression. The results are reported in Table 3.5. Column (4) presents the results from estimating model (8). The coefficient estimates of the interaction term of *SUE* STICKY* are significantly negative (t-stat = -3.69). However, the coefficient estimates on the interaction term of *SUE* STICKY* INV* are significantly positive (t-stat = 3.30), implying that the presence of innovation mitigates the negative effect of cost stickiness on ERC. In Column (5), I added the interaction terms of *SUE* with the control variables based on model (9), and the coefficient of the interaction term (*SUE* STICKY* INV) is* still positive and significant (t-stat = 3.45). Based on these results, I fail to reject the second hypothesis (H2) that the R&D intensity attenuates the association between cost stickiness and earnings informativeness. These findings support the argument that accounting earnings of R&D-intensive firms with sticky costs reflect the information captured by market participants that these firms are restructuring their productive facilities and exploring new opportunities by increasing their investments in innovation.

3.5.3 Additional analysis

Subsample analysis

Using models (6) and (7), I examine the effect of cost stickiness on the informativeness of earnings in firms with high and low intensity levels using ordinary least squares (OLS).

I divide the sample firms into these two groups using the R&D intensity indicator (*INV*). Column (1) in Table 3.6 presents the results of estimating model (6) in high R&D-intensive firms. The coefficient estimates on the interaction term of *SUE* with the cost stickiness level measure (*STICKY) are* positive and non-significant (t-stat = 1.16). However, after adding the control variables with their interactions with *SUE* based on model (7), the coefficient of the interaction term (*SUE* STICKY)* turns positive and significant (t-stat = 2.33). These results imply that cost stickiness level positively affects the informativeness of accounting earnings in firms with high R&D intensity. These findings support the argument that reported earnings capture in a meaningful and timely fashion the underlying causes of cost stickiness associated with high levels of R&D intensity.

In contrast, the interaction term (*SUE* STICKY)* in models (6) and (7) has a significantly negative coefficient in low R&D-intensive firms, which is consistent with the results reported in Weiss (2010). Cost stickiness increases the variability of the earnings distribution, resulting in less predictable future earnings.

Table 3-6: Subsample Analysis

	High R&D intensity		Low R&D intensity	
Variable	(1)	(2)	(3)	(4)
Intercept	2.821	0.800	2.695	1.034
	(185.57) ***	(4.65) ***	(236.08) ***	(5.95) ***
SUE	0.747	1.276	0.741	1.973
	(6.08) ***	(1.11)	(7.85) ***	(1.34)
STICKY	-0.089***	-0.066***	-0.076***	
	(-8.22)	(-6.23)	(-7.30)	
SUE × STICKY	0.094	0.194	-0.254	-0.134
	(1.16)	(2.33) **	(-3.71) ***	(-1.71) *
SUE × PERS		-0.207		-0.628
		(-0.43)		(-1.67) *
SUE × BETA		9.848		-4.026
		(2.05) **		(-1.14)
SUE × LEV		-0.031		-0.088
		(-0.55)		(-2.57) ***
SUE × MTB		-0.028		0.050
		(-0.86)		(1.57)
SUE× ln(SIZE)		-0.014		-0.046
		(-0.19)		(-0.77)
SUE× NON_LIN		-0.684		-0.321
		(-1.60)		(-0.79)
SUE× LOSS		-0.976		-0.845
		(-2.72) ***		(-3.24) ***
SUE× NON_DEC31		-0.252		-0.225
		(-0.82)		(-1.02)
SUE× LAG		0.003		-0.007
		(0.52)		(-1.41)
CONTROLS	No	Yes	No	Yes
Fixed effects × SUE	No	Year-quarter, Industry	No	Year-quarter, Industry
Nobs	23,406	23,406	39,874	39,874
Cluster	No	Firm	No	Firm
Adj R^2	0.49%	12.54%	0.36%	12.03%

1. This table reports OLS regression results for high and low R&D-intensive firms based on the following models:

   Model (6): $CAR = \alpha + \beta_1 SUE + \beta_2 STICKY + \beta_3 SUE * STICKY + \varepsilon$
   Model (7): $CAR = \alpha + \beta_1 SUE + +\beta_2 STICKY + \beta_3 SUE * STICKY + \beta_4 \sum CONTROLS + \beta_5 \sum SUE * CONTROLS + \varepsilon$
2. ***, **, * indicate two-sided significance at the 0.01, 0.05 and 0.1 levels, respectively.
3. All variables are defined in the Appendix.

Excluding observations with zero R&D costs from the sample

It was observed that the main sample includes a high volume of observations from firms with zero R&D. Therefore, I'm reinvestigating the main hypotheses for the main sample after excluding observations with zero R&D costs.

Using models (5), (6) and (7), I test the first hypothesis using ordinary least squares (OLS) regression. The results are reported in Table 3.7. The coefficient of *SUE* is positive and significant in all models, which indicates that accounting earnings are informative to their users and reflect information captured in the stock prices of the sample firms.

Column (2) presents results from estimating model (6). Inconsistent with the results of the main tests, the coefficient estimates on the interaction term of *SUE* with the cost stickiness level measure (*STICKY)* is negative but insignificant (t-stat = -1.34). These results imply that excluding firms with zero R&D converts the effect of cost stickiness on ERC to be insignificant, which is inconsistent with the results reported by Weiss (2010). In other words, higher cost stickiness is not associated with the reduced informative quarterly earnings information.

In Column (3), I added the interaction terms of *SUE* with the control variables based on model (7), and the coefficient of the interaction term (*SUE* STICKY)* turns positive but is still not significant. These results imply that the previously reported adverse effect of cost stickiness on the informativeness of earnings is not applicable to the sample firms, which represent firms engaged in R&D activities.

Using models (8) and (9), I test the second hypothesis (H2) on the sample firms after excluding firms with zero R&D using ordinary least squares (OLS) regression. The results are reported in Table 3.7. Column (4) presents the results from estimating model (8). The coefficient estimates of the interaction term of *SUE* STICKY* are significantly

negative (t-stat = -3.14), which is similar to the results of the main test. However, the coefficient estimates on the interaction term of *SUE* STICKY* INV* are significantly positive (t-stat = 3.14), implying that the presence of innovation mitigates the negative effect of cost stickiness on ERC. In Column (4), I added the interaction terms of *SUE* with the control variables based on model (9), and the coefficient of the interaction term *(SUE* STICKY* INV)* is still positive and significant (t-stat = 3.05). These findings support the argument that accounting earnings of R&D-intensive firms with sticky costs reflect the information captured by market participants that these firms are restructuring their productive facilities and exploring new opportunities by increasing their investments in innovation.

Table 3.7: Regression Analysis after excluding firms with zero R&D

Variable	Predicted sign	(1)	(2)	(3)	(4)	(5)
Intercept		2.755	2.756	0.771	2.694	0.754
		(262.28)***	(261.62)***	(4.92)***	(182.77)***	(4.83)***
SUE	+	1.053	0.950	2.015	1.111	2.102
		(11.11)***	(9.95)***	(1.79)*	(7.81)***	(1.83)*
STICKY			-0.077	-0.059	-0.062	-0.050
			(-9.52)***	(-7.20)***	(-5.07)***	(-3.89)***
INV					0.127	0.040
					(6.03)***	(1.72)*
SUE × *STICKY*	?		-0.084	0.027	-0.300	-0.198
			(-1.34)	(0.42)	(-3.15)***	(-1.96)**
SUE× *INV*					-0.300	-0.190
					(-1.56)	(-0.91)
STICKY × *INV*					-0.026	-0.015
					(-1.59)	(-0.92)
SUE×*STICKY* × *INV*	?				0.400	0.404
					(3.140)***	(3.05)***
SUE × *PERS*	+			-0.728		-0.740
				(-1.99)***		(-2.05)**
SUE × *BETA*	-			4.612		4.903
				(1.28)		(1.38)
SUE × *LEV*	-			-0.065		-0.070
				(-1.33)		(-1.41)
SUE × *MTB*	+			-0.004		-0.002
				(-0.17)		(-0.09)
SUE× *ln(SIZE)*	+			-0.051		-0.046
				(-0.92)		(-0.84)
SUE× *NON_LIN*	+			-0.1.29		-1.294
				(-2.97) **		(-2.99)***
SUE× *LOSS*	-			-0.986		-0.918
				(-3.74)***		(-3.51)***
SUE× *NON_DEC31*	-			-0.080		-0.076
				(-0.35)		(-0.34)
SUE× *LAG*	-			-0.007		-0.007
				(-1.42)		(-1.37)
CONTROLS		No	No	Yes	No	Yes
Fixed effects × *SUE*		No	No	Year-quarter, Industry	No	Year-quarter, Industry
Nobs		47,761	47,761	47,761	47,761	47,761
Cluster		No	No	Firm	No	Firm
Adj R^2		0.26%	0.45%	12.57%	0.54%	12.60%

1. This table reports OLS regression results after excluding firms with zero R&D for the following models:

Model (5): $CAR = \alpha + \beta_1 SUE + \varepsilon$

Model (6): $CAR = \alpha + \beta_1 SUE + \beta_2 STICKY + \beta_3 SUE * STICKY + \varepsilon$

Model (7): $CAR = \alpha + \beta_1 SUE + +\beta_2 STICKY + \beta_3 SUE * STICKY + \beta_4 \sum CONTROLS + \beta_5 \sum SUE * CONTROLS + \varepsilon$

Model (8): $CAR = \alpha + \beta_1 SUE + \beta_2 STICKY + \beta_3 INV + \beta_4 SUE * STICKY + \beta_5 STICKY * INV + \beta_6 SUE * INV + \beta_7 SUE * STICKY * INV + \varepsilon$

Model(9): $CAR = \alpha + \beta_1 SUE + \beta_2 STICKY + \beta_3 INV + \beta_4 SUE * STICKY + \beta_5 STICKY * INV + \beta_6 SUE * INV + \beta_7 SUE * STICKY * INV + \beta_8 \sum CONTROLS + \beta_9 \sum SUE * CONTROLS + \varepsilon$

2. ***, **, * indicate two-sided significance at the 0.01, 0.05 and 0.1 levels, respectively.
3. All variables are defined in the Appendix.

3.6 Conclusion

For a large panel of US firms, I provide evidence on the role of R&D intensity and cost behaviour in shaping the relationship between earnings and returns. I find that the negative effect of cost stickiness on the informativeness of earnings is attenuated by R&D intensity. More specifically, cost stickiness level positively affects the informativeness of accounting earnings in firms with high R&D intensity. These findings support the argument that accounting earnings of R&D-intensive firms with sticky costs capture the underlying motivation of this cost behaviour that managers are reinvesting their resources in new technologies and R&D activities to realign the organisation with its environment.

I contribute to the extant literature on cost stickiness. I extend Weiss's (2010) study by confirming that the previously reported adverse effect of cost stickiness on earnings informativeness is not observed in firms engaged in R&D activities. These firms have different managerial motivations regarding resource allocation decisions and work in a specific information environment. These results suggest that accounting earnings reflect information used by equity investors when firms with sticky costs invest in R&D activities.

I acknowledge the potential limitations of this study related to the reliance on ERC as a measure of earnings informativeness biases the final sample toward relatively larger firms. Future research might determine whether the inferences generalise to samples of smaller firms. I also acknowledge that using the firm-level cost stickiness measure developed by Weiss (2010) entails the disadvantage of a significant data loss as it restricts the sample to observations for which sales and costs change in the same direction. Moreover, the measure only identifies firm-year values, which entail quarterly increases and decreases in sales. I also recognise the limitations of R&D intensity as a measure of a firm's commitment to innovation, overlooking innovation activities based on other sources such as design activities, engineering developments and exploration of markets for new products. Future work can replicate this research using other direct measures of innovation, such as survey-based indicators. Future work can also investigate the effect of cost stickiness on the quality of accounting numbers in different sectors, such as in public and nonprofit organisations.

Appendix 3.1 Variables Definitions

Variable	Variable Name	Definition
Cost stickiness measure	*STICKY*	The difference between the rate of cost decrease for recent quarters with decreasing sales and the corresponding rate of cost increase for recent quarters with increasing sales;
Cost stickiness indicator	*DUM_STICKY*	An indicator variable that equals 1 if *STICKY* is negative, and 0 otherwise;
Cumulative abnormal returns	*CAR*	The monthly abnormal returns cumulated over a 3-month quarterly period. The monthly abnormal returns are estimated from the market model for 60 months prior to the abnormal return estimation period;
Earnings persistence	*PERS*	The regression coefficient from regressing quarterly EPS on the past quarter's EPS using 20 quarters data.
Firm size	*SIZE*	The market cap of the firm measured at the end of quarter *t*. The market cap equals the share price * the number of shares outstanding at the end of quarter *t*. I use the natural log of firm size in all the regression models.
R&D intensity	*INV*	An indicator variable that equals 1 if R&D intensity measure (*RD*) is greater than the R&D intensity for the industry, and 0 otherwise;
Lag effect	*LAG*	The number of days between the fiscal quarter-end and earnings announcement.
Leverage	*LEV*	The ratio of total debt (short-term debt + long-term debt) to the book value of equity;
Loss indicator	*LOSS*	An indicator variable that equals 1 if the basic earnings per share excluding extraordinary items are less than 0, and 0 otherwise.
Market beta	*BETA*	The regression coefficient from regressing the monthly returns of a firm over 60 months on the corresponding S&P 500 index returns prior to *t*;
Market to book ratio	*MTB*	The ratio of the market value of equity to the book value of equity, both measured at the end of the fiscal quarter *t*.
Non-Dec 31 FY-end	*Non_DEC31*	An indicator variable that is equal to 1 for firm-quarters with Non-Dec31 fiscal year-end and 0 otherwise;
Nonlinearity	*NON_LIN*	Unexpected earnings (UE) multiplied by the absolute value of the unexpected earnings |UE|.
R&D intensity	*RD*	Research and development expenses (xrd) divided by sales revenues (sale);
Standardized unexpected earnings	*SUE*	The announced quarterly earnings per share before discontinued operations and extraordinary items (EPS) minus the EPS for the prior year's same quarter scaled by price per share at the end of quarter q.

