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The Economic Impacts of Pandemic-Induced Non-Pharmaceutical Interventions in the Initial Stage of the COVID-19 Pandemic: Evidence from Developed and Emerging Markets

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Declaration: I, Weiwen Qi, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Signed: [redacted] **Date:** 24/04/2020

Abstract

Governments worldwide responded to the unprecedented COVID-19 pandemic with unconventional non-pharmaceutical interventions. This thesis is comprised of three empirical chapters, investigating the economic impacts of the pandemic and associated government interventions on stock markets (Chapter 2), industry resilience (Chapter 3), and labour market outcomes during the pandemic (Chapter 4), drawing evidence from both developed and emerging markets.

Using a macro-level analysis, Chapter 2 examines stock market reactions to pandemic-enforced lockdowns in developed and emerging markets by using a combination of a panel data approach and an event study method. The results suggest that the stock market, in general, has reacted negatively and significantly to increases in the daily stringency of lockdown measures. The dynamic evolution of stock markets indicates adaptive learning processes and updating expectations which are based on information about other countries' lockdown announcements as useful signals about the severity of the pandemic. This learning process suggests that the stock market reactions to pandemic-enforced interventions are not solely determined by sentiment, as rational decision-making also plays a role.

Zooming the focus to a meso (sectoral) level, Chapter 3 examines the role of pre-pandemic digitalisation in mitigating the shocks from lockdown measures on industry resilience in European countries. Panel data and IV-2SLS approaches reveal that industries with higher digitalisation investments have been more resilient to the adverse shocks from lockdown measures during the initial COVID-19 waves, particularly in contact-intensive industries. These findings provide empirical evidence for policymakers to accelerate digitalisation across industries, enhancing resilience to future crises.

Using a micro-level analysis, Chapter 4 examines the persistence of the motherhood penalty and the factors moderating its impact on employment outcomes during the early stage of the pandemic. With an intersectional approach, this chapter reveals that Black, Asian, and Minority Ethnic (BAME) migrant mothers, especially in blue-collar roles, experienced disproportionate unemployment risks, reflecting compounding disadvantages in the labour market. Being clinically vulnerable to Coronavirus and the lack of family support in childcare exacerbate job loss probabilities for this group, highlighting gender-based inequalities in the UK labour market.

Impact Statements

Examining the economic impacts of pandemic-induced non-pharmaceutical interventions from multilevel analyses, this thesis contributes to the academic discourse in various disciplines and has implications for policymaking and societal well-being outside of academia.

Impacts within Academia

This thesis contributes to the advancement of knowledge in economic literature, research methodologies, and scholarly discourse. First, the multifaceted approach to investigate the economic impacts of non-pharmaceutical interventions enriches our understanding of the diverse economic implications of health crises and government interventions.

The findings of the thesis contribute to ongoing academic debates as well. The macro-level analysis of stock market reactions reveals the adaptive learning behaviours of stock market, emphasizing the importance of rational decision-making in chaos times of pandemic outbreaks. The meso-level examination of industry resilience underscores the role of digitalisation as a critical factor in mitigating the adverse shocks of pandemic-enforced lockdown measures. These insights contribute to the academic debate on the factors influencing industry resilience, emphasising the importance of investing in digital technologies to enhance adaptability in the face of significant disruptions. The micro-level analysis informs the discourse on labour market disparities by revealing the persistence of the motherhood penalty and disproportionate unemployment risks faced by specific groups. Collectively, these findings add depth to the ongoing academic conversations on the economic and social implications of the pandemic and associated government interventions.

The thesis also demonstrates the importance of employing diverse methodologies in economic research by combining panel data analysis, event study method, and dynamic multinomial logistic models. Additionally, econometric techniques used to address endogeneity issues provide potential solutions for related studies facing similar challenges.

Impacts Outside Academia

Beyond its academic contributions, this thesis has significant implications for policymakers, practitioners, and the society at large in various aspects. First, the insights from stock market reactions to pandemic-induced interventions can guide policymakers in designing and implementing public health measures and macroeconomic policies. When implementing inventions in the context of managing public health crises and their economic consequences, stock market reactions provide useful information for policymakers on potential economic impacts of public health measures and macroeconomic mitigating policies. As markets respond to new information and changing circumstances, policies should be flexible and responsive to evolving conditions. Additionally, policymakers are recommended to provide transparent and well-reasoned explanations for policy decisions to help investors make informed decisions, supporting rational decision-making by providing accurate information about the economic landscape. Furthermore, regular monitoring and assessment of market dynamics should be conducted to provide policymakers with timely information on how investors are processing and reacting to new information, informing more effective policy interventions and helping maintain market stability.

The findings on the role of digitalisation in fostering industry resilience offer actionable insights for policymakers and industry leaders seeking to build robust economic systems. By identifying digitalisation as a key determinant of resilience, this research underscores the imperative for investments in digital infrastructure and skills development as a means of enhancing economic resilience in an increasingly uncertain world.

The insights from labour market outcome analysis have direct relevance for policymakers addressing inequalities exacerbated by the pandemic. The identification of factors exacerbating unemployment risks, such as parental status, ethnic migrant status, and health conditions, highlights the importance of designing targeted interventions to alleviate disparities and promote inclusive economic recovery from the pandemic.

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List of Abbreviation

AMH–Adaptive Market Hypothesis
AR—Abnormal Return
BAME—Black, Asian, and Minority Ethnic
CAR—Cumulative Abnormal Return
CT—Communication Equipment
DB—Computer Software and Databases
DJIA—Dow Jones Industrial Average
DMLM—Dynamic Multinomial Logistic Model
FDI—Foreign Direct Investment
FE—Fixed Effects
FTSE100—Financial Times Stock Exchange 100
GDP — Gross Domestic Product
GRANK Test—Generalised Rank Test
IT—Computing Equipment
IV—Instrumental Variable
IV-2SLS—Instrumental Variable-Two Stage Least Squares
IMF — International Monetary Fund
NHS—National Health Service
NPIs—Non-Pharmaceutical Interventions
PCA–Principal Component Analysis
S&P 500—Standard & Poor 500
USoc—Understanding Society
VIF—Variance Inflation Factor
WHO—World Health Organisation

Chapter 1 *Introduction*

1. Research Background

The COVID-19 pandemic, which emerged in late 2019 and rapidly spread across the globe, caused unprecedented challenges to public health, economies, and societies. In response to it, governments worldwide imposed stringent non-pharmaceutical interventions (NPIs), such as nationwide lockdowns, travel restrictions, social distancing guidelines, and the closure of non-essential businesses, to curb the transmission of the virus. While these interventions are crucial in mitigating the public health crisis, they have had far-reaching implications for economies, industries, and livelihoods. Amidst the multifaceted challenges posed by the pandemic, understanding the economic impacts of pandemic-enforced non-pharmaceutical interventions has arisen as a critical area of inquiry for researchers, policymakers, and stakeholders. Through a multi-faceted lens, this PhD thesis includes three empirical chapters which investigate the economic impacts of the pandemic-enforced non-pharmaceutical interventions from multiple aspects, drawing evidence from both developed and emerging markets.

The economic impacts of the pandemic and its associated NPIs are complex and multifaceted, spanning various sectors and dimensions of economic activity. Studies have documented the adverse effects of pandemic-related interventions on business activities (Alfaro *et al*., 2020), consumption patterns (Baker *et al*., 2020), employment levels (Gupta *et al*., 2020), trade (Baldwin and Mauro, 2020), and income distribution (Adams-Prassl *et al*., 2020). While these findings provide valuable insights into the broad economic implications of NPIs, a more nuanced understanding of the differential impact of these interventions across regions, industries, and demographic groups is essential for informed policymaking. This additional layer of complexity is evident in the varying degrees of impact on different sectors and population segments. For instance, research has shown that certain industries, such as hospitality, tourism, and retail, have been disproportionately affected by lockdown measures and social distancing mandates (Bounie *et al*., 2020). Similarly, vulnerable populations, including low-income workers and minorities, have borne the brunt of the economic fallout from the pandemic (Alon *et al*., 2020).

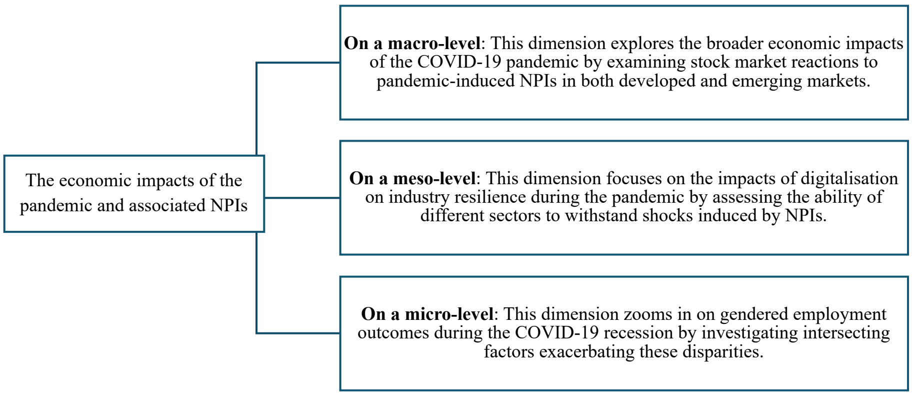
Despite the growing body of literature examining the economic consequences of the COVID-19 pandemic, there remains a need for research that provide a comprehensive understanding of the complex interplay between the pandemic, government interventions, and economic outcomes. To bridge this gap, this thesis focuses on pandemic-induced economic impacts in three key dimensions—stock market performance, industry resilience, and labour market outcomes.

2. Overview of the Thesis' Chapters and Their Interlinkages

In Chapter 2, I adopted a macro perspective to examine stock market reactions to lockdowns in both developed and emerging markets in the initial stage of the pandemic. As economic activities contracted due to the restrictive measures, stock markets experienced substantial volatility during the initial stage of the pandemic. Stock market performance serves as a critical indicator of investor sentiment and economic outlook. I conducted a cross-country analysis to look into the interconnectedness of global financial markets and the role of information dissemination in shaping stock market reactions. Employing a combination of panel data analysis and an event study method, I investigated the effects of overall lockdown measures on stock markets and examined the learning behaviours of stock markets towards lockdown announcements. At the meso-level analysis, I focused on the impacts of digitalisation on industry resilience during the pandemic in Chapter 3. By using panel data analysis and IV-2SLS approaches, I examined how investments in both tangible and intangible digitalisation mitigate the negative shocks from pandemic-enforced NPIs during the first two waves of the pandemic in European countries. Moving to a micro-level in Chapter 4, I examined the impact of the COVID-19 recession on gendered employment outcomes in the UK. I employed dynamic multinomial logistic regression to investigate the effect of negative labour market shocks borne by females with school-aged children, and the factors that moderate the "motherhood penalty" on employment outcomes during the initial stage of the pandemic by delving into the intersectionality of gender with other demographic factors.

The logic underpinning these three empirical chapters of this thesis is rooted in using a multilevel approach to understand the complex interplay between public health measures, economic outcomes, and societal implications, with the aim to inform policy responses to future crises. Each empirical chapter investigates different facets of the pandemic and associated NPIs' influence, from macro-level market reactions to meso-level industry resilience and micro-level employment outcomes. Chapter 2 looks into the macroeconomic landscape, examining how global stock markets responded to pandemic-induced interventions. By analysing the market behaviours, this chapter sheds light on the broader economic implications of non-pharmaceutical interventions in crisis times. Building on this foundation, Chapter 3 shifts the focus to the meso-level, exploring the role of digitalisation in fostering industry resilience amidst pandemic disruptions. By assessing industry-level responses to lockdown measures and the adoption of digital technologies, this chapter provides insights into strategies for enhancing economic adaptability and recovery. Finally, Chapter 4 narrows the scope to the micro-level, investigating the gendered impacts of the pandemic on employment outcomes in the UK. Through an intersectional lens, this chapter highlights the disproportionate vulnerabilities faced by women, particularly BAME migrant mothers with childcare responsibilities, in the labour market. The results reveal the complexities of economic inequality exacerbated by the pandemic. Together, these chapters build up a cohesive thesis, detailing the diverse economic effects of the pandemic and informing targeted policy interventions aimed at fostering resilience and inclusivity in the post-pandemic era.