Chapter 4 COVID-19 Uncertainty and Cost Stickiness

Abstract

The COVID-19 pandemic has led to dramatic economic disruptions posing unprecedented uncertainty, which calls for a better understanding of the pandemic's implications on corporate outcomes. This paper provides a comprehensive assessment of the impact of COVID-19 uncertainty on businesses' cost stickiness behaviour with a focus on R&D-intensive firms. Despite many studies documenting the positive influence of demand uncertainty on cost stickiness, I predicted that the extreme uncertainty caused by the pandemic would motivate managers to reduce their costs more when demand declines than they increase these costs when demand rises. Consistent with this prediction, I find that the COVID-19 outbreak reduces cost stickiness in US firms, which even the US governmental income support would not attenuate. However, I find evidence that the adverse impact of the COVID-19 crisis on cost stickiness is not observed in R&D-intensive firms. These results indicate that firms invested in R&D and technology during the crisis retain their resources and redirect them towards recovery.

4.1 Introduction

Cost stickiness is rooted in asymmetric cost behaviour – costs increase more when sales grow than they decline when sales fall (Anderson et al., 2003). Understanding cost stickiness requires identifying how managers adjust the acquired resources when demand fluctuates. Prior literature confirms that demand uncertainty motivates managers to purposefully delay reductions to committed resources until they are more certain about the permanence of the decline in demand, which increases cost stickiness. Consequently, Anderson et al. (2003) find that cost stickiness reverses in the subsequent period when uncertainty is resolved. They also find that cost stickiness falls with the aggregation of the estimated period. Based on this argument, Lee et al. (2020) find that cost stickiness increases during election periods due to increased political uncertainty. In this study, I am extending this stream of research and investigating the effects of COVID-19 extreme uncertainty on cost stickiness.

In late 2019 and into 2020, the world witnessed a viral disease spread, which infected over 531.5 million people globally and resulted in more than 6.3 million deaths up to mid-June 2022 (World Health Organization, 2022). By mid-March 2020, it was clear that a novel coronavirus (COVID-19) had reached the shores of the United States. State-mandated lockdowns temporarily shuttered many nonessential businesses, the U.S. government instituted travel bans to many countries, and, among companies still open, many saw depressed levels of sales activity (Meyer et al., 2022).

The novel 2019 coronavirus (COVID-19) pandemic has caused unprecedented uncertainty that has permeated every aspect of life and business (Baker et al., 2020). In March 2020, US financial markets experienced one of the most dramatic crashes in history: the S&P index declined by 9.51% and 11.98% on 12 and 16 March 2020,

respectively, representing the most significant daily declines since Black Monday on 19 October 1987 on which it declined by 20.4% (Imbert & Li, 2020). Likewise, the FTSE 100 fell by 8.5% and 9.3% on 9 and 12 March 2020, respectively (Tew, 2020), and the Dow Jones index declined by 23.2% in the first quarter of 2020 (Coy, 2020).

Therefore, COVID-19 disruptions represent a suitable context for estimating the effect of the extreme uncertainty caused by this unprecedented economic and health crisis on firms' cost behaviour. COVID-19 lockdowns, workforce restrictions and limited access to inputs due to supply chain disruption reduced firms' productivity and supply capacity. At the same time, demand slumped or shifted toward new products or services (Baker et al., 2020; Guerrieri et al., 2022). This simultaneity of shocks to supply and demand makes the present situation singular and dangerous for managers and businesses (D. Strauss-Kahn, 2020). These shocks were also compounded by unprecedented uncertainty about the virus, the extent and duration of public policy responses and future outlooks. According to the International Monetary Fund (IMF), "Never in the history of the IMF have we witnessed the world economy come to a standstill. It is worse than the Global Financial Crisis of 2008" (Mangan et al., 2020).

Uncertainty levels from previous global shocks do not approach the present COVID-19-triggered crisis (Finn et al., 2020). The COVID-19 shock is exogenous to the economic system. Therefore, the financial tools of the central banks used in economic crises are only temporary measures for reducing uncertainties (M. O. Strauss-Kahn, 2020). This extreme level of uncertainty – defined in terms of novelty, magnitude, duration, and the rapid pace of change – generates a challenging operating environment for managers and organisations. The severity and speed of the crisis call for examining the role of extreme uncertainty in shaping corporate decisions and whether the US government's response to

the crisis mitigates it. I also extend the analysis by evaluating whether innovative firms respond differently to extreme uncertainty and show a different level of cost stickiness in their financial statements.

However, US states have varied substantially in the measures they have adopted, how quickly they adopted them, and how long they have kept them in place. Limited national-level coordination, combined with the federal structure of the United States, makes the variation in state policies particularly significant for understanding the effects of the COVID-19 extreme uncertainty on cost behaviour in US firms. Differences in approaches between states have also generated debate as policymakers and the public deliberate over the level of income support that should be provided to businesses and how quickly to implement or roll back restrictions (Hale et al., 2021; Hallas et al., 2021).

The study combines data from the Oxford University COVID-19 Government Response Tracker (OxCGRT) and Compustat for the US states between the first quarter of 2020 and the fourth quarter of 2021. The results show that cost stickiness levels decline with the severity of the COVID-19 uncertainty, indicating that managers remove their resources and lay off their employees when demand decreases. However, it is hard for managers to accommodate the growth in the market by increasing their resources due to input scarcity and supply chain disruptions during the COVID-19 crisis. The results also indicate that the US government income support was insufficient to attenuate the negative effects of the COVID-19 uncertainty on firms' cost stickiness. However, the significant adverse impact of the COVID-19 crisis on cost stickiness is not observed in R&D-intensive firms, indicating that firms invested in R&D and technology during the crisis were able to retain their resources and redirect them towards the recovery process.

The findings of this study contribute to three significant strands of literature. The first strand relates to identifying the determinants of cost behaviour. Previous studies documented that managers' expectations for future sales under demand uncertainty are among the causes of cost stickiness (Anderson et al., 2003; Banker et al., 2014; Lee et al., 2020). This paper extends this literature by examining the effect of COVID-19 extreme uncertainty on cost behaviour, and shows that the managerial response to the COVID-19 uncertainty reduces cost stickiness. The severe demand shock caused by the pandemic and its containment measures drives managers to remove their committed resources. Simultaneously, they could not accommodate the increase in demand due to the effect of the crisis on productivity and supply chains. These results indicate that the impact of uncertainty on cost stickiness depends on the level of uncertainty and its root cause.

This paper also contributes to the limited literature examining the consequences of cost stickiness on earnings forecasts. For example, Weiss (2010) finds that investors do not rely on the earnings information of firms with sticky costs due to its lower predictive power. However, Banker and Chen (2006) report that incorporating cost stickiness information into the earnings forecast models increases their accuracy and improves the information content of the earnings forecast errors in explaining abnormal stock returns. Anderson et al. (2007) also document that considering the effects of cost stickiness enhances the fundamental financial ratio interpretation. These findings imply that investors would benefit from considering cost stickiness information when making investment decisions. Integrating the extreme levels of uncertainty caused by the COVID-19 pandemic into models that predict cost stickiness may help predict these firms' financial performance.

Finally, my results are relevant to the growing literature assessing the economic consequences of COVID-19 (Altig et al., 2020; Koren & Pető, 2020). This study extends this literature by providing first-hand evidence of the impact of the COVID-19 extreme uncertainty on cost behaviour as a reflection of the managerial operating decisions towards the crisis and the associated governmental response in the USA. The results indicate that the US governmental income support was insufficient to preserve the firms' productive capital and, more importantly, the workers' skills. The results also show that firms must be innovative in response to the enormous disruption caused by COVID-19.

The results of this paper are also relevant to managers and policymakers. While the inability of business managers to fully understand and appreciate uncertainty in regular times could hurt their decision-making, this is likely to be exacerbated when faced with an unexpected crisis like COVID-19. Hence, the business managers need to understand the effect of the financial and operational uncertainty caused by this crisis on the effectiveness and efficiency of their resource allocation decisions. It is also essential for them to learn how to manage uncertainty by knowing the outcome of the different coping mechanisms for this crisis. This will help them develop appropriate strategies to deal effectively with unpredictable and undesirable situations.

Our results are also crucial to policymakers as they provide an opportunity to reflect on their management during the pandemic. This study shows that the governmental actions to swiftly mitigate the effects of the extreme levels of uncertainty associated with COVID-19 on businesses were insufficient to preserve their physical and human resources. These results might motivate policymakers to address the crisis differently to ensure the effectiveness of their programs.

The remaining part of the chapter is structured as follows. The following section reviews the related literature and illustrates the hypotheses' development. The third section describes the research design. Section 4 presents the analysis process results, followed, in the final section, by the conclusion of this research.

4.2 Literature review and hypotheses development

Cost behaviour represents the firm's response to shifts in market conditions. Or in other words, it reflects how firms modify their supply capacity to react to the changes in customers' demand. Management accounting literature empirically investigates this behaviour and reports that firms respond asymmetrically to changes in market demand. This response is reflected in the financial statements as sticky cost behaviour – costs increase more when demand increases than they decline when demand falls by an equivalent amount (Anderson et al., 2003). Prior studies interpret this behaviour as evidence of managerial intervention in resource allocation decisions. Managers add more resources when sales volume increases to accommodate the demand growth. However, when sales fall, they keep the unused resources instead of removing them (Balakrishnan et al., 2014; Banker et al., 2013).

In late 2019 and into 2020, the world witnessed the spread of coronavirus (COVID-19), recent research has analysed the association between COVID-19 and the firms' cost behaviour. Wang et al. (2021) investigated interest expense stickiness as an indicator of the micro efficiency of government credit policies in China. They found that interest expense stickiness increased during the COVID-19 pandemic, indicating that firms obtained more bank loans when sales experienced a sharp decline. Yang and Chen (2023) examined how COVID-19 affects the degree of cost stickiness brought on by intellectual capital (IC) efficiency in Australia and China. Their findings suggest that both countries'

respective cost stickiness increases because of IC efficiency during COVID-19. However, the pandemic affected China's cost stickiness slightly more than Australia's. In this study, I am extending this stream of research and investigating the effects of COVID-19 extreme uncertainty on cost stickiness and whether the US government's response to the crisis mitigates it. I also extend the analysis by evaluating whether innovative firms respond differently to extreme uncertainty and show a different level of cost stickiness in their financial statements.

The novel 2019 coronavirus (COVID-19) pandemic caused unprecedented Organisational uncertainty levels, which differ from those of other global crises (Sharif et al., 2020). This extreme level of uncertainty was because COVID-19 is genuinely a global pandemic, interest rates are at historical lows, global financial markets are highly interconnected, and spill-over effects occurred throughout supply chains (Ozili & Arun, 2020). Moreover, the impact of the COVID-19 pandemic is more severe than previous pandemics and outbreaks, such as the Spanish Flu in 1918 and Ebola in 2014 (Baker et al., 2020). The absence of a similar historical event means that managers have little clarity about the effects of the pandemic on output, demand, employability and earnings both in the short and long term (Sharif et al., 2020).

Hassan et al. (2021) analyse transcripts of quarterly earnings calls held by public firms across the globe and find that COVID-19 manifests itself at the firm level as a simultaneous demand and supply shock, with supply concerns meaningfully larger during the COVID-19 crisis than in earlier pandemics. They also show that the supply and demand impacts of COVID-19 are equally significant in explaining variation in stock returns in 2020. Cochrane (2020) points out that the COVID-19 pandemic is unlike a

standard recessionary (aggregate demand) shock or a typical inflationary supply shock (oil prices shock). This “health shock” has characteristics of both.

Other researchers, such as Meyer et al. (2022), report that the COVID-19 shock is a demand rather than a supply shock. Based on the Federal Reserve Bank of Atlanta’s Business Inflation Expectations Survey, the authors find that a greater share of firms reports significant or severe sales activity disruptions than supply chains. The study also offers evidence that households disproportionately respond to a relative price shock to grocery store items rather than viewing the COVID-19 pandemic as a negative shock to aggregate supply.