Figure 1: The structure of this PhD thesis



Source: Author (2024)

3. Structure of the Thesis

The core of this thesis consists of three empirical chapters, each following a similar structure. The first empirical chapter, presented in Chapter 2, begins with an introduction to the background of pandemic development and the importance of studying stock market reactions during the initial stage of the pandemic. I moved on to review the theoretical basis of channels through which the pandemic can affect stock markets, empirical studies on stock markets' reactions to the pandemic-induced interventions, and the learning behaviours in stock markets under the pandemic. Subsequently, I elaborated the dataset construction and empirical techniques, including panel data analysis and event study methods, and discussed model selection tests. I then presented the estimation results from these two empirical strategies, followed by robustness checks accounting for industry composition and addressing the endogeneity issue in lockdown measures. With these results, I highlighted the adaptive learning behaviours of the global stock markets in responding to lockdown announcements by different countries. I concluded this chapter by summarising key findings, discussing limitations, and proposing recommendations for future studies.

Following a similar structure, Chapter 3 starts with an introduction to digitalisation and industry resilience in the pandemic context. Next, I reviewed theoretical concepts about resilience and digitalisation as well as the empirical evidence of the impacts of digitalisation on the firm level. I then outlined the data and the empirical approach for the following analyses. I presented and discussed the estimation results of the effects of different digitalisation on moderating the negative shocks from pandemic-induced lockdowns, including robustness checks using alternative indicators for digitalisation and industry resilience and addressing endogeneity issues. I finalised this chapter with key findings and recommendations for future studies.

Chapter 4 focuses on the gendered labour market outcomes during the early stage of the pandemic, starting with an introduction and reviewing the theoretical foundations of the economics of fertility and factors influencing the gender gap in labour market outcomes. Next, I elaborated on the data and estimation strategy, followed by the discussion of results derived from the entire sample and comparative analyses between gender sub-samples. I concluded the chapter with a summary of key findings and some recommendations for policymakers.

The thesis finalised with a summary of findings from all the three empirical chapters, with some recommendations for future studies in Chapter 5. The references and Appendixes are included at the end of this thesis.

Chapter 2 *How Stock Markets Reacted to the COVID-19 Pandemic in the Initial Pandemic Era?*

1. Introduction

In the modern history of humankind, health crises have forced regional or global pandemonium because of their high-level of transmission capacity, health responses, and economic impacts. The novel SARS-CoV-2 (Coronavirus), first identified at the end of 2019 in Wuhan China, emerged as a global COVID-19 pandemic. The coronavirus developed at unprecedented scale and speed since Wuhan's report of pneumonia cases to the World Health Organisation (WHO) on December 31, 2019. Due to an extremely high level of infectiousness, the WHO made six announcements of Public Health Emergency of International Concern for the disease within a month of Wuhan's report of clustered contagious cases. The rapid contagiousness of the disease across communities and the alarming severity of its symptoms led the WHO to declare it a global pandemic on March 11, 2020, a mere six weeks after the initial report. To mitigate the cluster transmission of this 'once-in-a-century pathogen' (Gates, 2020), almost half of the world's population had implemented non-pharmaceutical interventions such as social distancing measures, workplace closures, travel restrictions, self-quarantine, and even full lockdown by the first half of April in 2020. The pandemic-enforced government interventions have led to unprecedented economic slumps worldwide (García *et al.*, 2020, Eichenbaum *et al.*, 2020).

Global stock markets, providing valuable information in fast-evolving situations (Wagner, 2020), have experienced serious setbacks during the first wave of pandemic outbreaks. Global financial markets entered a 'risk-off' phase in March 2020, characterised by increased investor risk-aversion and a shift towards safer assets. This period coincided with a surge in market volatility across the board. As a result, major stock indices experienced significant declines, with the Standard & Poor 500 (S&P 500) and Dow Jones Industrial Average (DJIA) dropping by 29% and 33%, respectively, on March 20, 2020, following the initial report of a COVID-19 case to the WHO on December 31, 2019. Similarly, the Financial Times Stock Exchange 100 (FTSE100), the UK's primary stock index, declined by 24.8% and recorded its worst quarter since 1987 (London Stock Exchange, 2020). Throughout the COVID-19 pandemic and subsequent implementation of non-pharmaceutical interventions, stock markets experienced substantial fluctuations (Hartley and Rebucci, 2020; Wagner, 2020). This observed volatility aligns with Farmer and Lo's (1999; 2002) suggestion that financial market participants adjust their behaviour based on past experiences and prevailing market conditions. As participants learn from past experiences, their evolving strategies contribute to the dynamic nature of markets (Lo, 2004).

A growing body of literature has focused on the impacts of the COVID-19 pandemic and associated government interventions on stock markets. Recent evidence suggests that pandemic-enforced lockdown measures contribute to the increased volatility of the stock market in the U.S. (Zaremba *et al*., 2020; Zaremba *et al*., 2021). In addition to the impacts on stock market volatility, several attempts have been made to establish the correlation between lockdown measures and stock market returns. Capelle-Blancard and Desroziers (2020) suggested that stock returns reacted positively to lockdown measures based on a panel of 74 countries. Ashraf (2020), using a larger panel of 77 countries, claimed that stock markets reacted differently to various types of lockdown policies, with negative responses to government social distancing measures but positive responses to testing and quarantining policies. The impacts of the pandemic on stock markets are found to vary across regions, with Asian markets experiencing greater return drops compared to the other regions at the onset of outbreaks (Liu *et al*., 2020). The variation of stock market reactions can be attributed to a combination of pre-pandemic economic fundamentals and short-term reactions during the pandemic. Factors such as a country's level of democracy, corruption, and trade openness also influence stock market responses to the pandemic and associated interventions (Fernandez-Perez *et al*., 2020; Capelle-Blancard and Desroziers, 2020). However, existing studies have not adequately investigated the impacts of economic stimulus packages that are conditional on the implementation of lockdown measures.

With a focus on developed and emerging markets, this chapter investigates the short-term economic impacts on stock markets of the non-pharmaceutical interventions adopted by governments during the first wave of coronavirus outbreaks. Using panel data analysis, this chapter investigates the impacts of lockdown measures on stock markets, accounting for the influence of economic stimulus packages implemented during the initial outbreaks. An event study method is employed to analyse stock market reactions to lockdown announcements as well.

This chapter reveals that stock market, in general, reacted negatively and significantly to announcements of lockdown and escalations in the daily stringency of non-pharmaceutical interventions. From a cross-country perspective, the announcement of the first round of restrictive measures in several municipalities in Lombardy and Veneto of Italy triggered declines in stock market returns in the initial stage of the COVID-19 pandemic. Additionally, the overall development of global stock markets indicates a learning process, from averagely overlooking the effects of China's lockdown announcement, to provoking panic in response to Italy's announcement of restrictive measures, to strongly reacting to Italy's lockdown announcement, to gradually easing restrictions in response to lockdown announcements from the German government and the US government. The learning behaviours of stock markets indicate that market participants adjust their beliefs to incoming signals of the severity of the pandemic-induced impacts on one's economy based on a prior information about the development of the pandemic-enforced lockdown in other countries. The adaptive behaviours in processing information and adjusting expectations suggest that stock markets' responses to pandemic-enforced interventions are not solely driven by sentiment, as rational decision-making plays a role as well.

This chapter makes a three-fold contribution to the literature. Drawn new insights on stock market from the pandemic, this chapter contributes to understand stock markets' dynamic process of learning toward unprecedented non-economic events, such as the COVID-19 pandemic. The learning behaviours of stock markets, characterised by information adaption and expectation adjustments, reflects that the negative responses of stock markets are not fully driven by sentiment, with rationality playing a role as well. This finding from market behaviour analysis provides novel insights into how markets integrate, incorporate, and respond to the extraordinary circumstances during this extreme pandemic event. Secondly, this chapter enriches the behavioural finance literature by underscoring the learning process of global stock markets in response to incoming signals based on a prior information set in the COVID-19 context (Philippas *et al*., 2021). This contributes to our understanding of the complex interplay between new information, market expectations, and investor behaviours. Thirdly, this chapter adds to a growing body of literature on financial market reactions to exogenous events, such as natural disasters, geopolitical events, and health crises. While existing studies on the COVID-19 pandemic have mainly focused on the reactions of developed markets like the U.S, this chapter expands the scope to include both developed and emerging markets. By looking into how these diverse markets integrated information about pandemic-induced lockdown announcements and related measures, this study offers a more comprehensive understanding of the global financial landscape.

The remainder of this chapter is structured as follows. Section 2 reviews the relevant literature and establishes the hypotheses of our study. Section 3 presents the data and methodology adopted in our study. Section 4 discusses the findings from empirical estimations, followed by robustness checks to validate our results. Our chapter finalises with some concluding remarks.

2. Relevant Literature on Stock Market and the COVID-19 Pandemic

The pandemic-stock nexus is based on the theoretical foundation that stock market performances, including prices, returns, and volatility, respond to macroeconomic states, government policies, and investors' sentiments about financial markets (Haroon and Rizvi, 2020; Narayan, 2019, 2020; Salisu and Akanni, 2020). Previous studies have shown that financial market uncertainty and investor risk aversion are particularly high during pandemics (Eichenbaum *et al*., 2020; Ma *et al*., 2020; Salisu and Akanni, 2020). Therefore, the COVID-19 pandemic offers a valuable opportunity to investigate how pandemic-related interventions affect stock markets.

2.1 Theoretical Basis: Channels through Which Pandemics can Affect Stock Markets

Previous studies have identified three main channels through which pandemic-related interventions can affect stock market performances, in terms of the infrastructure channel, the economic fundamentals channel, and the sentiment channel.

Through the infrastructure channel, the pandemic-enforced lockdowns can affect the stock market by disrupting the supply chains and logistics systems that underpin business operations (Zaremba *et al*, 2021). The economic fundamentals channel focuses on the direct influence of pandemic-related interventions on economic indicators, such as GDP, inflation, and interest rates. As these indicators shift in response to the pandemic, stock market performance may be affected through changes in corporate earnings, investor expectations, and risk premiums (Zaremba *et al*., 2021; Chen *et al*., 2011). The sentiment channel captures the increased uncertainty and anxiety among investors in response to lockdowns and lockdown-like measures (Zaremba *et al*., 2021; Hale *et al*., 2020). This uncertainty may stem from doubts about the prospects of the economy and individual companies. According to Guiso *et al*. (2018), exogenous shocks can increase investors' risk aversion, resulting in their disposing of risky assets like stocks. Changes in risk appetite can decrease demand for stocks and result in lower stock prices (Guiso *et al*., 2018).

2.2 Empirical Studies on Stock Market Response to the Pandemic and Pandemic-Enforced Interventions

Based on the theoretical foundation of the pandemic-stock nexus, a group of research has examined stock market reactions, in terms of stock index return and volatility, to the COVID-19 pandemic and associated government policies. For instance, studies have evidenced the negative reactions of stock market indices to virus spread (e.g., Cao *et al*., 2020; Ashraf, 2020; Alber, 2020; Rahman *et al*., 2021; Ahmar and Del Val, 2020; Anh and Gan, 2020; Eleftheriou and Patsoulis, 2020; Camba and Camba, 2020). In addition to the direct impact of the pandemic, several studies have explored the impacts of pandemic-induced containment measures and economic policies on stock market returns. Employing a panel data approach, Capelle-Blancard and Desroziers (2020) found a positive relationship between stock market returns and lockdown measures in a sample of 74 countries. Conversely, Zaremba *et al*. (2021) claimed negative stock market reactions to lockdown measures during the early phase of the pandemic. Shifting the focus to economic policies, Rahman *et al*. (2021) combined an event study method with panel data analysis and concluded a positive association between the Job-Keeper stimulus package and stock market returns during the first wave of pandemic outbreaks.

Collectively, these studies investigate the complex interplay between pandemic-related factors and stock market performance. These studies, however, fail to reach consistent conclusions about stock market reactions to lockdown measures during the early stages of the pandemic. By controlling for the effects of economic stimulus policies, the research would have been more effective to disentangle the complex factors that shape stock market reactions during times of crisis.

2.3 Learning Behaviours in Stock Markets under the Pandemic Crisis

In addition to research on the general effects of the pandemic and pandemic-related interventions on stock markets, another body of research has focused on the evolution of stock market performance during the pandemic crisis. The Adaptive Market Hypothesis (AMH), a theoretical framework positing that financial markets are not entirely efficient as described by the Efficient Market Hypothesis, argues that market participants are not always rational and may exhibit behaviours influenced by emotions and cognitive biases (Lo, 2004).

Accounting for the occurrence of mispricing by integrating the differences between risk perception and reality (Fama, 1998; Shleifer and Vishny, 1997; Baker and Wurgler, 2006; Baker and Wurgler, 2007; Lo, 2004; Lo, 2005), the AMH provides a foundation for the studies on the evolution of stock market performances under the pandemic crisis. Market participants may fail to adapt their behaviour to financial conditions when confronted with unfamiliar situations, leading to behavioural biases such as overconfidence, overreaction, and loss aversion (Fama, 1998; Baker and Wurgler, 2007; Lo, 2012; Lo, 2005). According to the AMH, market participants' behaviours are expected to evolve over time, driving prices toward efficient values. Under the principles of Bayesian Inference, biases should decrease as market participants learn about their biases and adapt to market conditions (Lo, 2004; 2012).

Several empirical studies have explored the learning process of stock markets during the early stages of the pandemic. Bazzana *et al*. (2022) constructed a heterogeneous agent model to demonstrate that market participants became more sensitive to pandemic-related news following the largest single-day drop in the STOXX Europe 600 Index. Ramelli and Wagner (2020) observed underreactions to pandemic-related information in the US stock market during the incubation and outbreak periods (January 2, 2020, to January 17, 2020), followed by overreactions during the fever period (February 24, 2020, to March 20, 2020). Capelle-Blancard and Desroziers (2020) found similar patterns of underreaction and overreaction in their panel of 74 countries, with stock markets initially ignoring the pandemic before overreacting to its impacts. Shifting to emerging markets, Yunus-Kasim *et al*. (2022) found positive returns in Indonesian stock market following China's announcement the first confirmed Coronavirus case. However, market participants withdrew when domestic confirmed cases were announced, leading to sustained negative responses until the first vaccination announcement in Indonesia, which boosted confidence in the economy's development.

Overall, these studies highlight that stock markets, at least partially, integrate pandemic related information in price performances. One serious limitation of existing research is the lack of attention paid to the effects of government-implemented economic stimulus packages in conjunction with lockdown measures. The findings would have been more convincing if the impacts of pandemic-induced fiscal and monetary policies are disentangled, conditional on lockdown measures. Additionally, existing research fails to investigate the overall evolution of the global stock market's learning behaviours in early stages of the pandemic. A focus on the learning process could provide valuable insights on how big and unprecedented events, such as this novel pandemic, are priced by market participants.

3. Data and Methodology

This section introduces the dataset and main methods used to investigate the stock market reactions to lockdown measures and government announcements of lockdown. The sources of employed data and the construction of the dataset are first discussed, with the methodology adopted elaborated upon.

3.1 Data and Sources

3.1.1 Data for Panel Data Analysis

To examine the effects of lockdown measures and associated economic policies on stock markets, a comprehensive dataset was compiled from different sources. First, I computed the daily log returns of the leading stock indices from January 1st, 2020, to April 30th, 2020. Accounting for the inertia effect in stock returns (Narayan *et al.,* 2020), I included a lagged dependent variable as an explanatory variable in the analysis.

Considering the considerable heterogeneities and nuances of each country's pandemic-induced restrictive policies, I obtained the stringency index from the Oxford COVID-19 Government Response Tracker (OxCGRT) to proxy the intensity of containment measures adopted during the sample period. Aggregating the strictness of nine different containment measures, the stringency index computes the average value of school closures, workplace closures, public events cancellations, gathering restrictions, public transport closures, stay-at-home requirements, internal movement restrictions, international travel controls, and public information campaigns, with 100 denoting the most stringent government responses and 0 denoting the least stringent responses (OxCGRT, 2021).

Accounting for the influence of economic fundamentals such as government policies and interest rate (Chen *et al*., 1986; Ratanapakorn and Sharma, 2007; Blanchard *et al*., 2017), I included variables of economic packages (fiscal and monetary policies) to disentangle the potential impacts of these policies from lockdown measures. I compiled the data and information provided by the Database of International Monetary Fund COVID-19 Policy Tracker to construct variables of fiscal policies and monetary policies. The relevant data has been cross-checked with information published on the official website of sample countries' central banks and the OECD Database of Policy Responses to the COVID-19 Pandemic to ensure validity. For fiscal packages, I recorded the announcement dates of all relevant fiscal measures and coded the size of measures as a percentage of the country's GDP. For monetary policies, I recorded three main components, which are the interest rate cut, the macro-financial package, and other monetary policies. I constructed the variables of interest rate cut and macro-financial package by measuring the cut in key policy rate from December 31, 2019, and documenting the announcement dates and sizes of the macro-financial packages in each country as a percentage of GDP, respectively. A dummy variable was used to measure whether a country had announced other monetary policies (with value 1 denoting there were such monetary policies and 0, otherwise).

The potential impacts of lockdown measures in neighbouring countries on domestic stock market returns were considered, as suggested by Capelle-Blancard and Desroziers (2020). For each country, I computed the daily average stringency of lockdown measures in other countries, referred to as the world stringency index, to account for global influences on stock market performance during the pandemic. The term 'other countries' in the context of the world stringency index refers to the countries with stringency index information provided by the Oxford COVID-19 Government Response Tracker other than the sample countries included in this study. This comprehensive approach ensures that the world stringency index reflects the global context by including data from all available countries, except those already selected as sample countries for focused analysis. The inclusion of these 'other countries' is justified by the need to capture a global perspective on lockdown measures and their potential impact on domestic markets. Unlike previous studies, which often limit their scope to a narrower set of countries, this research enhances the robustness of the analysis by ensuring that the international context is thoroughly accounted for, offering a more accurate reflection of how global stringency levels might influence domestic economic outcomes.

In line with previous literature highlighting the role of emotions in shaping stock market reactions during pandemics (Zaremba *et al*., 2020; Zaremba *et al*., 2021), sentiment index data was included in the analysis as well. The sentiment index data is quantified using the RavenPack COVID-19 sentiment index via the Wharton Research Data Services. This index is derived from the analysis of millions of news articles and social media posts related to the COVID-19 pandemic. It ranges from -100 to +100, where -100 indicates extremely negative sentiment, 0 indicates neutral sentiment, and +100 represents extremely positive sentiment (RavenPack, 2021). The sentiment index is updated daily and reflects the real-time public mood and perceptions towards the pandemic in each country included in the study. The inclusion of public sentiment as a variable in this analysis is justified by the growing body of literature that highlights the significant role of psychological and emotional factors in economic decision-making, particularly during periods of crisis. Public sentiment influences consumer confidence, investment behaviour, and market dynamics, which are all critical components of economic activity. During a global crisis like the COVID-19 pandemic, where uncertainty and fear are pervasive, sentiment can drive market reactions more strongly than traditional economic indicators. By capturing the public's mood and perceptions, the sentiment index provides a real-time measure of the psychological impact of the pandemic, which can help explain fluctuations in stock market performance that might not be accounted for by traditional economic variables alone.

I used the rate of change in stringency index, fiscal package, monetary package (interest rate cut and macro-financial package), world stringency, and sentiment index to capture the impacts of changes on stock market responses.

3.1.2 Data for Event Study Methodology

To examine the stock market reactions to government announcements of lockdown by event study technique, I used two main variables - stock index return and event date, to construct our dataset. First, I obtained the daily dividend-adjusted closing prices of the leading stock index for each sample country from the Refinitiv DataStream database (Refinitiv DataStream, 2021). I computed the daily logarithmic returns (in percentage) to represent the continuously compounded percentage return of selected indices for each sample country (see Appendix 1.1 for detailed information). Secondly, I obtained the dates for government announcements of lockdown for each sample country from government official websites, which were cross-checked with Public Health and Social Measures data from the WHO to ensure accuracy.

Sample countries

29 countries were included in the dataset as sample country. These countries were selected based on the severity of the pandemic, measured by the total number of confirmed COVID-19 cases by the end of April 2020, when the first waves of the lockdown measures have been fully implemented, as well as the availability of relevant data on stock market indices, dates of government announcements of lockdown, economic packages, and sentiment index. This approach, while potentially introducing a bias towards more severely affected countries, is both deliberate and essential. By focusing on countries where the pandemic had the most profound impact, I aim to capture the full spectrum of economic disruptions caused by the pandemic and the subsequent government interventions. The logic behind this selection is that the economic effects of NPIs are likely to be more pronounced and detectable in these countries, providing a clearer understanding of the relationship between pandemic

severity and economic outcomes. Additionally, results from this sample selection ensure that the findings are highly relevant for policymakers and stakeholders who are managing or studying the economic impacts of severe health crises. While this might limit the generalizability of the results to less affected countries, it strengthens the study's ability to provide deep insights into the economic dynamics under extreme conditions, thereby contributing valuable knowledge that could inform future responses to similar global crises.

The sample countries are as follows: Australia, Belgium, Canada, China, France, Germany, India, Indonesia, Israel, Italy, Japan, Mexico, Netherlands, New Zealand, Pakistan, the Philippines, Poland, Russia, Saudi Arabia, Singapore, South Africa, South Korea, Spain, Sweden, Thailand, Turkey, United Arab Emirates, the United Kingdom, and the United States. See Appendix 2.1 for detailed information about sample countries, leading stock indices, and date of lockdown announcement.

3.2 Methodology

I used panel data techniques to investigate whether and to what extent lockdown measures impact the global stock markets' reaction during the first wave of the pandemic outbreaks. Based on results from the panel data analysis, I examined stock market reactions to government announcements of lockdown and key events during the pandemic by adopting an event study method.

3.2.1 Panel Data Method

I employed panel data analysis to investigate the relationship between lockdown measures induced by the COVID-19 pandemic and stock market performance. Adopting panel data analysis allows for an investigation of the effects of lockdown measures over a period within a country, properly corresponding with the evolving dynamics of the pandemic. In addition, panel data analysis enables to identify the time-varying relationship between explained variables and explanatory variables (Ashraf, 2020; Wooldridge, 2010). Furthermore, panel data regression controls for individual heteroskedasticity and alleviates the issues of multicollinearity and estimation bias (Baltagi, 2008).

Accounting for the differences in cultures, circumstances, and institutions between countries, I specified a panel regression model[1] with both country fixed effects and time fixed effects[2] and account for issues of cross-sectional correlation, autocorrelation,

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[1] A standard Hausman test has been conducted to decide whether a fixed effect model is more appropriate than a random effect model. With the Chi-square valuing 3.87 of a p-value of 0.0437, we can reject the null hypothesis that the difference in coefficients is not systematic. A fixed effect model is more preferred than a random effect model in this case.

[2] To test whether country-fixed effects are needed when conducting the regression model, a joint test, with a null hypothesis that all countries' coefficients are jointly equal to zero, is conducted to reject the null hypothesis at a 0.05 significance level. Therefore, country-fixed effects are needed in the regression model. Similarly, a joint test, with a null hypothesis that all the time coefficients are jointly equal to zero, was conducted. At a 0.05 significance level, the null hypothesis was rejected, and time-fixed effects were needed in the regression model as well.

and heteroscedasticity. The baseline regression model is as follows in Equation (2.1):

Equation (2.1):

$$Return_{c,t} = \alpha + \beta_1 Lockdown\ Measure_{c,t} + \beta_2 Economic\ Policies_{c,t} + \beta_3 Sentiment_{c,t} + \beta_4 Return_{c,t-1} + \mu_t + \mu_c + \varepsilon_{c,t}$$

where c and t denote country and day, respectively. The dependent variable, $Return_{c,t}$, represents the stock index return of country c's leading stock index on day t. $Lockdown\ Measure_{c,t}$ denotes daily changes in domestic lockdown stringency and world lockdown stringency for country c on day t. $Economic\ Policies_{c,t}$ represents the daily changes of the sizes of both fiscal and monetary policies announced by country c on day t. $Sentiment_{c,t}$ denotes country-level sentiment about COVID-19 related information. μ_t and μ_c represent the day fixed effects and country fixed effects, respectively.

To further explore the stock market performance before and after lockdown announcement in one country, I included a dummy variable in the baseline regression model, as follows in Equation (2.2):

Equation (2.2):

$$Return_{c,t} = \alpha + \beta_1 Announcement_{c,t} + \beta_2 Lockdown\ Measure_{c,t} + \beta_3 Economic\ Policies_{c,t} + \beta_4 Sentiment_{c,t} + \beta_5 Return_{c,t-1} + \mu_t + \mu_c + \varepsilon_{c,t}$$

where $Announcement_{c,t}$ denotes one-, two-, and three-week (s) prior (post) to domestic lockdown announcement of one country. For instance, I assign "one-week prior" a value of one if the date falls within a window of one week before the lockdown announcement in one country, and zero otherwise.