These significant declines in economic activity are undoubtedly attributable to the COVID-19 pandemic and the emergency actions forced by national governments to slow its spread, namely strict social distance measures, quarantine and lockdowns. Customers also changed their preferences due to their immediate response to the pandemic. Baker et al. (2020) find an increase in consumer spending at the early stage of the pandemic due to stockpiling and sharp declines in most consumption categories in the subsequent weeks.

The unavailability of some sectors’ goods during the COVID-19 crisis shifted spending towards other sectors through a substitution channel. When these businesses face an increase in their products’ demand, it is hard to accommodate this demand by increasing their output and supply capacity due to the closure of non-essential businesses and workers not being able to perform their activities from home (Baqaee & Farhi, 2022; Del Rio-Chanona et al., 2020). Even if advances in information and communication technology made it increasingly possible to communicate with co-workers and customers without the need for face-to-face physical interactions, personal contact is still inevitable

in some businesses, especially where the division of labour is essential (Gaudecker et al., 2020; Koren & Pető, 2020).

The literature also shows that adverse supply shocks caused by the COVID-19 outbreak can lead to a contraction in output and employment larger than the initial shock for sectors that are not directly affected by shutdowns. Guerrieri et al. (2022) find that supply constraints due to lack of labour under social distancing pass on downstream by creating input scarcity that can limit production even in cases where the availability of labour and demand would not have been an issue. Inoue and Todo (2020) model how shutting down firms in Tokyo would cause a loss of output in other parts of the economy through supply chain linkages. Their estimation shows that after a month of lockdown, the daily output represents only 14% of the pre-shock production.

The literature on the pandemic confirms that consumer demand in many industries fell dramatically because of COVID-19. The government-imposed restrictions, including regulations on which businesses could operate, forced millions of companies to temporarily close (Bartik et al., 2020; Fairlie, 2020). The lack of demand for final goods such as restaurants or transportation propagates upstream, reducing demand for the intermediate goods that supply these industries. The resulting demand constraints reduce production levels in these businesses, which may cause additional amplification of shocks that would generate a further reduction in the final demand (Pichler et al., 2020).

When managers face this dramatic reduction in demand, they may purposefully reduce their committed resources and employment, especially if they face liquidity constraints (Guerrieri et al., 2022). Bartik et al. (2020) highlight the financial fragility of many businesses in the United States during the first two months of the crisis. They reported that three-quarters of respondents only had enough cash on hand to last two months or

less. They also noted that businesses had reduced their active employment by 39%. Therefore, I expect that these managerial decisions towards changes in demand levels would be reflected in the financial statements as lower levels of cost stickiness.

Moreover, prior literature also stresses that cost stickiness would be weaker when the assessed probability of permanent demand decline is higher (Anderson et al., 2003). Banker et al. (2014) find that pessimistic expectations for future sales would reduce managers' willingness to acquire additional resources when sales increase and retain unused resources when sales decline, which reduces cost stickiness. At the time of the lockdowns, business owners had negative expectations around the projected future demand even after government-imposed operating restrictions were lifted, which in some cases might provide an insufficient margin to cover the costs of even limited operations. Humphries et al. (2020) surveyed more than 8,000 small business owners in the US during the first two months of the pandemic. They reported that 50% of the respondents believed their business would not recover within two years. The same ratio of respondents thinks their business will permanently close or go bankrupt within the next six months. Their results also show that the average proportion of respondents reporting these negative expectations increases by 0.7 percentage points daily. Balla-Elliott et al. (2022) also find that post-lockdown delays in business reopening in the United States can be explained by low expected demand levels rather than health concerns. The average firm in their sample expected demand for its services to be 35.3% of pre-crisis levels.

Based on the previous arguments, the COVID-19 crisis would not enable the firm's managers to accommodate the growth in demand due to workforce restrictions and limited access to inputs. At the same time, managers would deliberately reduce their committed resources and lay off their employees when demand declines to avoid retaining

them at a loss, especially when they have negative expectations about the recovery of economic activity. Therefore, I anticipate that the cost stickiness level will be lower with the intensity of the COVID-19 crisis, which leads to the following hypothesis:

> *H1: There is a negative association between cost stickiness and the intensity of the COVID-19 crisis.*

Many governments worldwide have offered COVID-19 state aid to businesses to minimise the adverse effects of the virus and its consequent social distancing measures on the economy. These COVID-19 business support measures include loan subsidies, financial support for different segments of the business population, tax deferrals and the temporary abolishment of the bankruptcy regulation (Groenewegen et al., 2021). For example, the US Congress passed The Coronavirus Aid, Relief and Economic Security (CARES) Act, which included 500 billion dollars to provide liquidity to businesses suffering the most from this crisis. Of these funds, $454 billion was for loans, loan guarantees, and other investments (i.e. obligations purchased directly from issuers or in secondary markets) for eligible businesses. Additionally, the CARES Act allocates $32 billion in financial assistance to industries such as air carriers and airline contractors that must be exclusively used to continue paying employees' wages, salaries, benefits, and other compensation. The legislation also requires those businesses to maintain existing employment levels as of March 24, 2020, to the extent possible, and, in any case, not to reduce employee levels by more than 10% (Courtney, 2020).

These measures have saved many firms and jobs in the long term. Groenewegen et al. (2021) find that the governmental support in the Netherlands tends to go to firms that are most in need in the short term and are more likely to be profitable in the longer run. Cowling et al. (2020) show that only a minority of UK companies had accumulated

precautionary savings before the COVID-19 shock, making government assistance necessary for many firms to survive the crisis. So, these policies that mitigate the cash flow and liquidity problems businesses face may motivate the managers to put enough weight on future profits relative to current losses and decide to keep and pay their workers (Guerrieri et al., 2022). These decisions would be reflected in the financial statements as higher levels of cost stickiness

However, Humphries et al. (2020) find that by the time the US Congress passed the CARES Act, business owners had already been severely impacted by COVID-19-related disruptions and had laid off many employees. By March 30th 2020, 59% of the surveyed respondents reported that they had already laid off a substantial portion of their employees. The survey also confirms that the passage of the CARES Act does not seem to have modified this trend, as businesses have continued to lay off workers. On average, respondents reported having laid off 0.2 percentage points more of their workforce in each new daily wave of responses. These findings indicate that government support would not significantly affect the resource reallocation decisions related to the severe demand reduction of the COVID-19 crisis.

Based on the previous alternative arguments, it is an empirical question as to whether the degree of government support attenuates the negative effects of the COVID-19 crisis on firms' cost stickiness level. Given the competing forces at work, I formulate our second hypothesis in the null form.

> *H2: Government support does not attenuate the negative effects of the COVID-19 crisis on firms' cost stickiness.*

The literature documents that R&D-intensive firms respond differently to recessions because cutting costs and laying off employees would be detrimental to them while facing

the crisis. The value of these firms is mainly based on their future growth options and their ability to keep developing and exploiting new products and market opportunities (Kogut & Zander, 1992). These efforts usually require substantial R&D, production, and marketing investments to keep pace with the industry's expansion. Cutting those costs during downturns will adversely impact the firms' ability to meet the changing market and customer preferences (Morrow et al., 2004).

Additionally, the most influential corporate resource in R&D-intensive firms is the knowledge embedded in the firms' human and social capital (Kogut & Zander, 1992). Retaining highly skilled employees and preserving social capital are important goals because losing crucial network members can severely damage relationships that create valued outcomes (Dess & Shaw, 2001). Therefore, the disruptions caused by cost-cutting strategy during downturns may lead to the loss of knowledge stored in firms' social system and negatively impact firms' ability to derive value from knowledge gained from broken relationships (Guthrie & Datta, 2008).

When R&D-intensive firms face a reduction in their products' demand, they pursue the recovery process by investing their resources in new technologies and innovations that realign them with their external environment (Barker & Mone, 1994; Holland & Katzin, 2019). Demand reductions accelerate the technological changes as digital technologies will provide new ways to move faster and simplify businesses, enhancing firms' ability to adapt to more fluctuating demand conditions (Frick, 2019). Additionally, firms are induced to adopt new technologies during downturns due to the digital transformation's lower opportunity costs during periods of weak demand (Hall et al., 2005). Specifically, investing in digital technologies requires scarce organisational resources that must be diverted from current production. But when demand declines, operations do not need to

be kept at maximum capacity, which frees up the operating budget to fund IT initiatives without affecting the firm's revenues (Frick, 2019).

Many firms were innovative in response to the enormous disruption caused by the COVID-19 pandemic. They shifted rapidly to online channels, automated production tasks, increased operational efficiency, and sped up the innovation of operating models (Mischke et al., 2021). Based on a survey of 375 UK businesses conducted in July 2020, Riom and Valero (2020) reported that over 60% of firms adopted new technologies or management practices since the onset of the pandemic, while a similar percentage introduced new products or services. Nearly all firms report that they expect the adoption of new technologies or practices to positively impact firm performance, increase employees' productivity or allow them to be reallocated to different tasks instead of reducing headcounts. The study also investigates how innovation responses differ across business types and finds that previous technology adoption is a stronger predictor of a rapid innovation response to the crisis.

Similarly, Krammer (2022) analyses data from two rounds of surveys involving more than 11,000 firms from 28 countries before and after COVID-19 and provides evidence that innovators are more likely to cope well with the challenges of COVID-19 than non-innovators. The study also finds that firms that rely more on internal knowledge sources than external ones would reallocate those resources more easily to adapt to the crisis. These findings indicate that innovative firms would retain their resources when demand declines and reinvest them into recovery.

On the other hand, accelerated digitisation and automation enable firms that experience increased customer demand to raise their productivity levels by substituting employees or contributing to raising output per worker (Mischke et al., 2021). New technologies

would also ramp up efficiencies in supply chain and manufacturing areas and help companies address the dwindling labour supply (Holland & Katzin, 2019). Consequently, innovative firms would be able to accommodate the increased demand by expanding their resources, which will raise cost stickiness levels.

Based on the previous argument, I suggest that the intensity of the COVID-19 crisis, combined with R&D intensity, positively affects cost stickiness level, leading to the following hypothesis.

H3: R&D intensity attenuates the negative effect of the COVID-19 crisis on firms' cost stickiness.

4.3 Research design and sample

4.3.1 Variables measurements

The firm-specific measure of cost stickiness

I use a measure developed by Weiss (2010) to assess cost stickiness at the firm level. This measure focuses on estimating the difference between the rate of cost decrease for recent quarters with decreasing sales and the corresponding rate of cost increase for recent quarters with increasing sales:

$$STICKY_{i,q} = -\left[log\left(\frac{\Delta Cost}{\Delta Sales}\right)_{i,\underline{\tau}} - log\left(\frac{\Delta Cost}{\Delta Sales}\right)_{i,\overline{\tau}} \right] with\ \underline{\tau},\ \overline{\tau} \in \{t, \dots, t-3\}$$

$\Delta Sales$ denotes changes in sales revenue between two quarters $\left(Sales_{tq} - Sales_{i,tq-1}\right)$ and $\Delta Cost$ represents the corresponding change in operating costs $\left(Cost_{i,tq} - Cost_{i,tq-1}\right)$. Where operating costs equal sales revenues minus income from operations, $\underline{\tau}$ is the most recent of the last four quarters in fiscal year t with a decrease in sales and $\overline{\tau}$ is the most recent of the last four quarters in fiscal year t with an increase in sales.

$STICKY_{i,q}$ compares the slope of a cost function between the two most recent quarters in fiscal year *t*, one with an increase and the other with a decrease in sales. If costs are sticky, meaning that they increase more when activity rises than they decrease when activity falls by an equivalent amount, then the term in square brackets exhibits a negative sign. Following Homburg et al. (2018), I multiply the sticky measure of Weiss (2010) by -1 so that the higher values of $Sticky_{i,t}$ imply more stickiness.

Using this measure entails the disadvantage of a significant data loss. For example, I follow Weiss (2010) and restrict the sample to observations for which sales and costs change in the same direction. Moreover, the measure only identifies values for firm-years, which entail quarterly increases and decreases in sales. However, the advantages outweigh these data restrictions. This measure can examine the effects and determinants of cost stickiness. Furthermore, it provides a clear reference point of a linear cost function (i.e., *STICKY* = 0) to distinguish between sticky and anti-sticky firms.[5] Based on this, I create the indicator variable (*DUM_ANTI*)[6] that equals 1 if *STICKY* is negative and 0 otherwise.

Measures of the intensity of the COVID-19 crisis and the governmental support

I use strictness of workplace closure during the lockdown as an indicator of the uncertainty of the COVID-19 crisis. The US context provides useful variation for estimating the impacts of lockdowns because the Tenth Amendment to the Constitution gives police powers to states, which limits the federal response to epidemics (Inglesby et al., 2006). Additionally, US states have varied substantially in the measures they have

[5] Costs are termed anti-sticky if they increase *less* when activity rises than they decrease when activity falls by an equivalent amount.

[6] In contrast to the previous chapter, I am using DUM_ANTI (and not DUM_STICKY) as the STICKY dummy as it is more relevant to the hypotheses of this study.

adopted, how quickly they adopted them, and how long they have kept them in place. Therefore, I am using data from The Oxford COVID-19 Government Response Tracker (OxCGRT), which includes real-time US-state level daily data on several common policy responses that have been taken to respond to the pandemic on 19 different indicators (Hale et al., 2021; Hallas et al., 2021).