To explore the interplay between government interventions and the spread of the pandemic within a country on stock markets, interactions were introduced in the baseline model, as follows in Equation (2.3):

Equation (2.3):

$$Return_{c,t} = \alpha + +\beta_1 Lockdown\ Measure_{c,t} + \beta_2 COVID_{c,t-1} + \beta_3 COVID_{c,t-1} * Lockdwon\ Measure_{c,t} + \beta_4 Economic\ Policies_{c,t} + \beta_5 Sentiment_{c,t} + \beta_6 Return_{c,t-1} + \mu_t + \mu_c + \varepsilon_{c,t}$$

3.2.2 Event Study Method

As a standard method of evaluating equity price reaction to some events or announcements, the event study method allows for an effective capture of the abnormal returns attributable to a specific event (Brown and Cliff, 2004; Kothari and Warner, 2007; Schell *et al.*, 2020), which in this case is lockdown announcements. Positive abnormal returns around the event date are expected if market participants react favourably to the event; alternatively, negative abnormal returns are expected if market participants react unfavourably to the event.

3.2.1.1 The Choice of Model

The choice of model and the choice of significance test are crucial in conducting an event study method. Following Chen and Siems (2007) and Liu *et al*. (2020), I adopted the mean-adjusted model to compute the abnormal returns of the sample countries. The mean-adjusted model enables the analysis of index return deviations from their mean values over the event windows (Chen and Siems, 2007). In contrast to the market model, the mean-adjusted model does not assume the consistency of risk-free interest rate over time (Armitage, 1995), which may not hold during the volatile period of pandemic outbreaks (Onali, 2020).

By accounting for historical variability, the significance and magnitude of an event can be inferred from the deviations of index returns from their past average returns in the mean-adjusted model (Schwert, 1981). A statistically significant deviation in returns, falling outside the normally expected range of returns, on trading days coinciding with an event indicates that the market views the event as significant. Alternatively, a statistically insignificant return deviation indicates that the market regards the event as inconsequential.

Drawing from Brown and Warner's excess returns approach (1985), the abnormal performance of the leading stock index is measured by calculating the deviation of index returns from the past average. Within the mean-adjusted model, the actual return $R_{c,t}$ is computed as follows in Equation (2.4):

Equation (2.4):

$$R_{c,t} = \ln\left(\frac{P_{c,t}}{P_{c,t-1}}\right)$$

where $P_{c,t}$ is the price of the leading stock of country *c* at time *t*.

The daily abnormal return is computed as follows in Equation (2.5):

Equation (2.5):

$$AR_{c,t} = R_{c,t} - \bar{R}_c$$

where $AR_{c,t}$ denotes the abnormal return of the leading stock index of country *c* at time *t*, $R_{c,t}$ is the actual return of the leading stock index of country *c* at time *t*. $\bar{R}_c$ is the mean of daily returns of the leading stock index in country *c* during the (-59, -30) estimation period.

The mean of daily returns, $\bar{R}_c$, is estimated over 30 days (from 59 days prior to and 30 days prior to the event date) relative to the event date, as follows in Equation (2.6):

Equation (2.6):

$$\bar{R}_c = \frac{1}{n}\sum_{t=-30}^{t=-59} R_{c,t}$$

Cumulative abnormal returns (CAR) are obtained by adding up individual abnormal returns for each of the event windows to measure the total impact of the event over a period (from t_0 to t_1). CARs are computed as follows in Equation (2.7):

Equation (2.7):

$$CAR_c(t_0, t_1) = \sum_{t=t_0}^{t_1} AR_{c,t}$$

Event date, estimation window, and event window

Event date

The main event of this research is the lockdown announcement made by each sample country during the first wave of the COVID-19 pandemic in 2020. The event date is denoted as t_0. For instance, the event date in the UK is March 16, 2020, as the UK government declared a lockdown on this date.

Estimation window

Following Chen and Siems (2007), I established the estimation window as [-59, -30], from 59 days before the event date to 30 days before the event, covering a total of 20 days. A key factor in selecting an appropriate estimation window is to avoid potential anticipation or contamination effects. As suggested by Pacicco *et al*. (2018), setting the estimation window at least one month before the event can help prevent the inclusion of anticipation effects.

To validate whether the selected estimation window [-59, -30] is contaminated by anticipations of lockdown-related announcements, the level of public attention towards lockdown was gauged by using Google Trends. The search terms “lockdown”, “non-pharmaceutical interventions”, “containment”, and “restrictive interventions” were selected based on their common usage in characterizing unconventional measures induced by the pandemic (Capelle-Blancard and Desroziers, 2020). Google Trends[3] data, characterized by its time-series and cross-sectional attributes, has been widely employed by scholars for investigating pandemic-related subjects (Capelle-Blancard and Desroziers, 2020). In this research, I used Google Trends data, ranging from 0 to 100, to assess public attention on lockdown-related announcements. With values around

[3] I used the Baidu Trends to find out whether the terms “lockdown”, “non-pharmaceutical interventions”, “containment”, and “restrictive interventions” have been intensively searched for during the event window of [-59, -30] in China, as Baidu is the most widely used search engine in China, as Google in other countries. Similarly, during the period [-59, -30] the level of attention on these related terms is less than 1, suggesting no worrisome anticipation issue.

0, analysis of the Google Trends data indicates minimal public attention to lockdown and lockdown-like announcements and suggests no significant anticipation issues. Therefore, the [-59, -30] estimation window provides a cushion against potential anticipation effects of lockdown announcements.

Event window

Due to the uncontrollable nature of the COVID-19 pandemic is uncontrollable and the irregular pandemic-related news, a short event window is preferred to isolate the effects of the lockdown announcement from other shocks. In this study, the main event window of interest is the event date (t=0) where the magnitude and the significance of the lockdown announcement is evaluated by analysing the abnormal returns. Following Xie *et al*. (2022), official lockdown announcements by governments are used as the main indicator of lockdown measures, because these government statements are based on public health data and scientific evidence. Government announcements aim to communicate crucial information regarding the implementation and duration of lockdown measures, significantly affecting businesses, industries, and the overall economy. While government announcements may have a political nature, they are generally expected to be based on factual information and data-driven decisions, rather than solely on political motivations. Official lockdown announcements by governments acts as a standardized and verifiable reference point for analysing stock market reactions, as they provide a clear and specific trigger for stock markets responses.

In addition, two event windows of [0,1] and [0, 2] were included to explore the immediate cumulative stock market reaction to lockdown announcements during the pandemic. These event windows allow for examining how well and how quickly the stock market digested the lockdown announcement (Armitage, 1995).

Considering the challenges of narrow event windows with insufficient time for market participants to internalise the context and implications of the complex lockdown announcement, I followed Liu *et al*. (2020) and Demirgüç-Kunt *et al*. (2021) and included a six-day event window [0, 5] and an eleven-day event window [0, 10] to report cumulative abnormal returns from the event date to five days after the announcement and from the event date to ten days after the announcement, respectively. Furthermore, I included a seven-day [-7, -1] event window to examine whether there is an expectation of lockdown announcements by governments one-week prior to lockdown announcements.

3.2.1.2 The Choice of Significance Test

The statistical significance of the event period abnormal returns and cumulative abnormal returns were calculated for each sample country using the Generalised Rank Test (the GRANK test) by Kolaria and Pynnonen (2011). This non-parametric test was selected based on the following considerations. First, compared with parametric tests, the non-parametric GRANK Test does not require stringent assumptions about return distributions (Cowan, 1992). To check the normality of the data, I used the Shapiro-Wilk, Shapiro-Francia, and Jarque-Bera tests and reported the test results in Table 1. With null hypothesis of normal distributions of these tests, nearly 90% of the data failed the normality tests based on Shapiro-Wilk and Shapiro-Francia results, while approximately 45% passed the Jarque-Bera test. Therefore, the non-parametric GRANK Test was selected to overcome the violation of the normal distribution assumption posed by parametric significance tests. Secondly, the GRANK Test's robustness to event-induced volatility (Kolaria and Pynnonen, 2011) could control for the surged pandemic related volatility as suggested by Onali (2020). Thirdly, the GRANK Test accounts for the possible cross-correlation due to event day clustering and potential serial correlations of abnormal returns (Kolaria and Pynnonen, 2011). Fourthly, the empirical power of the GRANK Test is at least as competitive as parametric tests such as the Adjusted Patell Test and the Adjusted Standardized Cross-Sectional Test[4] (Kolaria and Pynnonen, 2011).

Table 1: Results of the normality test

Index of country	Shapiro-Wilk Test (Prob>z)	Shapiro-Francia Test (Prob>z)	Jarque-Bera Test Prob>chi2
Australia	**0.00138**	**0.00124**	0.0191
Belgium	**0.00000**	**0.00001**	**0.0000**
Canada	**0.00000**	**0.00001**	**0.0008**
China	0.18580	0.11904	0.1252
France	**0.00001**	**0.00001**	**0.0000**
Germany	**0.00000**	**0.00001**	**0.0000**
India	**0.00371**	**0.00203**	0.0197
Indonesia	0.06771	0.04839	0.1177
Israel	**0.00422**	**0.00288**	0.0323
Italy	**0.00000**	**0.00001**	0.0000
Japan	**0.00459**	**0.00266**	0.0122
Mexico	0.13351	0.07037	0.1437
Netherlands	**0.00001**	**0.00001**	**0.0001**
New Zealand	**0.00000**	**0.00001**	**0.0001**
Pakistan	**0.00156**	**0.00131**	**0.0064**
Philippines	**0.00004**	**0.00004**	**0.0001**
Poland	**0.00000**	**0.00001**	**0.0001**
Russia	**0.00000**	**0.00001**	**0.0001**
Saudi Arabia	**0.00004**	**0.00003**	**0.0004**
Singapore	**0.00100**	**0.00081**	0.0050
South Africa	**0.00025**	**0.00017**	0.0010
South Korea	**0.00123**	**0.00064**	0.0166

[4] I conducted the parametric tests of the T Test by Brown and Warner (1985), the Adjusted Patell Test by Kolari and Pynnönen (2010), and the Adjusted Standardized Cross-Sectional Test by Kolari and Pynnönen (2010) to test the statistical significance of the event period abnormal returns and cumulative abnormal returns as well. The results from the parametric tests are largely the same as the results of the non-parametric test-the GRANK Test.

Spain	**0.00000**	**0.00001**	**0.0000**
Sweden	**0.00016**	**0.00010**	0.0000
Thailand	**0.00000**	**0.00001**	0.0001
Turkey	**0.00091**	**0.00051**	0.0043
UAE	**0.00003**	**0.00005**	0.0499
UK	**0.00004**	**0.00003**	**0.0001**
US	**0.00280**	**0.00166**	0.0357
Number of indices (not in normality)	26 out of 29	26 out of 29	13 out of 29

Notes: (1) The null hypothesis of these three tests is that the returns are normally distributed; (2) The figures in bold indicate significance being less than the p-value of 0.01, and therefore reject the null hypothesis of being normally distributed.

3.3 Preliminary Analysis

A preliminary analysis was conducted to capture the basic characteristics of the sample, as reported in Table 2. See Appendix 2.2 for more detailed information about these variables.

With a total of 2,428 observations, the daily average stock return is around -0.18%, with a maximum of +13.28% and a minimum of -18.54%, demonstrating relatively strong fluctuations over the early stage of pandemic outbreaks, despite the general market decline. Regarding restrictive interventions, the stringency index ranges from a minimum value of 0 to a maximum value of 100. In terms of the economic policies in response to the COVID-19 pandemic, the fiscal package of sample countries, on average, was approximately two per cent of GDP, with the largest fiscal package constituting 21% of a country's GDP. Concerning monetary policies, the average interest rate cut is roughly 0.29% from the rate on December 31, 2019, with the most significant cut being 4.25% among sample countries. The macro-financial package averages approximately 3%, with a wide range from 0% (the smallest financial package relative to GDP) to 29.08% (the largest financial package relative to GDP). The sentiment index has an average of -4.70, ranging from -58.85 to 17.55, revealing predominantly negative sentiment towards COVID-19-related news within countries. The daily growth rate for confirmed COVID-19 cases is around 6.5%, with the maximum growth rate around 14%.

Table 2: Descriptive statistics of variables

Variable	Obs	Mean	Std. dev.	Min	Max
Daily stock return	2,428	-0.1797563	2.500927	-18.54119	13.28113
Stringency index	3,509	36.68502	34.69115	0	100
Fiscal package	3,509	2.153092	4.689086	0	21.1
Interest rate cut	3,509	0.2913086	0.5814861	0	4.25
Macro-financial package	3,509	2.857871	6.417551	0	29.08

Other monetary policies (dummy)	3,509	0.3291536	0.4699728	0	1
World stringency	3,509	33.839751	30.415938	0	81.865
Sentiment index	2,862	-4.704071	9.268475	-58.85	17.55
Daily growth rate of COVID-19 cases	3,509	6.486277	3.616065	0	13.89347

To check multicollinearity issues, I computed the Pearson correlations between every pair of main variables. No multicollinearity issues were diagnosed at a 0.10 significance level, indicating no variables needed to be excluded from further regression analysis. Besides, I computed the Variance Inflation Factors (VIFs) for the key independent variables. With a value of 8.46, I found no worrisome collinearity problem in the regression model as a rule of thumb (8.46<10). In addition, all the variables, in the form used in model specifications, were examined to be stationary by the Im-Pesaran-Shin test (Im *et al*., 2003).

4. Empirical Results and Discussions

4.1 Panel Data Analysis

This section employed a panel data approach to evaluate how stock markets integrated information about lockdown measures and subsequent economic policies. By using panel data techniques, I disentangled the possible negative or positive effects of lockdown measures from other relevant factors by controlling for economic packages enacted by each country.

4.2.1 Baseline Model

This section presents empirical analyses of the impacts of the lockdown measures on stock markets using panel data analysis. It aims to investigate the impacts of pandemic-induced measures on stock market returns, rather than assessing the effectiveness in boosting or reducing returns. Table 3 reports the baseline regression results from all sample countries in Column (1). The coefficient suggests a statistically significant negative relationship between stock market return and changes in the daily lockdown stringency at a 0.05 level. This result indicates that on days with greater tightening of lockdown policies relative to the previous day, stock market returns have tended to be lower. For one unit increase in the change in lockdown stringency, stock market returns have decreased by approximately 0.03%, after controlling for other factors. The greater the increase in the changes in intensities of domestic lockdown measures imposed by a country, the more likely that market returns declined during the early stage of the pandemic. The negative effect of daily changes in lockdown stringency could be explained by the fact that these containment and restrictive interventions result in difficulties in operating businesses and reduced expected profits and macroeconomic outlooks, which are then reflected in stock valuations.

The change in the interest rate cut, a primary pandemic-induced monetary policy, enters negatively on stock market returns at a 0.10 significance level. This result indicates that one-unit increase in the change in interest rate cuts enacted by a country leads to an approximate 0.12% decrease in stock market return, after controlling for other factors. This result suggests that on days with a larger interest rate cut compared to previous days, stock market returns have tended to decline. This negative impact of changes in interest rate cuts can be explained by the economic fundamentals channel. The announcement of an interest rate cut serves as a signal of the state of the economy. Stock markets may not adequately reflect the true state of the economy until monetary authorities announce rate cuts, revealing a more distressing economic situation than previously anticipated (Klose and Tillmann, 2020). As a primary component of pandemic-induced monetary policy, changes in interest rate cuts lead to declines in stock market returns because the informational aspect of the policy takes precedence (Jarocinski and Karadi, 2020).

On the other hand, the changes in macro-financial packages announced by governments, another key monetary policy induced by the pandemic, has a significant and positive effect on stock market return, with one-unit increase in the size of a macroeconomic package bringing about a 0.06% increase in stock market return. This positive effect can be attributed to the role of macro-financial packages as economic reliefs and financial supports. These measures can provide liquidity to markets and financial institutions as well as loan guarantees to businesses, boosting public confidence during the pandemic.

Considering impacts from other countries, the coefficient of world stringency reveals that one-unit increase in other countries' daily change in lockdown stringency leads to an average 0.75 percentage point average decrease in domestic market return. This result suggests that investors react to escalating lockdown measures abroad as negative signals about the global economic outlook and prospects for international business linkages. Tighter restrictions internationally have dampened risk appetite.

Accounting for domestic sentiment towards pandemic-related information, the change in sentiment index shows a significant and negative correlation with stock market return. This suggests that as sentiment worsens, reflecting heightened pessimism, market participants tend to reduce their risk appetite.

Given the potential for correlation in the control variables, I have reported an equivalent of the baseline specification in Column (1) of Table 3, where the control variables are added sequentially, instead of all being automatically included at once in Appendix 2.3.

4.2.2 Analysis of Stock Market Behaviours Before and After Lockdown Announcements

Investigations into stock market reactions before and after lockdown announcements allows for understanding how market participants interpret and respond to government announcements from a behavioural perspective. Column (2) to (4) of Table 3 present the estimation results for the relationship between lockdown measures and stock market returns one, two, and three weeks before domestic lockdown announcements, respectively.

From Column (2) of Table 3, the coefficient of the indicator variable for one week before the domestic lockdown announcements is negative at a significance level of 0.10. By contrast, stock returns show no significant drops two and three weeks prior to lockdown announcements, as indicated by the non-significant coefficients for time dummies in Column (3) and (4). The results suggest that only in the week leading up to domestic lockdown announcements had stock returns fallen significantly. The decline of stock returns during the week prior to lockdown announcements might be internalised by investors' perception that initial measures such as information campaigns about the pandemic and restrictions on public gatherings may be a negative signal and a precursor to stricter interventions such as stay-at-home orders and lockdown measures, resulting in negative impacts on stock market returns across different sample countries. Therefore, it has not been the announcement of lockdown triggered the declines of stock returns, but the expectation of further government interventions has led the market to go down. Additionally, the insignificance coefficients of non-pharmaceutical interventions on stock returns prior to lockdown announcements (two and three weeks prior) may be an early reflection of the ambiguity of the initial political response to the pandemic, which mainly revolved around the announcements of lockdown policies.

Column (4) to (6) of Table 3 report the estimation results with dummy variables of one, two, and three weeks after domestic lockdown announcements. The negative and significant coefficient of the dummy variable of one-week post lockdown announcements suggests that stock returns are approximately 0.56% lower in the week following domestic lockdown announcements. The market decline is possibly because hysteresis, as markets process and absorb the shocks from lockdown announcement and restrictive measures. The dummy variable for two-week post lockdown announcements is not significant, as in Column (5). The stabilisation of stock markets can be attributed to the announcement of macro-financial packages by governments, which internalizes the negative shocks from the pandemic and associated interventions. Column (6) shows that stock returns are approximately 0.543% higher three weeks after domestic lockdown announcements. In general, stock market returns rebound during the third week after the lockdown announcement, which can be attributed to the stock markets' learning process in adjusting to the unfolding pandemic crisis.

Table 3 Benchmark regression results and market reactions before and after domestic lockdown announcements

VARIABLES	(1) Baseline	(2) One week prior	(3) Two weeks prior	(4) Three weeks prior	(5) One week post	(6) Two weeks post	(7) Three weeks post
Lockdown measure	-0.03161**	-0.03397**	-0.0308**	-0.03252**	-0.03095**	-0.03306**	-0.03236**
	(0.0159)	(0.0162)	(0.0156)	(0.0155)	(0.0146)	(0.0165)	(0.0158)
Fiscal package	-0.0838	-0.0827	-0.0857	-0.0842	-0.0883	-0.0830	-0.0875
	(0.0656)	(0.0656)	(0.0669)	(0.0658)	(0.0652)	(0.0663)	(0.0651)
Interest rate cut	-0.1150*	-0.1167*	-0.1142*	-0.1147*	-0.1162	-0.1155	-0.1146
	(0.0669)	(0.0629)	(0.0633)	(0.0657)	(0.0621)	(0.0785)	(0.0797)
Macro-financial package	0.0598**	0.0690**	0.0688*	0.0697**	0.0640*	0.0631*	0.0602*
	(0.0265)	(0.0347)	(0.0352)	(0.0346)	(0.0332)	(0.0367)	(0.0363)
Other monetary policies	0.553	0.496	0.567	0.552	0.550	0.549	0.548
	(0.360)	(0.389)	(0.385)	(0.394)	(0.343)	(0.337)	(0.357)
World stringency	-0.752*	-0.798*	-0.747*	-0.750	0.769*	0.745*	0.0742
	(0.454)	(0.469)	(0.434)	(0.507)	(0.455)	(0.438)	(0.0501)
Sentiment index	-0.00558*	-0.00551*	-0.00548*	-0.00549*	-0.00534*	-0.00528*	-0.00567*
	(0.00336)	(0.00323)	(0.00327)	(0.00371)	(0.00314)	(0.00317)	(0.00335)
Lagged return	-0.214***	-0.217***	-0.215***	-0.214***	-0.214***	-0.220***	-0.215***
	(0.0674)	(0.0662)	(0.0671)	(0.0673)	(0.0669)	(0.0682)	(0.0679)
1-week prior		-0.507*					
		(0.298)					
2-week prior			0.167				
			(0.380)				

3-week prior				-0.146			
				(0.198)			
1-week post					-0.559*		
					(0.332)		
2-week post						0.507	
						(0.390)	
3-week post							0.543*
							(0.325)
Constant	-0.537**	-0.480*	-0.543**	-0.538**	-0.537**	-0.532**	-0.533**
	(0.261)	(0.263)	(0.259)	(0.261)	(0.263)	(0.261)	(0.261)
Observations	2,427	2,427	2,427	2,427	2,427	2,427	2,427
R-squared	0.606	0.609	0.607	0.607	0.607	0.606	0.606
Number of countries	29	29	29	29	29	29	29
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: (1) Robust standard errors in parentheses; (2) *** p<0.01, ** p<0.05, * p<0.1.

4.2.3 The Interplay of Government Measures and the Spread of the Pandemic

To test whether the effects of lockdown measures and economic measures on stock market performances are dependent on a country's exposure to the spread of the Coronavirus, I introduced the interactions between the change in lockdown stringency and the daily growth rate of COVID-19 confirmed cases, as well as interactions between the change in different economic policies and the daily growth rate of COVID-19 confirmed cases. Table 4 presents the estimation results with different interaction terms. Column (1) reveals a negative and significant association between stock market return and the interaction between the change in lockdown stringency and the daily growth in Coronavirus confirmed cases. This suggests that the negative relationship between tightening lockdown measures and stock market returns exacerbates on days with faster spread of the virus. This result suggests that the combined impact of escalating lockdowns and worsening pandemic conditions exacerbates negative market perspectives.

Interacting different economic measures with the daily growth rate of COVID-19 confirmed cases, I found that the negative effect of increasing in the change of the size of the fiscal package will be enlarged as the Coronavirus spread within a country, as in Column (2) of Table 4. This result suggests that the effect of change in boosting the size of the fiscal package will be more pronounced in countries with a faster spread of the coronavirus. Combined with the estimation results in Column (1) of Table 3, the effect of the change in the size of fiscal package announced by governments depends on the extent that a country is exposed to the COVID-19 pandemic. In addition, this suggests that although fiscal stimulus signals government support, coupling the change in the size of fiscal package with worsening pandemic conditions has heightened uncertainty and investor caution disproportionately. The combined escalation of fiscal response and infections interacted to negatively influence risk appetite beyond their distinct associations.

Table 4: Regression results with interaction terms

	(1)	(2)	(3)	(4)
VARIABLES	Stringency#COVID	Fiscal#COVID	Interest#COVID	Macro#COVID
Lockdown measure	-0.061068*	-0.00125	-0.00170	-0.00121
	(0.0359)	(0.0315)	(0.0317)	(0.0315)
Fiscal package	-0.0853	-0.301**	-0.0842	-0.0844
	(0.0645)	(0.113)	(0.0648)	(0.0642)
Interest rate cut	-0.924	-0.913	-0.204	-0.931
	(0.752)	(0.747)	(1.779)	(0.753)
Macro-financial package	0.0655*	0.0754*	0.0455	0.0788
	(0.0368)	(0.0409)	(0.0361)	(0.0733)

Other monetary policies	0.549	0.562	0.553	0.545
	(0.397)	(0.400)	(0.397)	(0.395)
World stringency	-1.329	-1.301	-1.402	-1.337
	(1.526)	(1.525)	(1.496)	(1.523)
Sentiment index	-0.00308*	-0.00300	-0.00341	-0.00319
	(0.00178)	(0.00572)	(0.00572)	(0.00588)
Lagged return	-0.206***	-0.209***	-0.206***	-0.205***
	(0.0681)	(0.0685)	(0.0671)	(0.0675)
COVID growth	-0.0481*	-0.0424	-0.0566	-0.0516
	(0.0290)	(0.0770)	(0.0732)	(0.0759)
Lockdown#COVID	-0.0334*			
	(0.0194)			
Fiscal#COVID		-0.0765*		
		(0.0411)		
Interest#COVID			-0.368	
			(0.545)	
Macro#COVID				-0.00772
				(0.0384)
Constant	-0.639**	-0.631**	-0.665***	-0.651**
	(0.249)	(0.257)	(0.255)	(0.257)
Observations	2,393	2,393	2,393	2,393
R-squared	0.609	0.609	0.608	0.608
Number of countries	29	29	29	29
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Notes: (1) Robust standard errors in parentheses; (2) *** p<0.01, ** p<0.05, * p<0.1.