As a measure of work closure (*WORK_CLOS),* I use an ordinal variable representing the strength of government response concerning the closure of businesses. It equals 0 if the state is not applying any measures. It would equal 1 if the government recommended closure (or work from home). It would equal 2 if the government required closure (or work from home) for some sectors or categories of workers. The measure equals 3 to indicate the necessary closure (or work from home) for all but essential workplaces (e.g., grocery stores, and hospitals). The average of these daily indicators had been calculated for each quarter to obtain the state-quarter *WORK_CLOS* measure.

I also use an index (*GOV_SUPPORT*) provided by OxCGRT representing governmental economic support. The index shows the financial support the local administration has made available. According to Hale et al. (2021), OxCGRT uses simple, additive, unweighted indices because this approach is the most transparent and easiest to interpret. The *GOV_SUPPORT* index is composed of two ordinal individual policy response indicators, which are income support and debt relief. For each indicator, a score is created by taking the ordinal value and subtracting half a point if the policy is targeted to a specific industry rather than general. Then, those scores are rescaled by the maximum value of each indicator to create a score between 0 and 100, with a missing value contributing 0. These scores are then averaged to obtain the composite index. The index also has an additional binary flag variable, either 0 or 1 based on the sectoral scope of income support.

This calculation is described in the equation below, where k is the number of component indicators in the index and Ij is the sub index score for an individual indicator.

$$Index = \frac{1}{k}\sum_{j=1}^{k} I_j$$

The R&D intensity measure

I follow Chan et al. (2001) and Eberhart, Maxwell, and Siddique (2008) and use the ratio of R&D expenses to sales revenues (RD) to measure the intensity of the research and development activities. On the Compustat database, R&D expenses cover all costs incurred, including salaries and departmental fees related to developing new products or services during the fiscal quarter. I follow previous research and replace missing values with 0 (Ciftci & Cready, 2011). I also develop an indicator variable, *INV*, that represents R&D-intensive firms. Following Ciftci, Lev, and Radhakrishnan (2011), I use the industry-adjusted R&D expenses to sales ratio as a benchmark to classify firms into high and low R&D-intensive firms. The benchmark is the weighted average R&D expenses to sales ratio of all firms in the four-digit SIC industry group, where the weights are sales. Firms whose R&D intensity exceeds the benchmark are classified as high R&D-intensive firms (*INV* =1), and the rest as low R&D-intensive firms (*INV* =0).

4.3.2 Data and samples

The initial sample comprises 27,294 firm-quarter observations from quarter industrial files for public firms in the North America Compustat database whose headquarters are located in the USA from the first quarter of 2020 to the last quarter of 2021. Table 4.1 describes the construction of this sample. I merge this data with another dataset extracted from OxCGRT, including workplace closure and government support measures.

Following prior literature (Kama & Weiss, 2013; Zhong, 2018), I exclude financial institutions and public utilities firms (four-digit SIC codes 6000-6999 and 4900-4999) as these two industries are highly regulated, and I also remove duplicate observations. Moreover, I discard invalid observations with missing or negative values of either total assets, sales revenues or operating costs (Anderson et al., 2003; Venieris et al., 2015). I also follow Weiss (2010) and exclude observations with sales and costs changing in the opposite direction. In addition, I dropped observations with missing firm-level cost stickiness measures. Finally, I drop observations with missing data on control variables. The final sample size consists of 1,615 firm-quarter observations for 938 firms. All continuous variables are winsorised to the 1st and 99th percentile to reduce the influence of extreme outliers.

Table 4-1:Sample Selection Procedures

Initial Sample: Firm-quarter observations in Compustat NA for USA public firms over the period 2020 Q1-2021 Q4.	27,294
Excluding financial and utility firms and duplicate observations.	18,681
Drop observations with missing or negative total assets, sales revenues or operating costs	18,516
Drop observations with sales and costs change in the opposite direction	15,657
Exclude observations with missing stickiness measure (*STICKY*)	4,664
Final Sample: Drop observations with missing data on control variables.	1,615

This table presents the sample firms' selection procedures.

Table 4.2 shows the sample distribution by industry, where industry classification is based on the two-digit SIC code. The business services industry accounts for the most significant portion of the sample (13.31%), followed by chemical & allied products (10.15%), instruments and related products (8.79), electronics & other electrical

equipment (7.86%) and industrial and commercial machinery and computer equipment (6.13%), respectively.

Table 4-2:Sample Distribution

SIC code	Industry	Number of obs.	Percentage of sample	Cumulative percentage
73	Business Services	215	13.31	13.31
28	Chemical & Allied Products	164	10.15	23.46
38	Instruments & Related Products	142	8.79	32.25
36	Electronics & Other Electrical Equipment	127	7.86	40.11
35	Industrial and Commercial Machinery & Computer Equipment	99	6.13	46.24
50	Wholesale Trade -Durable Goods	62	3.84	50.08
37	Transportation Equipment	59	3.65	53.73
13	Oil & Gas Extraction	54	3.34	57.07
20	Food & Kindred Products	45	2.79	59.86
48	Communications	44	2.72	62.58
-	Other	604	37.40	100.00
	Total	1,615	100.00	

This table reports the sample distribution by industry, respectively.

4.4 Models

To test H1, I estimate ordinary least-squares regression to examine the effect of the COVID-19 crisis and workplace closure on cost stickiness levels. In this regression, the firm-level cost stickiness measure *STICKY* is the dependent variable and workplace closure measure *WORK_CLOS* is the explanatory variable.

$$STICKY = \beta_0 + \beta_1 WORK\_CLOS + \varepsilon \qquad (1)$$

I also add control variables employed in prior studies. I control for the asset intensity and employee intensity as measures for the adjustment costs. Following previous research, I used the natural log form of employee intensity *EMP_INT* and asset intensity *AST_INT*

to control their effect on cost stickiness (Anderson et al., 2003). To capture the impact of anticipations of future sales on the degree of cost stickiness, I include an indicator variable *SUCC_DEC* that equals 1 if sales decrease in two consecutive years and 0 otherwise. I also control for the managerial empire-building incentives by adding free cash flows *FCF* to the model based on the results of Chen et al. (2012). The definition of these variables is provided in the Appendix. To control firms' differences over time, demography and industries, I include the year, quarter, state and industry indicator variables (one-digit SIC code) and correct the standard errors for the firm clustering effects.

$$STICKY = \beta_0 + \beta_1 WORK\_CLOS + \beta_2 ln\, EMP\_INT + \beta_3 LN\, AST\_INT + \beta_4 SUCC\_DEC + \beta_5 FCF + \varepsilon \quad (2)$$

To the extent that firms headquartered in areas with strict workplace closure regulations are more likely to have lower levels of cost stickiness, I expect a negative and significant coefficient on *WORK_CLOS.*

To test H2, I examine whether government support attenuates the negative effect of the COVID-19 crisis on firms' cost stickiness. I expect an interactive relationship between workplace closure measure and government support index with respect to cost stickiness level. Thus, I extend model (1) to include the interaction term between *WORK_CLOS* and *GOV_SUP* as follows:

$$STICKY = \beta_0 + \beta_1 WORK\_CLOS + \beta_2 GOV\_SUP + \beta_3 WORK\_CLOS * GOV\_SUP + \beta_4 ln\, EMP\_INT + \beta_5 LN\, AST\_INT + \beta_6 SUCC\_DEC + \beta_7 FCF + \varepsilon \quad (3)$$

To test H3, I examine whether the R&D intensity indicator *INV* attenuates the negative effect of the COVID-19 crisis on firms' cost stickiness. I expect an interactive relationship

between workplace closure measure and R&D intensity indicator concerning cost stickiness. Thus, I extend model (1) to include the interaction term between *WORK_CLOS* and *INV* as follows:

$$STICKY = \beta_0 + \beta_1 WORK\_CLOS + \beta_2 INV + \beta_3 WORK\_CLOS * INV + \beta_4 ln\, EMP\_INT + \beta_5 LN\, AST\_INT + \beta_6 SUCC\_DEC + \beta_7 FCF + \varepsilon \quad (4)$$

4.5 Empirical results

4.5.1 Descriptive statistics

Table 4.3 provides descriptive statistics on the main variables used in the analysis. Firm-level cost stickiness yields a negative mean of -0.091 (median = -0.078). As assumed, the sample, on average, is subject to anti-cost stickiness during the COVID-19 crisis as they reduce their costs more when demand declines than when demand rises. Moreover, *DUM_ANTI* indicates that 57% of the sample firms exhibit cost anti-stickiness. The standard deviation of *STICKY* is 1.152, showing considerable variation among the firms' cost behaviour.

The table also indicates that the strictness of the workplace closure measures for the average firm is 1.61 (median = 1.95) out of the maximum value for the indicator (3). The government support provided to the average firm represents around 50.72% (median = 47.01) of the available fund, which indicates that not all US firms have access to the funds provided by the federal government.

The average firm spends more than 150% (median = 0%) on R&D expenditures scaled by sales revenues, suggesting that the sample includes firms that intensively invest in innovation and technology. However, the median firm spends 0% on R&D expenditures,

which indicates that more than 50% of the sample do not report their R&D expenditures. This result is a logical consequence of replacing the missing R&D with 0. The *INV* indicator supports this observation, showing that only 27% of the sample represents high R&D-intensive firms.

On average, the sample firms have 36,000[7] (median = 13,000) employees and $18,800 million (median = $5,060 million) of assets to support every million dollars in sales revenues. Free cash flow accounts for 0.9% of the sample firms' total assets (median = 0.16%). Finally, 10.3% of the sample firms experienced two consecutive years of sales reduction in the past two years.

Table 4-3:Descriptive Statistics

(N = 1,615 firm-quarter observations)

VARIABLES	Mean	Standard deviation	P1	P25	Median	P75	P99
STICKY	-0.091	1.152	-3.587	-0.604	-0.078	0.313	3.943
DUM_ANTI	0.570	0.495	0	0	1	1	1
WORK_CLOS	1.613	0.631	0	1	1.946	2	2.924
GOV_SUP	50.720	31.487	0	25	47.011	62.704	100
RD	1.555	41.755	0	0	0	0.059	3.579
INV	0.271	0.444	0	0	0	1	1
EMP_INT	0.036	0.292	0.001	0.007	0.013	0.021	0.285
AST_INT	18.800	203.251	0.980	3.232	5.060	8.032	163.555
FCF	0.009	0.066	-0.289	-0.011	0.016	0.037	0.193
SUCC_DEC	0.103	0.304	0	0	0	0	1

This table presents descriptive statistics for all the variables in the different regression models. All variables are defined in the Appendix.

[7] This value has been calculated by multiplying the mean of the employee intensity variable by 1 million dollars of sales revenues.

Table 4.4 reports Spearman and Pearson correlations between the main variables used in the main models. The cost stickiness measure *STICKY* is negatively and significantly correlated with the measure of workplace closure strictness *WORK_CLOS*. These results provide univariate evidence of a negative association between cost stickiness level and the crisis intensity measure. Additionally, cost stickiness measure *STICKY* positively and significantly correlates with R&D intensity measure RD. However, the correlation between cost stickiness and the government support index is positive but insignificant. These preliminary results would provide some primary indications about the analysis, but further investigation is needed to reach more robust results regarding the hypotheses' testing. On the other hand, most of the correlations between the main variables are significant but small in magnitude. As such, collinearity should not be a concern for this study.

Table 4-4:Correlation Matrices

(N = 1,615 firm-quarter observations)					
	STICKY	*WORK_CLOS*	*GOV_SUP*	*RD*	*EMP_INT*
STICKY		-0.048*	-0.002	0.015	-0.019
WORK_CLOS	-0.046*		0.540***	0.052**	-0.011
GOV_SUP	0.012	-0.028		0.174***	-0.032
RD	0.085***	0.020	-0.005		0.073***
EMP_INT	0.017	-0.007	0.015	0.111***	
AST_INT	0.057	0.115***	0.028	0.146***	0.363***
FCF	-0.031	0.098***	-0.010	-0.056**	-0.207***
SUCC_DEC	0.045*	-0.038	-0.011	-0.012	-0.090***
	AST_INT	*FCF*	*SUCC_DEC*		
STICKY	0.008	-0.016	0.062**		
WORK_CLOSURE	0.141***	-0123***	-0.074***		
GOV_SUP	0.091***	-0.046*	0.114***		
RD	0.248***	-0.121***	0.036		
EMP_INT	0.225***	-0.146***	-0.101***		
AST_INT		-0.231***	-0.054**		
FCF	-0.245***		-0.010		
SUCC_DEC	-0.081***	-0.033			

1. This table reports cross-sectional correlation coefficients for the period 2020-2021.
2. Each matrix provides Spearman (Pearson) correlations above (below) the diagonal, respectively.
3. ***, **, * indicate two-sided significance at the 0.01, 0.05 and 0.1 levels, respectively.
4. All variables are defined in the Appendix.