4.2 Robustness Checks

To ensure the robustness of previous estimations, I first controlled for other possible pre-pandemic macroeconomic characteristics and then addressed the endogeneity issues related to domestic lockdown measures.

4.2.1 Controlling for Other Possible Country-Level Pre-Pandemic Factors

Industrial composition, the shares of the major economic sectors in the gross product of a regional economy (Atikian, 2013), is argued to affect a region's resilience to external shocks (Hu *et al*., 2022; Kim *et al*., 2022). Restrictive policies enacted to contain the spread of COVID-19 have disrupted and adversely affected various supply-side and demand-side sectors (Nicola *et al*., 2020). Particularly, the manufacturing sector has suffered the most from these disruptions because of the production ceasing of raw materials and replacement components, various logistical setbacks, and the uncertainty about recovery (Okorie *et al*., 2020). I included the variable of the added value of the manufacturing sector as a proportion of GDP in 2019[5] to account for potential bias stemming from heterogeneous industrial compositions of sample countries. Sourced from the World Bank Group, industrial composition is used to proxy the percentage of net output of the manufacturing sector after aggregating all outputs and subtracting intermediate inputs in production at a country level (World Bank, 2022). I generated a dummy variable from the industrial composition by denoting 1 if the value of the industrial composition is greater than the world average in 2019 (15.937%), and 0 otherwise.

The estimation results controlling for the industrial composition are reported in Column (2) of Table 5. After accounting for industrial composition, the effect of the change in lockdown stringency on stock market performance remains negative and significant, as the baseline regression. The result suggests that when the change in lockdown stringency increases by one unit, its associated decline in stock market return is around 0.03%. The effect directions and significance levels of the changes in interest rate cut, macro-financial package, sentiment index and stringency levels of other countries' restrictive measures remain the same.

4.2.2 Controlling for the Endogeneity Issue of Lockdown Measures

4.2.2.1 Mitigating the Endogeneity Issue with the IV-2SLS Approach

Potential endogeneity issues that arise in examining the relationship between stock market return and lockdown stringency is another potential concern for robustness of the estimation results. Although the pandemic itself can be regarded exogenous, the encouragement and implementation of lockdown measures by governments are not random. Considering potential omitted variable bias, it is important to consider time-variant country-specific characteristics that may affect stock market performance through changes in lockdown measures. Failing to account for these factors could lead to a correlation between lockdown stringency and the residuals in the model, resulting in biased estimates (Wooldridge, 2010). From a statistical standpoint, Durbin test and the Wu-Hausman test were conducted to examine the exogeneity of lockdown stringency. With both test statistics significant at 1%[6], the null hypothesis of the exogeneity of lockdown stringency was rejected and therefore treated the variable as endogenous.

Adopting an instrumental variable (IV) is a common approach to control for omitted variable bias and address the endogeneity issues (Bascle, 2008; Wooldridge, 2010; Sargan, 1958). I used the quotient of the daily log growth rate of COVID-19 confirmed

[5] No available data of manufacturing as a percentage of GDP in 2019 is available for Canada and New Zealand on the official website of the World Bank Group; therefore, we used the data in 2018 for Canada and New Zealand.
[6] The statistics of the Durbin test is 12.8462 with a p-value of 0.0002. The statistics of the Wu-Hausman test is 15.3649 with a p-value of 0.0000.

cases and the number of hospital beds per thousand people as the instrumental variable to instrument lockdown stringency[7].

This instrument, capturing the stress on the healthcare system in response to the influx of the growing Coronavirus cases, was carefully chosen to capture the exogenous variation in lockdown stringency that is plausibly unrelated to other direct economic factors influencing stock market performance. This ratio is intended to reflect the strain on the healthcare system, which in turn influences the government's decision to implement more stringent lockdown measures. The rationale behind this choice is that healthcare capacity, as indicated by the number of hospital beds relative to the surge in COVID-19 cases, directly influences the urgency and extent of lockdowns, independent of other economic conditions. The instrument is designed to isolate the effect of lockdown stringency on the stock market by focusing on a measure that reflects healthcare system stress—a factor that triggers policy responses rather than being a direct economic variable. However, recognizing potential concerns, one might argue that the ratio of COVID-19 cases to hospital beds could affect stock markets through channels other than lockdown stringency, such as through its impact on workforce availability or investor expectations. This concern is mitigated by the fact that the primary role of this ratio is to indicate the necessity for government intervention, not to directly influence economic activities. By adjusting for hospital beds per thousand people, the instrument focuses on a key aspect of the healthcare system's capacity to manage the pandemic, thus separating it from economic conditions prior to the pandemic.

The exclusion restriction—that this instrument influences the stock market solely through its effect on lockdown stringency—is further justified by the nature of the pandemic response. The ratio serves as a proxy for the severity of the health crisis, which directly dictates the stringency of lockdowns rather than other economic outcomes. This separation is crucial because it aligns with the theoretical framework that government-imposed lockdowns, in response to healthcare system strain, are the primary drivers of economic disruption during the pandemic, rather than the number of COVID-19 cases alone. Regarding the expected direction of bias, if the exclusion restriction were to be violated, the bias would likely be upward—meaning that the IV estimate might overstate the impact of lockdown stringency on stock market performance. This could occur if the instrument also indirectly captures other factors influencing the stock market, such as overall economic uncertainty or labor market disruptions due to rising COVID-19 cases. However, given that robustness checks and sensitivity analyses—detailed in the appendix—show that the core findings remain consistent even when alternative instruments or specifications are used, we believe that the potential bias is minimal and does not materially affect the conclusions.

This rigorous approach, backed by theoretical considerations, empirical validation, and

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[7] I have tested that the instrumental variable is not correlated with the dependent variable as the result is not significant at a 0.10 level (with a p-value of 0.129).

a transparent discussion of potential biases, ensures that the instrument used in this study meets the necessary conditions for validity, thereby enhancing the credibility of the IV-2SLS results and allowing for a more accurate comparison with the baseline estimates.

Comparing the results between the benchmark and IV-2SLS specifications in Column (1) and (3)[8] of Table 5, the effect of the changes in the intensity of lockdown measures on stock markets remains negative and significant; however, the magnitude of the impact drops. The endogeneity of lockdown measures causes an upward bias in the benchmark model as the IV-2SLS estimated effect is lower than that of the benchmark model. The IV-2SLS estimation suggests that one-unit increase in the change in lockdown stringency of a country leads to approximately 0.02% drop in stock market return. Despite this adjustment, the significance and direction of coefficients for other main independent variables in the IV-2SLS regression remain consistent with the findings in previous results, confirming the robustness of the estimation.

4.2.2.2 Postestimation Tests for the IV-2SLS Approach

Three postestimation tests were conducted to ensure the validity of the selected instrumental variable. First, the under-identification test was conducted to determine whether the selected IV is correlated with the endogenous regressor (lockdown stringency) and meet the relevance criterion. With an extremely small p-value of the Kleibergen-Paap rk LM statistic, the null hypothesis that the instrument is unrelated to the endogenous regressor is strongly rejected. The selected instrument's relevance to the endogenous regressor is validated.

Secondly, the weak instrument test was conducted to test the strength of the selected IV and avoid the weak instrument problem. The strength of the selected instrument is verified by the Cragg-Donald Wald F statistic (86.261), greatly surpassing the critical values (16.38) in 10% maximal IV size established by Stock and Yogo (2005). Therefore, the validity of the selected instrument does not suffer from the weak instrument problem.

Thirdly, the selected instrument should be validated by its uncorrelation with the error term (Angrist *et al*., 1999), which can be examined by the over identification test. However, the over identification test requires having additional instruments beyond the minimum needed, which in this case, at least two instruments are required for identification with one endogenous regressor. As there is only one instrument for this endogenous regressor, that the selected instrument only affects the dependent variable through its effect on the endogenous regressor and is not directly correlated with the outcome cannot be empirically tested with the over identification test. Based on the conceptual argument, one can conjecture that the daily growth rate of Coronavirus cases

[8] The results of the first-stage regression are reported in the Appendix 2.4 for the sake of completeness of reporting.

and the number of hospital beds of a country can affect stock market returns through the impact on lockdown stringency. There are no other pathways for the selected IV to directly influence stock market returns except through lockdown stringency in the main model. Therefore, the selected instrument meets the exogeneity criterion. Based on the diagnostic tests, the selected instrument is econometrically sound for the IV-2SLS estimations due to its satisfaction with the relevance criterion, the avoidance of the weak instrument problem, and the exogeneity criterion.

Table 5 Results of robustness checks

	(1)	(2)	(3)
VARIABLES	Baseline	Industrial composition	IV-2SLS
Lockdown measure	-0.03161**	-0.03089**	-0.02090**
	(0.0151)	(0.0154)	(0.0105)
Fiscal package	-0.0838	-0.0803	-0.232
	(0.0656)	(0.0661)	(0.166)
Interest rate cut	-0.1150*	-0.1175*	-0.1128*
	(0.0682)	(0.0698)	(0.0667)
Macro-financial package	0.0598**	0.0587**	0.0469**
	(0.0265)	(0.0255)	(0.0209)
Other monetary policies	0.553	0.553	0.494
	(0.360)	(0.360)	(0.381)
World stringency	-0.752*	-0.778*	-0.694
	(0.406)	(0.435)	(0.548)
Sentiment index	-0.00558*	-0.00488*	-0.00471*
	(0.00326)	(0.00289)	(0.00277)
Lagged return	-0.214***	-0.214***	-0.0877*
	(0.0674)	(0.0674)	(0.0464)
Industrial composition		-0.00538	
		(0.0628)	
Constant	-0.537**	-0.237*	-0.0301
	(0.261)	(0.142)	(0.128)
Observations	2,427	2,427	2,392
R-squared	0.606	0.606	0.700
IV Tests			
Kleibergen-Paap rk LM statistic			58.154
p-value			0.000
Cragg-Donald Wald F statistic			86.261
Stock-Yogo 10% maximal IV size			16.38

Stock-Yogo 15% maximal IV size	8.96

Notes: (1) Robust standard errors in parentheses; (2) *** p<0.01, ** p<0.05, * p<0.1; (3) Stock-Yogo 10% maximal IV size and Stock-Yogo 15% maximal IV size are Stock and Yogo (2005) weak identification test with critical values for 10% and 15%, respectively. According to Stock and Yogo (2005), when Cragg-Donald F statistic > 10% maximal IV size, instruments are very powerful; when 10% maximal IV size <Cragg-Donald F statistic <15% maximal IV size, instruments are powerful.