4.5.2 Multivariate results

The effect of workplace closure on cost stickiness

Using models (1) and (2), I test the first hypothesis using ordinary least squares (OLS) regression. The results are reported in Table 4.5. The coefficient of *WORK_CLOS* is negative and significant in the two models (t =-1.91 & -2.47), indicating that the COVID-19 crisis and its containment measures significantly reduce cost stickiness. These results confirm that the recession caused by the pandemic motivates managers to shrink their committed resources and employees when demand declines more than increasing these

resources when demand increases. These results support hypothesis (H1) that cost stickiness declines with the intensity of the COVID-19 crisis and the strictness of the workplace closure.

In column (2), I added the control variables based on model (2). The coefficient of *ln AST_INT* is positive and significant (t = 2.20), which matches with the findings of the prior literature that assets' adjustment costs are one of the determinants of cost stickiness (Anderson et al., 2003). However, *ln EMP_INT* coefficient is not significant, which indicates that the challenging circumstances of COVID-19 might encourage managers to make their employees redundant when demand declines regardless of the costs associated with this decision. The coefficient of *FCF* is also not significant, referring to the fact that opportunistic behaviour is not a relevant explanation for cost stickiness during recessions. *SUCC_DEC* is significantly positive (t = 2.03), not consistent with the previous literature findings (Banker et al., 2014). These results imply that managers retain their resources during recessions and lockdown even if they are pessimistic about future demand, increasing cost stickiness.

Column (3) presents results from estimating model (3). The coefficient estimation on the interaction term of *WORK_CLOS* with the government support index (*GOV_SUP)* is positive but not significant (t-stat = 0.36). These results imply that the governmental fund did not change the manager's decisions to modify their resource levels when demand changed during the COVID-19 crisis. These results support the second hypothesis (H2) that government support does not attenuate the negative effect of the COVID-19 crisis on firms' cost stickiness.

In column (4), the interaction term coefficient (*WORK_CLOS* × *INV*) turns positive and significant. These results imply that the previously reported adverse effect of workplace

closures on cost stickiness does not apply to firms engaged in R&D activities. In contrast, firms involved in R&D activities would retain their resources and employees during the crisis and reinvest them into future growth and recovery. These results support hypothesis (H3) that R&D intensity attenuates the negative effect of the COVID-19 crisis on firms' cost behaviour.

Table 4-5: Regression analysis

Variable	Predicted sign	(1)	(2)	(3)	(4)
Intercept		0.050	0.556	0.577	0.671*
		(0.63)	(1.63)	(1.61)	(1.94)
WORK_CLOS		-0.087*	-0.156**	-0.238*	-0.218***
		(-1.91)	(-2.47)	(-1.67)	(-3.31)
GOV_SUP				0.002	
				(0.57)	
INV					-0.221
					(-1.16)
WORK_CLOS × *GOV_SUP*	?			0.001	
				(0.36)	
WORK_CLOS × *INV*	?				0.242**
					(2.20)
ln EMP_INT	+		-0.007	-0.005	-0.002
			(-0.16)	(-0.12)	(-0.06)
ln AST_INT	+		0.120**	0.121**	0.108**
			(2.20)	(2.20)	(1.97)
SUCC_DEC	-		0.862**	0.871**	0.894**
			(2.03)	(2.05)	(2.07)
FCF	+		-0.570	-0.525	-0.419
			(-1.07)	(-0.99)	(-0.79)
Fixed effects		No	Year-quarter, state, Industry	Year-quarter, state, Industry	Year-quarter, state, Industry
Nobs		1,615	1,615	1,615	1,615
Cluster		No	Firm	Firm	Firm
Adj R^2		0.16%	8.3%	8.4%	9.0%

1. This table reports OLS regression results for the following models:

Model (1): $STICKY = \beta_0 + \beta_1 WORK\_CLOSURE + \varepsilon$

Model (2): $STICKY = \beta_0 + \beta_1 WORK\_CLOS + \beta_2 ln\ EMP\_INT + \beta_3 LN\ AST\_INT + \beta_4 SUCC\_DEC + \beta_5 FCF + \varepsilon$

Model (3): $STICKY = \beta_0 + \beta_1 WORK\_CLOS + \beta_2 GOV\_SUP + \beta_3 WORK\_CLOS * GOV\_SUP + \beta_4 ln\, EMP\_INT + \beta_5 LN\, AST\_INT + \beta_6 SUCC\_DEC + \beta_7 FCF + \varepsilon$

Model (4): $STICKY = \beta_0 + \beta_1 WORK\_CLOS + \beta_2 INV + \beta_3 WORK\_CLOS * INV + \beta_4 ln\, EMP\_INT + \beta_5 LN\, AST\_INT + \beta_6 SUCC\_DEC + \beta_7 FCF + \varepsilon$

2. ***, **, * indicate two-sided significance at the 0.01, 0.05 and 0.1 levels, respectively.
3. All variables are defined in the Appendix.

Subsample analysis

Using models (1) and (2), I examine the effect of workplace closure on cost stickiness in high R&D-intensive firms and low R&D-intensive firms using ordinary least squares (OLS). I divide the sample firms into these two groups using the R&D intensity indicator (*INV*). Column (1) in Table 4.6 presents estimating model (1) results in low R&D-intensive firms. The coefficient estimates for the workplace closure measure (*WORK_CLOS*) *are* negative and significant (t-stat = -2.86). After adding the control variables based on model (2), I get the same results (t-stat = -2.58) as illustrated in column (2). These results support the primary findings of this study that the strictness of the workplace closure measures would reduce the level of cost stickiness.

In contrast, the coefficient for the workplace closure measure (*WORK_CLOS*) in columns (3) and (4) is not significant. These results support the argument that the previously reported adverse effect of the COVID-19 crisis and its containment measures on cost stickiness is not notable in high R&D-intensive firms.[8]

[8] To mitigate the effect of the observations with zero R&D on the subsample analysis, I use the weighted industry-adjusted R&D expenses to sales ratio as a benchmark to classify firms into high and low R&D-intensive firms.

Table 4-6: Subsample analysis

	Low R&D intensity		High R&D intensity	
Variable	(1)	(2)	(3)	(4)
Intercept	0.101	0.934	-0.096	-0.866
	(1.17)	(2.88) ***	(-0.54)	(-1.05)
WORK_CLOS	-0.144***	-0.182**	0.064	-0.033
	(-2.86)	(-2.58)	(0.63)	(-0.25)
ln EMP_INT		0.012		-0.092
		(0.26)		(-0.84)
ln AST_INT		0.114*		0.869
		(1.82)		(0.74)
SUCC_DEC		0.939		1.131
		(1.88)		(1.64)
FCF		-0.374		-0.196
		(-0.62)		(-0.18)
Fixed effects	No	Year-quarter, state, Industry	No	Year-quarter, state, Industry
Nobs	1,178	1,178	437	437
Cluster	No	Firm	No	Firm
R^2	0.69%	9.19%	0.09%	19.47%

1. This table reports OLS regression results for high and low R&D-intensive firms based on the following models:

Model (1): $STICKY = \beta_0 + \beta_1 WORK\_CLOSURE + \varepsilon$

Model (2): $STICKY = \beta_0 + \beta_1 WORK\_CLOS + \beta_2 ln\, EMP\_INT + \beta_3 LN\, AST\_INT + \beta_4 SUCC\_DEC + \beta_5 FCF + \varepsilon$

2. ***, **, * indicate two-sided significance at the 0.01, 0.05 and 0.1 levels, respectively.
3. All variables are defined in the "Appendix".

4.6 Conclusion

For a sample of US firms during the COVID-19 period, I provide evidence on the effect of the extreme uncertainty introduced by the pandemic and its containment measures on cost behaviour. I find that the strictness of workplace closure adversely affects cost stickiness levels as managers reduce their input levels when demand declines more than they increase their costs when demand increases during the COVID-19 pandemic.

Additionally, the results report that government support would not significantly mitigate the adverse effect of the crisis on cost stickiness. However, the significant negative impact of the COVID-19 crisis on cost stickiness is not observed in R&D-intensive firms, indicating that firms invested in R&D and technology during the crisis were able to retain their resources and redirect them towards the recovery process.

I offer the following caveats. First, I cannot directly measure the COVID-19 uncertainty level. As such, I depend on the strictness of workplace closure as its indirect measure. Additionally, I cannot rule out the possibility that this measure is affected by the political beliefs of the governors controlling each US state, leading to confusion regarding the interpretation of the severity of the closures. Additionally, I acknowledge that the measures of government support reflect different state-level responses; but firm data reflects total firm results, which may be related to business activities across states and across different countries (for multinational US firms), which might affect the results. I also acknowledge that using the firm-level cost stickiness measure developed by Weiss (2010) entails the disadvantage of a significant data loss as it restricts the sample to observations for which sales and costs change in the same direction. Moreover, the measure only identifies firm-year values, which entail quarterly increases and decreases in sales. Finally, I do not consider how the firms' operating decisions in response to the COVID-19 uncertainty might interact with governance mechanisms. Future research might be directed at determining these effects.

Appendix 4.1: Variables Definitions

Variable	Variable Name	Definition
Anti-cost stickiness indicator	*ANTI-DUM*	An indicator variable that equals 1 if *Sticky* < 0 and 0 otherwise;
Assets intensity	*AST_INT*	Total assets divided by total sales revenues (at / sale);
Employees intensity	*EMP_INT*	The number of employees at fiscal year-end divided by total sales revenues (emp /sale);
Free cash flow	*FCF*	Cash flow from operating activities (oancf) minus common (dvc) and preferred dividends (dvp) scaled by total assets (at) (oancf – [dvc+ dvp] / at);
Government support index	*GOV_SUP*	An index represents the economic support provided by the government during the COVID-19 crisis. Its value varies between 0 and 100.
R&D intensity indicator	*INV*	An indicator variable that equals 1 if R&D intensity measure (RD) is greater than the R&D intensity for the industry, and 0 otherwise;
R&D intensity measure	*RD*	Research and development expenses (xrd) divided by sales revenues (sale);
Cost stickiness measure	*STICKY*	Cost stickiness measure;
Successive decrease measure	*SUCC_DEC*	An indicator variable that equals 1 if $Sales_{it-4} < Sales_{it-8}$ and 0 otherwise;
Workplace closure indicator	*WORK_CLOS*	An indicator that equals 0 if the state is not applying any measures. It would equal 1 if the government recommended closure (or recommended work from home). It would equal 2 if the government required closure (or work from home) for some sectors or categories of workers. The measure equals 3 to indicate the necessary closure (or work from home) for all but essential workplaces.

Chapter 5 Conclusion

5.1 Research summary and main findings

This thesis includes three empirical studies on cost stickiness, a topic of much controversy in the accounting discipline. Cost stickiness is rooted in asymmetric cost behaviour – costs increase more when sales grow than they decline when sales fall (Anderson et al., 2003). Cost stickiness literature was heavily involved in identifying the determinants and consequences of this cost behaviour in non-innovative firms (Weiss, 2010; Banker et al., 2013). However, firms in the modern economy work in a dynamic environment with rapidly evolving technologies, fast-changing consumer preferences, accelerated product cycles and globalised operations and markets (Hidma et al., 2020). Thus, innovation in new products and processes has become increasingly important for companies to achieve and maintain their competitive advantage in this rapidly changing environment (Lome et al., 2016). Therefore, Banker et al. (2018) called for examining the consequences of the innovative operating process dynamics on cost behaviour. In this thesis, I am responding to this call and extending Anderson et al. (2003) study to the research and development context by investigating the determinants and consequences of this behaviour in innovative firms.

The first study, entitled "The Pursuit of Innovation: Cost Stickiness in R&D-intensive Firms", empirically tests whether R&D intensity is one of the determinants of cost stickiness in innovative firms. I complement the previous cost stickiness literature in this study by adopting the evolutionary theory of the firm to simulate the resource allocation process in R&D-intensive firms (Nelson & Winter, 1982, 2002). Based on the

evolutionary theory of the firm, I argue that R&D intensity would increase the level of cost stickiness in innovative firms. When managers of these firms face a reduction in their products' demand, they would retain the existing resources to avoid the loss of any part of the organisational memory that stores the employees' operational skills and knowledge. Additionally, these resources would also persist to avoid any disruption to the current agreement between the organisation and its members. Simultaneously, managers of R&D-intensive firms would redirect the acquired resources toward the recovery process by investing them in new technologies and R&D activities that realign the organisation with its external environment (Nelson & Winter, 1982).

Retaining the existing resources while revenues decline would be reflected in the financial statements as an increased cost stickiness. I test the previous proposition on a sample of 74,815 firm-quarter observations for 3,086 US public firms engaged in R&D activities over 20 years. The empirical results reveal a significant positive association between R&D intensity and cost stickiness. The results of the subsample analysis also confirm that the positive association between R&D intensity and cost stickiness prevails only in R&D-intensive firms.

Cost stickiness literature also shows that sticky costs negatively affect the informativeness of earnings in manufacturing firms due to the increased variability of the earning distribution when activity levels fall, which reduces earnings' predictability (Weiss, 2010). However, innovation is playing an increasingly essential role in all sectors of the modern economy. It fundamentally changes the "DNA" of many emerging and existing firms, the various stakeholders in these firms, the capital markets that finance these firms, and the role of accounting information in allocating capital to them (Zimmerman, 2015). Consequently, I have extended the prior research and examined the

relationship between cost stickiness and earnings informativeness for R&D firms. I have also investigated whether higher R&D intensity moderates the association between cost stickiness and the earnings-returns relationship.

The previous research objectives were addressed in the second study of this thesis, which is entitled "Cost Stickiness Behaviour, R&D Intensity and the Informativeness of Earnings". Based on a sample of 63,280 firm-quarter observations for 3,641 US public firms engaged in R&D activities from 2000 through 2019, the results imply that the previously reported adverse effect of cost stickiness on earnings informativeness is not applicable for R&D firms. These results suggest that accounting earnings reflect information used by equity investors when firms with sticky costs invest in R&D activities.

The study also shows that high R&D intensity attenuates the previously reported negative impact of cost stickiness on earnings informativeness. However, I find evidence that the informativeness of earnings increases with the increased levels of cost stickiness only in R&D-intensive firms. These results suggest that accounting earnings signal relevant information when firms with sticky costs increase their R&D investments. These findings indicate that the reported earnings of R&D-intensive firms with sticky costs capture the underlying causes of this cost behaviour. These firms are investing in R&D activities during difficult times to improve their performance and increase their ability to compete.

Prior literature also confirms that demand uncertainty motivates managers to purposefully delay reductions to committed resources until they are more certain about the permanence of the decline in demand, which increases the cost stickiness (Anderson et al., 2003; Lee et al., 2020). However, In late 2019 and into 2020, the world witnessed the spread of the COVID-19 pandemic, which has caused an unprecedented level of uncertainty that

permeates every aspect of life and business (Baker et al., 2020). This extreme uncertainty was because COVID-19 is genuinely a global pandemic, interest rates are at historical lows, global financial markets are highly interconnected, and spill-over effects occurred throughout supply chains (Ozili & Arun, 2020). Additionally, the COVID-19 shock is exogenous to the economic system. Therefore, the financial tools of the central banks used in economic crises are only temporary measures of reducing the uncertainties (M. O. Strauss-Kahn, 2020). Moreover, the impact of the COVID-19 pandemic is more severe than previous pandemics and outbreaks, such as the Spanish Flu in 1918 and Ebola in 2014 (Baker et al., 2020). The absence of a similar historical event means that managers have little clarity about the effects of the pandemic on output, demand, employability and earnings both in the short and long term (Sharif et al., 2020).

This extreme level of uncertainty – defined in terms of novelty, magnitude, duration, and the rapid pace of change – calls for examining the role of uncertainty in shaping cost behaviour and whether the government's reaction to the crisis mitigates it. I also extend the analysis by evaluating whether innovative firms respond differently to uncertainty and show a different level of cost stickiness in their financial statements. The third study, entitled "COVID-19 Uncertainty and Cost Stickiness", has investigated the effect of the extreme uncertainty associated with the COVID-19 crisis on the firms' cost stickiness with a focus on R&D-intensive firms. I also have examined whether the government's reaction to the situation mitigates this effect.

Based on a sample consisting of 1,615 firm-quarter observations for 938 firms whose headquarters are located in the USA from the first quarter of 2020 to the last quarter of 2021, the results show that cost stickiness levels decline with the severity of the COVID-19 crisis, indicating that managers remove their resources and lay off their employees

when demand decreases to avoid retaining them at a loss, especially when they have negative expectations about the recovery of the economic activity. However, it is hard for managers to accommodate the growth in demand by increasing their resources due to input scarcity and supply chain disruptions during the COVID-19 crisis. The results also indicate that the government income support was insufficient to attenuate workplace closures' negative effect on firms' cost stickiness. However, the significant adverse impact of the COVID-19 crisis on cost stickiness is not observed in R&D-intensive firms, indicating that firms that invested in R&D and technology during the crisis were able to retain their resources and redirect them towards the recovery process.

In sum, cost stickiness behaviour observed in the financial statements of R&D-intensive firms is driven by the capabilities' retention triggers and has other consequences on earnings properties than those observed in non-R&D firms. Cost stickiness is a natural result of how managers in R&D-intensive firms make their operating decisions and allocate resources during hard times. Even in the case of an unprecedented crisis such as the COVID-19 recession, managers of innovative firms preserve the firm's resources and capabilities to retain their competitive advantage and reinvest them in the recovery process.

5.2 Conclusions and implications

The findings from the studies in this thesis provide critical implications for investors and analysts, managers of R&D-intensive firms, and regulators and policymakers. This thesis indicates that the observed cost behaviour in the financial statements of R&D-intensive firms reflects the innovative managerial operating model. The intensity of R&D activities increases cost stickiness in innovative firms. These results should be considered by investors and analysts while evaluating the performance of R&D-intensive firms. Cost

stickiness is a sign of the managerial decisions to preserve the firm's capabilities and competencies during hard times and reinvest them in new technologies and R&D activities to realign the organisation with its external environment.

Additionally, I find evidence that the informativeness of earnings increases with the increased levels of cost stickiness in R&D-intensive firms. The results also show that higher R&D intensity attenuates the previously documented negative effect of cost stickiness on the informativeness of earnings. These results suggest that investors can depend on the accounting earnings of R&D firms with sticky costs while making investment decisions. These figures signal relevant information about the performance of the firms and capture the underlying events of this cost behaviour, which is part of the information set reflected in stock prices. Investors may also benefit from integrating the extreme levels of uncertainty caused by the COVID-19 pandemic into models that predict cost stickiness while evaluating the financial performance of these firms. The findings may motivate managers of R&D-intensive firms to disclose more information about their firms' R&D activities and future investment opportunities to enable the investors to incorporate this information into their analysis models.

Regulators might consider requiring R&D-intensive firms to disclose more information about their operational decisions to enhance the decision-making process of the market participants. Policymakers may be interested in recognising the impact of the COVID-19 extreme uncertainty on cost behaviour as a reflection of the managerial operating decisions towards the crisis and the associated governmental response. I find that the strictness of workplace closure adversely affects cost stickiness. Managers reduce their input levels when demand declines more than they increase their resources when demand increases during the COVID-19 crisis. The results also indicate that the governmental

income support was insufficient to preserve the firms' productive capital and, more importantly, the workers' skills. The results also show that firms must be innovative in response to the enormous disruption caused by COVID-19.

5.3 Limitations and suggestions for future research

I acknowledge the potential limitations of this study related to measurement errors. I recognise the limitations of R&D intensity as a measure of the firm's commitment to innovation, overlooking innovation activities based on other sources such as design activities, engineering developments and exploration of markets for new products. Future work can replicate this research using other direct measures of innovation, such as survey-based indicators. I also acknowledge that using the firm-level cost stickiness measure developed by Weiss (2010) entails the disadvantage of a significant data loss as it restricts the sample to observations for which sales and costs change in the same direction. Moreover, the measure only identifies firm-year values, which entail quarterly increases and decreases in sales. The empirical study of this research is also constrained due to the difficulty of measuring the main constructs of the evolutionary theory of the firm such as routines, employees' knowledge and interorganizational conflict and their relationship with cost stickiness in R&D-intensive firms. Future research could examine these relationships if data for the specific constructs are available.

In addition, I recognise that my reliance on ERC as a measure of earnings informativeness biases the final sample toward relatively larger firms. Future research could determine whether the inferences generalise to samples of smaller firms. I also acknowledge that I could not directly measure the COVID-19 uncertainty level. As such, I depend on the strictness of workplace closure as its indirect measure. Additionally, I cannot rule out the possibility that this measure is affected by the political beliefs of the governors controlling

each US state, leading to confusion regarding the interpretation of the severity of the closures. Moreover, I do not consider how the firms' operating decisions in response to the COVID-19 uncertainty might interact with governance mechanisms. Future research might be directed at determining these effects.

I also recognise that innovation processes are contingent on the economic sector, the field of knowledge, type of innovation, historical period, and the country concerned. Future research might determine whether the inferences can be generalised to samples that cover these different aspects of innovation in the economy. Future work can also investigate the determinants and consequences of cost stickiness in other sectors such as the public and non-profit organisations.

References

Acharya, V. V., Baghai, R. P., & Subramanian, K. V. (2014). Wrongful discharge laws and innovation. *The Review of Financial Studies, 27*(1), 301-346. https://doi.org/10.1093/rfs/hht009

Ahmed, A. S. (1994). Accounting earnings and future economic rents: An empirical analysis. *Journal of Accounting and Economics, 17*(3), 377-400. https://doi.org/https://doi.org/10.1016/0165-4101(94)90034-5

Aiken, L. S., & West, S. G. (1991). *Multiple regression: Testing and interpreting interactions*. SAGE Publications.

Altig, D., Baker, S., Barrero, J. M., Bloom, N., Bunn, P., Chen, S., Davis, S. J., Leather, J., Meyer, B., Mihaylov, E., Mizen, P., Parker, N., Renault, T., Smietanka, P., & Thwaites, G. (2020). Economic uncertainty before and during the COVID-19 pandemic. *Journal of Public Economics, 191*, 104274. https://doi.org/https://doi.org/10.1016/j.jpubeco.2020.104274

Amir, E., Guan, Y., & Livne, G. (2007). The association of R&D and capital expenditures with subsequent earnings variability. *Journal of Business Finance & Accounting, 34*(1/2), 222-246. https://doi.org/10.1111/j.1468-5957.2006.00651.x

Anderson, M. C., Banker, R. D., & Janakiraman, S. (2003). Are selling, general, and administrative costs 'sticky'? *Journal of Accounting Research, 41*(1), 47-63. https://doi.org/10.1111/1475-679x.00095

Anderson, M. C., Banker, R. D., Rong, H., & Janakiraman, S. N. (2007). Cost behavior and fundamentala analysis of SG&A costs. *Journal of Accounting, Auditing & Finance, 22*(1), 1-28. https://doi.org/10.1177/0148558X0702200103

Anderson, S. W., & Lanen, W. N. (2009). *Understanding cost management: What can we learn from the empirical evidence on 'sticky costs'?* Rice University and University of Michigan. https://dx.doi.org/10.2139/ssrn.975135

Anthony, S. D., Cobban, P., Nair, R., & Painchaud, N. (2019). Breaking down the barriers to innovation. *Harvard Business Review, 97*(6), 92-101. https://hbr.org/2019/11/breaking-down-the-barriers-to-innovation

Archibugi, D., Filippetti, A., & Frenz, M. (2013). Economic crisis and innovation: Is destruction prevailing over accumulation? *Research Policy, 42*(2), 303-314. https://doi.org/https://doi.org/10.1016/j.respol.2012.07.002

Asdemir, O., Fernando, G. D., Schneible, R. A., & Tripathy, A. (2017). Impact of strategy on analyst information. *Advances in Accounting, 37*, 103-110. https://doi.org/https://doi.org/10.1016/j.adiac.2016.12.003

Baker, S. R., Farrokhnia, R. A., Meyer, S., Pagel, M., & Yannelis, C. (2020). How does household sending respond to an epidemic? Consumption during the 2020 COVID-19 pandemic. *The Review of Asset Pricing Studies, 10*(4), 834-862. https://doi.org/10.1093/rapstu/raaa009

Balakrishnan, R., Labro, E., & Soderstrom, N. S. (2014). Cost structure and sticky costs. *Journal of Management Accounting Research, 26*(2), 91-116. https://doi.org/10.2308/jmar-50831

Ball, R., & Brown, P. (1968). An empirical evaluation of accounting income numbers. *Journal of Accounting Research, 6*(2), 159-178. https://doi.org/10.2307/2490232

Balla-Elliott, D., Cullen, Z. B., Glaeser, E. L., Luca, M., & Stanton, C. (2022). Determinants of small business reopening decisions after COVID restrictions were lifted. *Journal of Policy Analysis and Management, 41*(1), 278-317. https://doi.org/https://doi.org/10.1002/pam.22355

Bamber, L. S. (1987). Unexpected earnings, firm size, and trading volume around quarterly earnings announcements. *The Accounting Review, 62*(3), 510-532. http://www.jstor.org/stable/247574

Banker, R. D., Basu, S., Byzalov, D., & Chen, J. Y. S. (2016). The confounding effect of cost stickiness on conservatism estimates. *Journal of Accounting and Economics, 61*(1), 203-220. https://doi.org/https://doi.org/10.1016/j.jacceco.2015.07.001

Banker, R. D., & Byzalov, D. (2014). Asymmetric cost behavior. *Journal of Management Accounting Research, 26*(2), 43-79. https://doi.org/10.2308/jmar-50846

Banker, R. D., Byzalov, D., & Chen, L. (2013). Employment protection legislation, adjustment costs and cross-country differences in cost behavior. *Journal of Accounting and Economics, 55*(1), 111-127. https://doi.org/https://doi.org/10.1016/j.jacceco.2012.08.003

Banker, R. D., Byzalov, D., Ciftci, M., & Mashruwala, R. (2014). The moderating effect of prior sales changes on asymmetric cost behavior. *Journal of Management Accounting Research, 26*(2), 221-242. https://doi.org/10.2308/jmar-50726

Banker, R. D., Byzalov, D., Fang, S., & Liang, Y. (2018). Cost management research. *Journal of Management Accounting Research, 30*(3), 187-209. https://doi.org/10.2308/jmar-51965