4.3 Event Study Method

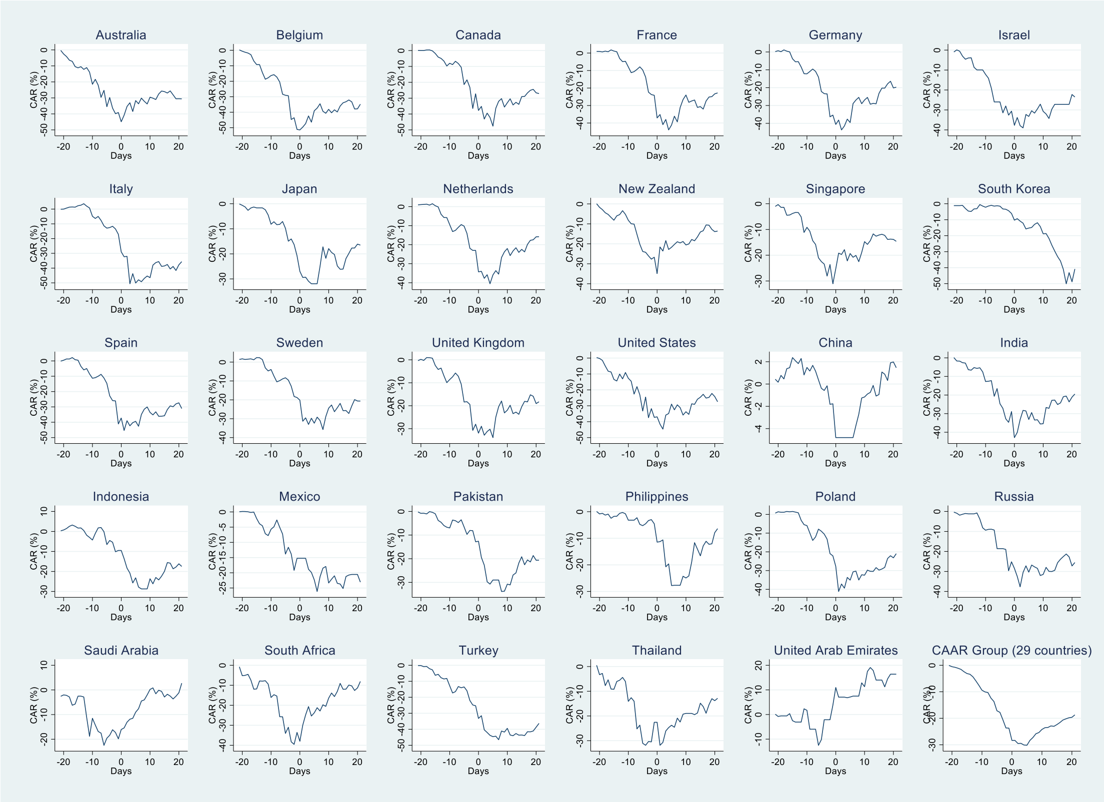
In this section, an event study method was adopted to further investigate stock market reactions to lockdown announcements.

4.3.1 Market Reactions to Major Events during the Initial Pandemic Outbreak Period

Figure 1 presents the cumulative abnormal returns in percentage points along the timing of domestic lockdown announcements, with the horizontal axis demonstrating days within the event window (with "0" corresponding to the event date, when governments announced its domestic lockdown). An overall "V-shaped" curve can be observed, with a cumulative abnormal return around 0 three weeks before the announcements. A steep drop occurs during the three weeks prior to the announcements, followed by a less steep drop from the event day to five days after the event (event window [0, 5]). On average, there is an approximately 30% decline from 21 days before the announcements to five days after for all sample countries. From five days following the event, the negative cumulative abnormal return on average starts to approach the positive direction, as seen in the last graph of Figure 1.

Intuitively, one would expect negative or positive reactions of the market returns occur around the event day or afterwards. The downward trend presented in Figure 1 raises questions about whether other critical announcements triggered the downward trend rather than domestic lockdown announcement. To understand this puzzling market behaviour, I examined market reactions to five critical lockdown information, including China's announcement of lockdown, Italy's announcement of restrictive measures, Italy's announcement of lockdown, Germany's announcement of lockdown, and the US's announcement of lockdown. The estimation results of these five events are reported in Table 6.

Figure 1: The cumulative abnormal returns of sample countries around the event date[9]



From Table 6, no significant reactions, on average, to China's announcement of lockdown (Event 1) can be observed. By contrast, significant and negative reactions to Italy's announcement of first round restrictive measures, Italy's lockdown announcement, Germany's lockdown announcement, and the US's lockdown announcement (Event 2 to Event 5) can be observed, demonstrated by both the

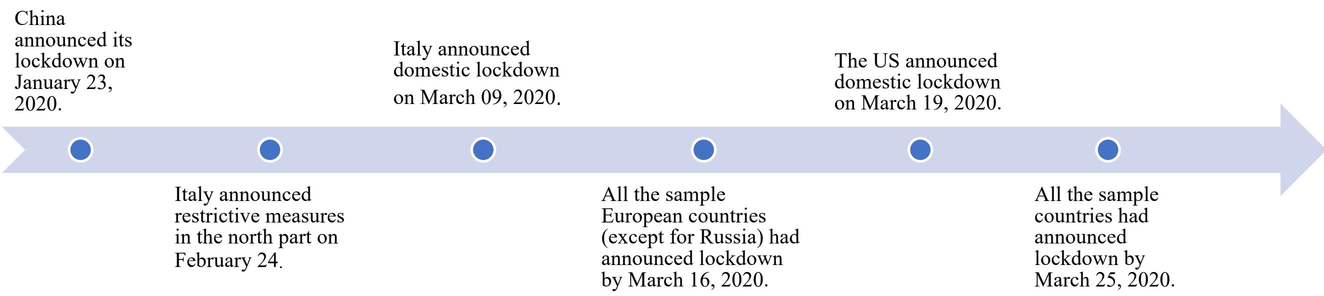
[9] In almost all sample countries, "V-shaped" curves can be observed in cumulative abnormal returns from three weeks prior to the event to three weeks after the event, except for South Korea, Saudi Arabia, and the United Arab Emirates. The overall downward trend of South Korea can be attributed to the continuous negative shocks from both domestic and foreign lockdown and lockdown-related information. South Korea announced its domestic lockdown on February 24, 2020, which is approximately three weeks earlier than the majority of sample countries. Before its lockdown announcement, South Korea declared some restrictive measures to contain the spread of coronavirus across the country. These restrictive measures, together with the official lockdown announcement, provoked a negative sentiment toward the stock market, as demonstrated in its downward trend before and on the event day. Following the first and second week of South Korea's domestic lockdown announcement, some European countries, including Italy and France, started to announce restrictive policies and national lockdowns. The announcements of some European lockdowns suggested an escalating uncertainty about curbing the coronavirus, resulting in an escalating negative sentiment and further plunges in the stock market. The stock market, however, rebounded about 10 per cent because of the confidence boost from the US announcement of economic rescue on March 13, 2020 (corresponding to Day 18 on the Figure). This upward trend was interrupted by the continuous shocks from lockdown announcements in other countries such as Germany and the US. The overall downward trend of South Korea's cumulative abnormal returns can be generally attributed to the adverse shocks from South Korea's early domestic lockdown announcement and the later lockdown announcements of other countries.

In contrast to other sample countries where markets rebound occurred after domestic lockdown announcements, the market returns of Saudi Arabia and the United Arab Emirates started to rebound on the sixth day prior to their domestic lockdown announcement (lockdown was announced on March 25, 2020, in these two countries). From late February 2020, these two large oil exporters had been adversely affected by the oil price war, leading to negative sentiment toward the stock market. In addition to the adverse shocks from the oil price war, these two economies also reacted significantly and negatively to Italy's lockdown announcement on March 9, 2020, as demonstrated in Column (3) of Table 4. The sentiment-driven drop sustained until March 19, 2020, when the oil price rose by approximately 23% as the WTI crude oil's best day on record since 1991. This positive information suggested the stabilisation of the oil price war and therefore stock markets of these two large oil exporters started to boost, as demonstrated in the rebounding process since the sixth day before event date in Figure 3. Although lockdown has been announced in these two countries in late March 2020, there were no significant return drops as we observed in Figure 3. This is because, as large oil exporters, their worst-case scenario was the adverse shocks from the oil price war rather than pandemic-related lockdowns, therefore their stock markets were largely unaffected by domestic and foreign lockdown announcements.

abnormal returns on the event day and the cumulative abnormal returns from one day before to three days after the event. In addition, the significant reaction to Italy's announcement of lockdown (Event 3) has the largest magnitude among Event 2 to Event 5. This estimation results, in a way, suggests that markets were partially revived when Event 4 and Event 5 occurred, compared with the period of Event 3. These two main findings led one to question 1) why did the announcement of lockdown in China (Event 1), on average, have insignificant effects compared with Event 2-5, despite China being the second-largest economy with great economic connections with the rest of the world, and 2) why did Italy's lockdown announcement (Event 3) yield the most negative reactions among Event 2 to Event 5?

To examine the first question, it is crucial to consider the timeline of these key lockdown events (see Figure 2). China, being the first global epicentre, announced its domestic lockdown on January 23, 2020. With the pandemic spreading to Europe, Italy became the continent's initial epicentre. On February 24, Italy declared restrictive measures in its northern regions, including public event suspensions, movement controls, public building closures, and transportation cancellations in several municipalities, controls on freedom of movement, closure of public buildings, transportation cancellations, and surveillance of individuals potentially exposed to COVID-19 (WHO, 2020). Italy announced a national lockdown on March 9, applying similar measures to the entire country as in China. Following Italy's lockdown announcement, most European sample countries (except for Russia) announced their domestic lockdowns in the following week. By March 25, all the sample countries had implemented domestic lockdown to contain the spread of the virus.

Figure 2: Timeline of lockdown related information



When China announced its lockdown on January 23, 2020, the rest of the world had only ten confirmed COVID-19 cases (WHO, 2020). Due to limited historical insights and statistical analysis of similar health crises like the Spanish Flu and SARS (Bazzana *et al.*, 2021; Philippas *et al.*, 2021), market participants inaccurately interpreted the pandemic's development, presuming its impact would be confined to China or some Asian regions. Such an assumption, in general, had not led to extremely negative sentiment towards the market; therefore, the initial risk perception remained below a certain threshold and global stock markets did not reveal an average significant response.

However, some countries, such as France and the US, showed significant and negative reactions both on the event day (China's lockdown announcement) and over a five-day event window. The significant reactions to China's lockdown announcement in these countries can be attributed to their relatively large foreign direct investment (FDI) exposure to China and significant reliance on visits from Chinese tourists. As China was the original epicentre of the world before Italy took over, China's lockdown announcement increased financial risk exposure for countries with substantial FDI in China due to production halts and losses for FDI investors. Furthermore, the lockdown announcement articulated restrictive mobilities of Chinese citizens and suspension of civil transportation services. Therefore, enormous tourism spending from China has come to a halt, causing significant losses, especially for countries like Japan, Singapore, and Thailand. I conducted an OLS regression to statistically explain the relationship between financial and tourism exposures to China and stock market reactions to China's lockdown announcement. Among the countries with significant reactions to China's lockdown announcement, greater FDI exposure to China and higher acceptance of Chinese tourists were found to negatively affect the cumulative returns over a five-day event window of [-1, 3]. The results show that one-unit increase in the FDI exposure to China[10] led to around a 0.06396 decrease in cumulative abnormal returns at a 0.01 significance level (p-value of 0.002). Significant at a 5%, one-unit increase in acceptance of mainland Chinese tourists[11] results in approximately a -0.1036 decrease in cumulative abnormal returns with a p-value of 0.034.

Building upon the understanding of the insignificant reactions to China's lockdown announcement, I proceeded to investigate why Italy's announcements (Event 2 and Event 3) resulted in greater impacts on the markets than that of other countries. Stock markets dropped by an average of 3.18% on the day when Italy announced restrictive measures (Event 2). Over the event window of [-1, 3], the stock markets accumulated about a 3.36% drop, see Column (2) in Table 6. The main reason is that market participants associated Italy's announcement of restrictive measures with that the disease becoming more international. The surge in confirmed cases and alert of insufficient hospitalisation resources led to Italy's restrictive measures, driving market participants to learn about potential adverse implications of the contagiousness of the disease. Therefore, market participants started to respond negatively, leading to a market downturn. Italy's announcement of restrictive measures acted as the prologue of containment and restrictive policies in countries other than China, triggering negative sentiment towards global stock markets. Additionally, it should be noted that all sample European sample countries reacted significantly, both in immediate and cumulative terms, to Italy's announcement of restrictive measures. This is because these countries, due to relatively strong geographical connection to Italy, were prone to be affected by the virus spread in Italy and anticipated similar restrictive measures if infections surged

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[10] FDI exposure to China is proxied by the outward FDI stocks by partner country (China, % of total FDI, 2019), obtained from the OECD International Direct Investment Statistics (https://data.oecd.org/fdi/outward-fdi-stocks-by-partner-country.htm#indicator-chart).

[11] The acceptance of mainland Chinese tourists is proxied by the percentage of mainland Chinese tourist visits as a share of total tourist visits in a country, obtained from the Economist Intelligence Unit (http://country.eiu.com/article.aspx?articleid=1429060926&Country=China&topic=Economy).

within their countries.