Banker, R. D., & Chen, L. (2006). Predicting earnings using a model based on cost variability and cost stickiness. *The Accounting Review, 81*(2), 285-307. http://www.jstor.org/stable/4093140

Baqaee, D., & Farhi, E. (2022). Supply and demand in disaggregated keynesian economies with an application to the COVID-19 crisis. *American Economic Review, 112*(5), 1397-1436. https://doi.org/10.1257/aer.20201229

Barker, V. L., & Mone, M. A. (1994). Retrenchment: Cause of turnaround or consequence of decline? *Strategic Management Journal, 15*(5), 395-405. www.jstor.org/stable/2486782

Barron, O. E., Byard, D., Kile, C., & Riedl, E. J. (2002). High-technology intangibles and analysts' forecasts. *Journal of Accounting Research, 40*(2), 289-312. http://www.jstor.org.ezproxy.aut.ac.nz/stable/3542384

Barron, O. E., Harris, D. G., & Mary, S. (2005). Evidence that investors trade on private event-period information around earnings announcements. *The Accounting Review, 80*(2), 403-421. http://www.jstor.org.ezproxy.aut.ac.nz/stable/4093063

Barth, M. E., Beaver, W. H., & Landsman, W. R. (2001). The relevance of the value relevance literature for financial accounting standard setting: Another view. *Journal of Accounting and Economics, 31*(1), 77-104. https://doi.org/https://doi.org/10.1016/S0165-4101(01)00019-2

Barth, M. E., Kasznik, R., & McNichols, M. F. (2001). Analyst coverage and intangible assets. *Journal of Accounting Research, 39*(1), 1-34. http://www.jstor.org/stable/2672943

Bartik, A. W., Bertrand, M., Cullen, Z., Glaeser, E. L., Luca, M., & Stanton, C. (2020). The impact of COVID-19 on small business outcomes and expectations. *Proceedings of the National Academy of Sciences, 117*(30), 17656-17666. https://doi.org/10.1073/pnas.2006991117

Beaver, W. H. (1968). The information content of annual earnings announcements. *Journal of aAccounting Research, 6*, 67-92. https://www.jstor.org/stable/pdf/2490070.pdf

Beaver, W. H., McNichols, M. F., & Wang, Z. Z. (2020). Increased market response to earnings announcements in the 21st century: An empirical investigation. *Journal of Accounting and Economics, 69*(1), 101244. https://doi.org/https://doi.org/10.1016/j.jacceco.2019.101244

Bentley, K. A., Omer, T. C., & Sharp, N. Y. (2013). Business strategy, financial reporting irregularities, and audit effort. *Contemporary Accounting Research, 30*(2), 780-817. https://doi.org/https://doi.org/10.1111/j.1911-3846.2012.01174.x

Bentley-Goode, K. A., Omer, T. C., & Twedt, B. J. (2019). Does business strategy impact a firm's information environment? *Journal of Accounting, Auditing & Finance, 34*(4), 563-587. https://doi.org/10.1177/0148558X17726893

Bentolila, S., & Bertola, G. (1990). Firing costs and labour demand: How bad is eurosclerosis? *The Review of Economic Studies, 57*(3), 381-402. https://doi.org/10.2307/2298020

Biddle, G. C., & Seow, G. S. (1991). The estimation and determinants of associations between returns and earnings: Evidence from cross-industry comparisons. *Journal of Accounting, Auditing & Finance, 6*(2), 183-232. https://doi.org/10.1177/0148558X9100600203

Chan, L. K. C., Lakonishok, J., & Sougiannis, T. (2001). The stock market valuation of research and development expenditures. *The Journal of Finance, 56*(6), 2431-2456. http://www.jstor.org/stable/2697829

Chen, C. X., Lu, H., & Sougiannis, T. (2012). The agency problem, corporate governance, and the asymmetrical behavior of selling, general, and administrative costs. *Contemporary Accounting Research, 29*(1), 252-282. https://doi.org/doi:10.1111/j.1911-3846.2011.01094.x

Chi, S. S., & Shanthikumar, D. M. (2017). Local bias in google search and the market response around earnings announcements. *The Accounting Review, 92*(4), 115-143. https://doi.org/10.2308/accr-51632

Ciftci, M., & Cready, W. M. (2011). Scale effects of R&D as reflected in earnings and returns. *Journal of Accounting and Economics, 52*(1), 62-80. https://doi.org/https://doi.org/10.1016/j.jacceco.2011.02.003

Ciftci, M., Lev, B., & Radhakrishnan, S. (2011). Is research and development mispriced or properly risk adjusted? *Journal of Accounting, Auditing & Finance, 26*(1), 81-116. https://doi.org/10.1177/0148558X11400581

Cochrane, J. (2020). Coronavirus monetary policy. In R. Baldwin & B. Weder di Mauro (Eds.), *Economics in the time of COVID-19*. CEPR Press. http://iteachmsu-staging.s3.amazonaws.com/staging/uploads/post/post_media/5053/covid-19.pdf#page=112

Cohen, W. M., & Klepper, S. (1996). A reprise of size and R&D. *The Economic Journal, 106*(437), 925-951. https://doi.org/10.2307/2235365

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 35*(1), 128-152. https://doi.org/10.2307/2393553

Collins, D. W., & Kothari, S. P. (1989). An analysis of intertemporal and cross-sectional determinants of earnings response coefficients. *Journal of Accounting and Economics, 11*(2), 143-181. https://doi.org/https://doi.org/10.1016/0165-4101(89)90004-9

Courtney, J. (2020). *The Coronavirus Aid, Relief and Economic Security (CARES) Act,* . https://www.congress.gov/bill/116th-congress/house-bill/748

Cowling, M., Brown, R., & Rocha, A. (2020). Did you save some cash for a rainy COVID-19 day? The crisis and SMEs. *International Small Business Journal: Researching Entrepreneurship, 38*(7), 593-604.

Coy, P. (2020). The great coronavirus crash of 2020 is different. *Bloomberg Businessweek*. https://www.bloomberg.com/news/articles/2020-03-19/the-great-coronavirus-crash-of-2020-is-different#xj4y7vzkg

Del Rio-Chanona, R. M., Mealy, P., Pichler, A., Lafond, F., & Farmer, J. D. (2020). Supply and demand shocks in the COVID-19 pandemic: An industry and occupation perspective. *Oxford Review of Economic Policy, 36*(Supplement_1), S94-S137. https://doi.org/10.1093/oxrep/graa033

Dess, G. G., & Shaw, J. D. (2001). Voluntary turnover, social capital, and organizational performance. *Academy of Management Review, 26*(3), 446-456. https://doi.org/10.5465/AMR.2001.4845830

Dichev, I. D., & Tang, V. W. (2008). Matching and the changing properties of accounting earnings over the last 40 years. *The Accounting Review, 83*(6), 1425-1460. http://www.jstor.org/stable/30243802

Easton, P. D., & Zmijewski, M. E. (1989). Cross-sectional variation in the stock market response to accounting earnings announcements. *Journal of Accounting and Economics, 11*(2), 117-141. https://doi.org/https://doi.org/10.1016/0165-4101(89)90003-7

Eberhart, A. C., Maxwell, W. F., & Siddique, A. R. (2008). A reexamination of the tradeoff between the future benefit and riskiness of R&D increases. *Journal of Accounting Research, 46*(1), 27-52. https://doi.org/https://doi.org/10.1111/j.1475-679X.2007.00264.x

Edwards-Schachter, M. (2018). The nature and variety of innovation. *International Journal of Innovation Studies, 2*(2), 65-79. https://doi.org/https://doi.org/10.1016/j.ijis.2018.08.004

Fagerberg, J., Mowery, D. C., & Nelson, R. R. (2005). *The Oxford handbook of innovation*. Oxford University Press.

Fairlie, R. W. (2020). The impact of COVID-19 on small business owners: The first three months after social-distancing restrictions. *Journal of Economics & Management Strategy, 29*, 727-740. https://doi.org/10.1111/jems.12400

Ferri, F., Zheng, R., & Zou, Y. (2018). Uncertainty about managers' reporting objectives and investors' response to earnings reports: Evidence from the 2006 executive compensation disclosures. *Journal of Accounting and Economics, 66*(2), 339-365. https://doi.org/https://doi.org/10.1016/j.jacceco.2018.08.001

Finn, P., Mysore, M., & Usher, O. (2020). *When nothing is normal: Managing in extreme uncertainty*. https://www.mckinsey.com/business-functions/risk-and-resilience/our-insights/when-nothing-is-normal-managing-in-extreme-uncertainty

Frick, W. (2019). How to survive a recession & thrive afterward. *Harvard Business Review, 97*(3), 98-105. https://hbr.org/2019/05/how-to-survive-a-recession-and-thrive-afterward

Furr, N., & Shipilov, A. (2019). Digital doesn't have to be disruptive. *Harvard Business Review, 97*(4), 94-103. https://hbr.org/2019/07/digital-doesnt-have-to-be-disruptive

Galindo-Rueda, F., & Verger, F. (2016). *OECD Taxonomy of Economic Activities Based on R&D Intensity*. The Organization for Economic Cooperation and Development (OECD). https://www.oecd-ilibrary.org/docserver/5jlv73sqqp8r-en.pdf?expires=1685070597&id=id&accname=guest&checksum=1D632275D1D23CA1909A38E8319A8B03

Gaudecker, V. H., Holler, R., Janys, L. S., B. M., & Zimpelmann, C. (2020). Labour supply in the early stages of the COVID-19 pandemic: empirical evidence on hours, home office, and expectations. *IZA Discussion Papers, No. 13158*. https://doi.org/https://dx.doi.org/10.2139/ssrn.3579251

Groenewegen, J., Hardeman, S., & Stam, E. (2021, 2021/11/01/). Does COVID-19 state aid reach the right firms? COVID-19 state aid, turnover expectations, uncertainty and management practices. *Journal of Business Venturing Insights, 16*, e00262. https://doi.org/https://doi.org/10.1016/j.jbvi.2021.e00262

Guerrieri, V., Lorenzoni, G., Straub, L., & Werning, I. (2022). Macroeconomic implications of COVID-19: Can negative supply shocks cause demand shortages? *American Economic Review, 112*(5), 1437-1474. https://doi.org/10.1257/aer.20201063

Gulati, R., Nohria, N., & Wohlgezogen, F. (2010). Roaring out of recession. *Harvard Business Review*(March). https://hbr.org/2010/03/roaring-out-of-recession

Gupta, A. (2020). *R&D and firm resilience during bad times*. Düsseldorf Institute for Competition Economics (DICE). https://dx.doi.org/10.2139/ssrn.3703103

Guthrie, J. P., & Datta, D. K. (2008). Dumb and dumber: The impact of downsizing on firm performance as moderated by industry conditions. *Organization Science, 19*(1), 108-123. www.jstor.org/stable/25146166

Hagedoorn, J. (2002). Inter-firm R&D partnerships: An overview of major trends and patterns since 1960. *Research Policy, 31*(4), 477-492. https://doi.org/https://doi.org/10.1016/S0048-7333(01)00120-2

Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S., & Tatlow, H. (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour, 5*(4), 529-538. https://doi.org/10.1038/s41562-021-01079-8

Hall, B. H., Jaffe, A. B., & Trajtenberg, M. (2005). Market value and patent citations. *The RAND Journal of Economics, 36*(1), 16-38. http://www.jstor.org/stable/1593752

Hallas, L., Hatibie, A., Koch, R., Majumdar, S., Pyarali, M., Wood, A., & Hale, T. (2021). Variation in US states' COVID-19 policy responses. *BSG Working Paper Series*. https://www.bsg.ox.ac.uk/sites/default/files/2021-05/BSG-WP-2020-034-v3.pdf

Hassan, T. A., Hollander, S., Lent, L. V., Schwedeler, M., & Tahoun, A. (2021). Firm-level exposure to epidemic diseases: COVID-19, SARS, and H1N1. *NBER Working Paper Series*(26971), 1-15. https://www.nber.org/system/files/working_papers/w26971/w26971.pdf

He, J., Tian, X., Yang, H., & Zuo, L. (2020). Asymmetric cost behavior and dividend policy. *Journal of Accounting Research, 58*(4), 989-1021. https://doi.org/10.1111/1475-679x.12328

Hidma, A., Kuchler, S., & Sandstrom, V. (2020). *The present-focused, future-ready R&D organization*. https://www.mckinsey.com/business-functions/operations/our-insights/the-present-focused-future-ready-rd-organization

Hill, D. (2020). *Production and trade of knowledge -and technology- intensive industries*. National Science Board. https://ncses.nsf.gov/pubs/nsb20205/production-patterns-and-trends-of-knowledge-and-technology-intensive-industries

Hitt, M. A., Hoskisson, R. E., Johnson, R. A., & Moesel, D. D. (1996). The market for corporate control and firm innovation. *The Academy of Management Journal, 39*(5), 1084-1119. https://doi.org/10.2307/256993

Holland, T., & Katzin, J. (2019). *Beyond the downturn: Recession strategies to take the lead*. https://www.bain.com/insights/beyond-the-downturn-recession-strategies-to-take-the-lead/

Homburg, C., Hoppe, A., Nasev, J., Reimer, K., & Uhrig-Homburg, M. (2018). *How cost stickiness affects credit risk*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2792085

Humphries, J. E., Neilson, C., & Ulyssea, G. (2020). The evolving impacts of Covid-19 on small businesses since the CARES Act. https://dx.doi.org/10.2139/ssrn.3584745

Imbert, F., & Li, Y. (2020). *Stocks suffer their worst day since March, with the Dow plunging more than 1,800 points*. CNBC. https://www.cnbc.com/2020/06/10/stock-market-futures-open-to-close-news.html

Inglesby, T. V., Nuzzo, J. B., O'Toole, T., & Henderson, D. A. (2006). Disease mitigation measures in the control of pandemic influenza. *Biosecurity and Bioterrorism: Biodefense Strategy, Practice, and Science, 4*(4), 366-375. https://doi.org/10.1089/bsp.2006.4.366

Inoue, H., & Todo, Y. (2020). The propagation of economic impacts through supply chains: The case of a mega-city lockdown to prevent the spread of COVID-19. *PLoS ONE, 15*(9), e0239251. https://doi-org.ezproxy.aut.ac.nz/10.1371/journal.pone.0239251

Kállay, B. (2012). Evolutionary and competence-based theories of the firm. *Journal of International Studies, 5*(1), 38-45. https://www.jois.eu/?24,en_evolutionary-and-competence-based-theories-of-the-firm

Kama, I., & Weiss, D. (2013). Do earnings targets and managerial incentives affect sticky costs? *Journal of Accounting Research, 51*(1), 201-224. https://doi.org/doi:10.1111/j.1475-679X.2012.00471.x

Kim, O., & Verrecchia, R. E. (1991). Market reaction to anticipated announcements. *Journal of Financial Economics, 30*(2), 273-309. https://doi.org/https://doi.org/10.1016/0304-405X(91)90033-G

Kogut, B., & Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science, 3*(3), 383-397. www.jstor.org/stable/2635279

Koren, M., & Pető, R. (2020). Business disruptions from social distancing. *PLoS One, 15*(9), e0239113. https://doi.org/10.1371/journal.pone.0239113

Kothari, S. P., Laguerre, T. E., & Leone, A. J. (2002). Capitalization versus expensing: Evidence on the uncertainty of future earnings from capital expenditures versus R&D outlays. *Review of Accounting Studies, 7*(4), 355-382. http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=9964695&site=ehost-live&scope=site

Krammer, S. M. S. (2022). Navigating the new normal: Which firms have adapted better to the COVID-19 disruption? *Technovation, 110*, 102368. https://doi.org/https://doi.org/10.1016/j.technovation.2021.102368

Laitinen, E. K. (2000). Long-term success of adaptation strategies: Evidence from finnish companies. *Long Range Planning, 33*(6), 805-830. https://doi.org/https://doi.org/10.1016/S0024-6301(00)00088-1

Lam, A. (2005). Organizational innovation. In J. Fagerberg & D. C. Mowery (Eds.), *The Oxford handbook of innovation* (pp. 115-147). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199286805.003.0005

Lazonick, W. (2002). Innovative enterprise and historical transformation. *Enterprise and Society, 3*(1), 3-47. https://doi.org/10.1093/es/3.1.3

Lee, W., Pittman, J., & Saffar, W. (2020). Political uncertainty and cost stickiness: Evidence from national elections around the world. *Contemporary Accounting Research, 37*(2), 1107-1139. https://doi.org/10.1111/1911-3846.12547

Leonard-Barton, D. A. (1995). *Wellsprings of knowledge: Building and sustaining the sources of innovation*. Harvard Business School Press.

Lev, B. (1983). Some economic determinants of time-series properties of earnings. *Journal of Accounting and Economics, 5*, 31-48. https://doi.org/https://doi.org/10.1016/0165-4101(83)90004-6

Lev, B., & Sougiannis, T. (1996). The capitalization, amortization, and value-relevance of R&D. *Journal of Accounting and Economics, 21*(1), 107-138. https://doi.org/https://doi.org/10.1016/0165-4101(95)00410-6

Lome, O., Heggeseth, A. G., & Moen, Ø. (2016). The effect of R&D on performance: Do R&D-intensive firms handle a financial crisis better? *The Journal of High Technology Management Research, 27*(1), 65-77. https://doi.org/https://doi.org/10.1016/j.hitech.2016.04.006

Lundvall, B. Å. (2016). *The learning economy and the economics of hope*. Anthem Press. https://books.google.co.nz/books?id=T8xRDwAAQBAJ

Makkonen, H., Pohjola, M., Olkkonen, R., & Koponen, A. (2014). Dynamic capabilities and firm performance in a financial crisis. *Journal of Business Research, 67*(1), 2707-2719. https://doi.org/https://doi.org/10.1016/j.jbusres.2013.03.020

Mangan, D., Berkeley, L. J., & Feuer, W. (2020). *Coronavirus pandemic economic fallout 'way worse than the global financial crisis,' IMF chief says*. https://www.cnbc.com/2020/04/03/coronavirus-way-worse-than-the-global-financial-crisis-imf-says.html

Manso, G. (2011). Motivating innovation. *The Journal of Finance, 66*(5), 1823-1860. http://www.jstor.org.ezproxy.aut.ac.nz/stable/41305176

Meyer, B. H., Prescott, B., & Sheng, X. S. (2022). The impact of the COVID-19 pandemic on business expectations. *International Journal of Forecasting, 38*(2), 529-544. https://doi.org/https://doi.org/10.1016/j.ijforecast.2021.02.009

Mischke, J., Woetzel, J., DSmit, S., Manyika, J., Brishan, M., Windhagen, E., Schubert, J., Hieronimus, S., Dagorret, G., & Noguer, M. C. (2021). *Will productivity and growth return after the COVID-19 crisis?* https://www.mckinsey.com/industries/public-and-social-sector/our-insights/will-productivity-and-growth-return-after-the-covid-19-crisis

Morrow, J. L., Johnson, R. A., & Busenitz, L. W. (2004). The effects of cost and asset retrenchment on firm performance: The overlooked role of a firm's competitive environment. *Journal of management, 30*(2), 189-208. https://doi.org/10.1016/j.jm.2003.01.002

Nelson, R. R. (2020). A perspective on the evolution of evolutionary economics. *Industrial & Corporate Change, 29*(5), 1101-1118. https://doi.org/10.1093/icc/dtaa045

Nelson, R. R., & Winter, S. G. (1982). *An evolutionary theory of economic change*. Belknap Press of Harvard University Press. https://www.google.co.nz/books/edition/An_Evolutionary_Theory_of_Economic_Chang/6Kx7s_HXxrkC?hl=en&gbpv=1&pg=PA1&printsec=frontcover

Nelson, R. R., & Winter, S. G. (2002). Evolutionary theorizing in economics. *The Journal of Economic Perspectives, 16*(2), 23-46. http://www.jstor.org.ezproxy.aut.ac.nz/stable/2696495

O'Sullivan, M. (2000). The innovative enterprise and corporate governance. *Cambridge Journal of Economics, 24*(4), 393-416. https://doi.org/10.1093/cje/24.4.393

O'Sullivan, M. (2004). Finance and innovation. In J. Fagerberg, D. C. Mowery, & R. R. Nelson (Eds.), *The Oxford handbook of innovation* (pp. 240-265). Oxford University Press.

OECD. (2017). OECD digital economy outlook 2017. https://www.oecd.org/digital/oecd-digital-economy-outlook-2017-9789264276284-en.htm

Ozili, P., & Arun, T. (2020). *Spillover of COVID-19: Impact on the global economy*. https://mpra.ub.uni-muenchen.de/99850/1/MPRA_paper_99850.pdf

Pavitt, K. (2005). Innovation processes. In J. Fagerberg, D. C. Mowery, & R. R. Nelson (Eds.), *The Oxford handbook of innovation* (pp. 86-114). Oxford University Press.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies, 22*(1), 435-480. http://www.jstor.org/stable/40056916

Petra, S. (2007). The effects of corporate governance on the informativeness of earnings. *Economics of Governance, 8*(2), 129-152. https://doi.org/10.1007/s10101-006-0018-8

Pichler, A., Pangallo, M., Rio-Chanona, R. M., Lafond, F., & Farmer, J. D. (2020). *Production networks and epidemic spreading: How to restart the UK economy?* https://arxiv.org/abs/2005.10585

Powell, W. W., & Grodal, S. (2005). Networks of innovators. In J. Fagerberg, D. C. Mowery, & R. R. Nelson (Eds.), *The Oxford handbook of innovation* (pp. 56-85). Oxford University Press.

PwC. (2020). *Capital markets 2020: Will it changes for good?* https://www.pwc.co.nz/

Rajagopalan, N. (1997). Strategic orientations, incentive plan adoptions, and firm performance: Evidence from electric utility firms. *Strategic Management Journal, 18*(10), 761-785. http://www.jstor.org.ezproxy.aut.ac.nz/stable/3088200

Riom, C., & Valero, A. (2020). The business response to COVID-19: The CEP-CBI survey on technology adoption *Centre For Economic Performance*(009), 1-23. https://cep.lse.ac.uk/pubs/download/cepcovid-19-009.pdf?platform=hootsuite

Roychowdhury, S., & Watts, R. L. (2007). Asymmetric timeliness of earnings, market-to-book and conservatism in financial reporting. *Journal of Accounting and Economics, 44*(1), 2-31. https://doi.org/https://doi.org/10.1016/j.jacceco.2006.12.003

Schumpeter, J. A. (1943). *Capitalism, socialism & democracy*. Routldge.

Schumpeter, J. A. (2005). *Business cycles: A theoretical, historical, and statistical analysis of the capitalist process*. McGraw-Hill

Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International Review of Financial Analysis, 70*, 101496. https://doi.org/https://doi.org/10.1016/j.irfa.2020.101496

Srinivasan, R., Gray, L. L., & Sridhar, S. (2011). Should firms spend more on research and development and advertising during recessions? *Journal of Marketing, 75*(May), 49-65. https://journals.sagepub.com/doi/10.1509/jmkg.75.3.49

Srivastava, A. (2014). Why have measures of earnings quality changed over time? *Journal of Accounting and Economics, 57*(2), 196-217. https://doi.org/https://doi.org/10.1016/j.jacceco.2014.04.001

Strauss-Kahn, D. (2020). Being, having and power during the crisis. https://www.slideshare.net/DominiqueStraussKahn/being-having-and-power-during-the-crisis

Strauss-Kahn, M. O. (2020). Can we compare the COVID-19 crisis and 2008 crises? . https://www.atlanticcouncil.org/blogs/new-atlanticist/can-we-compare-the-covid-19-and-2008-crises/

Subramaniam, C., & Weidenmier, W. M. (2016). Additional evidence on the sticky behavior of costs. In M. J. Epstein & M. A. Malina (Eds.), *Advances in Management Accounting* (Vol. 26, pp. 275-305). Emerald Group Publishing Limited. https://doi.org/doi:10.1108/S1474-787120150000026006

Tew, I. (2020). FTSE on track for biggest fall in 30 years after 9% drop. *The Financial Times*. https://www.ftadviser.com/investments/2020/03/12/ftse-on-track-for-biggest-fall-in-30-years-after-9-drop/

Venieris, G., Naoum, V. C., & Vlismas, O. (2015). Organisation capital and sticky behaviour of selling, general and administrative expenses. *Management Accounting Research, 26*, 54-82. https://doi.org/https://doi.org/10.1016/j.mar.2014.10.003

Volberda, H. W., & Lewin, A. Y. (2003). Co-evolutionary dynamics within and between firms: From evolution to co-evolution. *Journal of Management Studies, 40*(8), 2111-2136. https://doi.org/https://doi.org/10.1046/j.1467-6486.2003.00414.x

Wang, R., Wang, H., & Chen, Y. (2021). COVID-19 shock and interest expense stickiness: Evidence from Chinese listed firms. *Emerging Markets Finance and Trade*, 1-14. https://doi.org/10.1080/1540496X.2021.1990750

Weiss, D. (2010). Cost behavior and analysts' earnings forecasts. *The Accounting Review, 85*(4), 1441-1471. https://doi.org/10.2308/accr.2010.85.4.1441

World Health Organization. (2022). *WHO Coronavirus (COVID-19) Dashboard*. https://covid19.who.int/

Wu, M., & Wilson, M. (2022). How well do analysts really understand asymmetric cost behaviour? *Accounting & Finance, 62*(3), 3951-3985. https://doi.org/https://doi.org/10.1111/acfi.12911

Yang, Y., & Chen, D. (2023). Influence of COVID-19 on asymmetric cost behavior and intellectual capital efficiency: A comparison of Australian and Chinese listed firms. *Asia-Pacific Journal of Accounting & Economics*, 1-17. https://doi.org/10.1080/16081625.2023.2194887

Zhong, R. (2018). Transparency and firm innovation. *Journal of Accounting and Economics, 66*(1), 67-93. https://doi.org/https://doi.org/10.1016/j.jacceco.2018.02.001

Zimmerman, J. L. (2015). The role of accounting in the twenty-first century firm. *Accounting and Business Research, 45*(4), 485-509. https://doi.org/10.1080/00014788.2015.1035549