The negative reactions of stock markets continued and peaked with Italy's lockdown announcement (Event 3), resulting in an average 7.17% drop on the event day and over 20% over a five-day event window, see Column (3) in Table 6. All sample countries accumulated significant and negative abnormal returns from one day prior to and three days after the announcement of Event 3. A possible reason for the substantial drops brought by Event 3 is that an official lockdown announcement in Italy more clearly divulges the acuteness of the pandemic and the globality of this health crisis, compared with Event 1 and Event 2. Italy, perceived as more democratic than China, was assumed to be more cautious in announcing and implementing measures that restrict citizens' freedoms. The announcement of lockdown in Italy made market participants to be fully convinced with the severity of the pandemic. Event 3 marked the actual beginning of the simultaneous lockdowns and mass quarantines around the world, intensifying sentiment of panic and fear across global financial markets. The significant reactions to Event 3, in general, reflected that market agents were updating their beliefs as Italy declared a national lockdown, and it became easier to envision similar announcements in their home countries. The panic-induced stock market plunges in response to Italy's lockdown-like and lockdown announcements endured for a short term, suggesting that such responses are more reflective of sentiment than rationality (Brounen and Derwall, 2010).

Although global markets reacted significantly and negatively to the lockdown announcements of Germany and the US (Event 4 and Event 5), the magnitudes were not as great as that of Italy's lockdown announcement (Event 3). Compared to Event 3, the market reactions to Events 4 and 5 can be considered "partial recoveries". On average, the global stock market immediately dropped by approximately 5.62% and 3.05% in response to Events 4 and 5, respectively, see Columns (4) and (5) in Table 6. The negative abnormal returns piled up to about 6.24% and 4.68% over the [-1, 3] event window of Event 4 and Event 5, respectively. Although the US and Germany stand as larger economies by both total GDP and GDP per capita than Italy, their lockdown announcements had a smaller negative impact compared to Italy's. From a Bayesian perspective (Philippas *et al*., 2021; Andrei and Hasler, 2015), market participants would update their beliefs to Germany and the US's governments' responses to the pandemic based on prior information about Italy's lockdown announcement. Given the situations of virus spread in Germany and the US, market participants already expected similar lockdown announcements. Therefore, the sentiment-driven drops by lockdown announcements of these two countries were not as substantial as Italy's, both in immediate and cumulative terms.

Overall, the evolution of global stock markets indicates the "learning" process in markets, starting from initially overlooking the effects of China's lockdown announcement, provoking panic in response to Italy's announcement of restrictive measures, reacting strongly to Italy's lockdown announcement, and then gradually easing towards lockdown announcements in Germany and the US. This learning process can be attributed to market participants updating their beliefs regarding incoming government responses based on prior information about Italy's lockdown announcement.

Table 6: Market reactions to critical events during the initial pandemic period

	(1) Event 1 China's announcement of lockdown		(2) Event 2 Italy's announcement of restrictive measures		(3) Event 3 Italy's announcement of lockdown		(4) Event 4 Germany's announcement of lockdown		(5) Event 5 The US's announcement of lockdown	
	AR Day 0	CAAR [-1, 3]	AR Day 0	CAAR [-1, 3]	AR Day 0	CAAR [-1, 3]	AR Day 0	CAAR [-1, 3]	AR Day 0	CAAR [-1, 3]
Australia	-1.1261%*	-2.9807%	-3.6223%***	-7.4412%***	-7.9745%***	-20.5193%***	-10.2475%***	-10.5751%***	-6.7079%***	-9.8850%***
	(0.0995)	(0.1241)	(0.0001)	(0.0004)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Belgium	-0.8570%	-0.9538%	-4.2214%***	-6.1908%***	-7.8591%***	-27.0848%***	-7.3571%***	-1.7686%	1.6755%	4.0289%
	(0.1628)	(0.5345)	(0.0000)	(0.0009)	(0.0000)	(0.0000)	(0.0000)	(0.2521)	(0.1201)	(0.1316)
Canada	-0.0592%	-1.2628%*	-3.2735%***	-2.6385%***	-11.0018%***	-28.8611%***	-10.4608%***	-2.9997%***	-8.0301%***	-10.2449%***
	(0.8100)	(0.0933)	(0.0000)	(0.0004)	(0.0000)	(0.0000)	(0.0000)	(0.0077)	(0.0000)	(0.0000)
France	-0.6528%*	-1.5119%*	-3.3811%***	-3.6588%**	-8.7457%***	-28.0978%***	-5.7032%***	-3.6742%*	-6.0664%***	1.1066%
	(0.1433)	(0.0700)	(0.0000)	(0.0141)	(0.0000)	(0.0000)	(0.0000)	(0.0796)	(0.0000)	(0.6512)
Germany	-1.0128%	-1.8968%	-4.0361%***	-5.7050%***	-8.3659%***	-26.9741%***	-5.2398%***	-5.1400%**	-5.7374%***	-0.0748%
	(0.2955)	(0.4550)	(0.0001)	(0.0041)	(0.0000)	(0.0000)	(0.0000)	(0.0307)	(0.0001)	(0.9782)
Israel	0.8723%	-1.3696%	-4.9368%***	-6.4513%***	-5.0820%***	-13.9838%***	3.6657%***	-10.4016%***	2.0537%	-9.4462%***
	(0.2455)	(0.1919)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0048)	(0.0019)	(0.1172)	(0.0080)
Italy	-0.0447%	1.0901%	-3.6353%***	-6.4826%***	-11.8828%***	-37.1354%***	-6.1527%***	4.5052%*	-1.3651%	3.3540%
	(0.9399)	(0.5028)	(0.0002)	(0.0022)	(0.0000)	(0.0000)	(0.0000)	(0.0817)	(0.2522)	(0.2574)
Japan	-1.6726%*	-5.4848%**	-3.7574%**	-6.1943%*	-5.3576%***	-14.7073%***	-2.2055%*	-10.0082%***	-1.4902%	-2.0814%
	(0.0692)	(0.0351)	(0.0110)	(0.0713)	(0.0008)	(0.0005)	(0.0630)	(0.0031)	(0.1958)	(0.3187)
Netherlands	-0.9409%*	-0.9204%	-3.6920%***	-3.9413%***	-7.9696%***	-24.6567%***	-3.5762%***	-1.1402%	-4.9145%***	1.4232%
	(0.0652)	(0.4436)	(0.0000)	(0.0051)	(0.0000)	(0.0000)	(0.0010)	(0.6035)	(0.0006)	(0.6148)
New Zealand	-0.0039%	-1.5941%	-1.7429%***	-1.9722%	-3.1519%***	-12.8367%***	-3.6326%***	-12.5840%***	-1.8329%**	-11.3107%***
	(0.9932)	(0.2284)	(0.0039)	(0.1293)	(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.0283)	(0.0000)
Singapore	-0.6681%	-2.3648%*	-3.2528%***	-2.8407%**	-6.1987%***	-11.8221%***	-5.1329%***	-13.4745%***	-1.0861%*	-10.6101%***
	(0.2562)	(0.0795)	(0.0001)	(0.0473)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0883)	(0.0003)
South Korea	-1.2968%	-0.4030%*	-3.6252%***	-2.1738%*	-4.4925%***	-13.8915%***	-3.2461%***	-22.9860%***	-4.9969%***	-14.6497%***
	(0.2606)	(0.0569)	(0.0038)	(0.0505)	(0.0004)	(0.0001)	(0.0059)	(0.0000)	(0.0004)	(0.0001)
Spain	-0.3663%	0.3851%	-2.9136%***	-4.1970%***	-8.2134%***	-30.2298%***	-8.0910%***	0.6596%	-3.6158%***	1.4297%
	(0.1365)	(0.5265)	(0.0002)	(0.0090)	(0.0000)	(0.0000)	(0.0000)	(0.6840)	(0.0011)	(0.5257)
Sweden	-0.6517%	-0.6086%	-3.1054%***	-4.4367%**	-5.4304%***	-21.7525%***	-3.4478%***	2.3236%	-2.8191%**	-3.7913%
	(0.3793)	(0.7587)	(0.0010)	(0.0284)	(0.0000)	(0.0000)	(0.0004)	(0.2325)	(0.0117)	(0.1391)
UK	-0.8818%	-1.8327%*	-3.1534%***	-2.9090%**	-7.9835%***	-24.6323%***	-3.8620%***	-0.5147%	-4.0200%***	-2.5398%
	(0.1393)	(0.0887)	(0.0001)	(0.0464)	(0.0000)	(0.0000)	(0.0002)	(0.7946)	(0.0006)	(0.2815)
US	0.0173%	-1.9208%*	-1.1231%**	-1.0396%	-8.0020%***	-20.3093%***	-12.7277%***	-2.7269%	-5.4416%***	-7.0328%***

	(0.9760)	(0.0731)	(0.0220)	(0.3442)	(0.0000)	(0.0000)	(0.0000)	(0.1629)	(0.0000)	(0.0074)
China	-3.7854%***	-2.6831%*	-3.4308%**	2.5494%	-3.3317%**	-6.3424%**	-3.5758%	-8.4558%	-1.5871%	-3.4369%
	(0.0000)	(0.0509)	(0.0111)	(0.3877)	(0.0209)	(0.0401)	(0.1220)	(0.1600)	(0.5205)	(0.5970)
India	0.5594%	-0.7908%	-3.8170%***	-4.3033%**	-5.3036%***	-16.0033%***	-8.0478%***	-13.5171%***	-5.6451%***	-18.3720%***
	(0.6154)	(0.7899)	(0.0002)	(0.0346)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Indonesia	0.1696%	-2.4405%	-1.4704%**	-0.4835%	-6.7657%***	-13.9216%***	-4.1191%***	-15.5989%***	-2.5458%**	-14.5704%***
	(0.8222)	(0.2553)	(0.0179)	(0.7236)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0124)	(0.0000)
Mexico	-0.3752%	-1.5829%	-0.9279%	0.3238%	-6.7363%***	-14.9712%***	0.0000%	-0.6895%	-3.5142%***	-10.5352%***
	(0.4824)	(0.2845)	(0.2515)	(0.8714)	(0.0000)	(0.0000)	(.)	(0.6952)	(0.0034)	(0.0003)
Pakistan	-0.3398%	-2.7815%	-0.3916%	0.8762%	-3.1066%**	-9.2114%***	-6.4973%***	-16.0868%***	-6.6157%***	-7.9042%***
	(0.8558)	(0.5843)	(0.7387)	(0.7702)	(0.0255)	(0.0099)	(0.0000)	(0.0000)	(0.0000)	(0.0020)
Philippines	1.8756%*	-0.4662%*	-2.3743%*	0.5915%	-6.9039%***	-17.7657%***	-7.6922%***	-5.5853%**	0.0000%	3.6123%
	(0.0727)	(0.0673)	(0.0840)	(0.8555)	(0.0000)	(0.0000)	(0.0000)	(0.0276)	(.)	(0.1914)
Poland	-0.1109%	-2.7374%	-4.0777%***	-3.6368%*	-7.7842%***	-31.0926%***	-2.1602%**	10.7945%***	-1.4209%	4.4324%*
	(0.9236)	(0.4194)	(0.0004)	(0.0999)	(0.0000)	(0.0000)	(0.0131)	(0.0001)	(0.1142)	(0.0529)
Russia	-1.0711%	-3.9727%	-4.5990%***	-9.1560%***	-4.4651%***	-20.6975%***	-3.2688%***	-0.9120%	-5.2120%***	-2.0457%
	(0.3313)	(0.2841)	(0.0002)	(0.0011)	(0.0003)	(0.0000)	(0.0016)	(0.6684)	(0.0000)	(0.3765)
Saudi Arabia	-0.3254%	-4.2630%	-1.3018%	-3.7459%	-8.7051%***	-13.9346%***	-1.1281%	-6.3887%**	2.6188%***	-0.9722%
	(0.8409)	(0.3463)	(0.1968)	(0.1507)	(0.0000)	(0.0001)	(0.3226)	(0.0349)	(0.0069)	(0.6437)
South Africa	-1.9421%	-3.2690%	-4.5968%***	-3.7469%	-6.7692%***	-18.4637%***	-8.2572%***	-13.7564%***	-7.3992%***	-4.6102%
	(0.1191)	(0.1035)	(0.0007)	(0.1564)	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0001)	(0.1819)
Turkey	-0.7472%	-6.0721%	-4.7940%***	-7.4075%*	-6.0304%***	-19.3700%***	-8.4821%***	-9.7806%***	-1.5006%	-4.7662%*
	(0.7414)	(0.3362)	(0.0057)	(0.0602)	(0.0014)	(0.0001)	(0.0000)	(0.0003)	(0.1402)	(0.0655)
Thailand	0.0135%	-2.8988%*	-3.9286%***	1.1931%	-8.1918%***	-21.5940%***	-7.2805%***	-4.8544%*	1.4545%	-1.0464%
	(0.9911)	(0.0898)	(0.0008)	(0.5838)	(0.0000)	(0.0000)	(0.0000)	(0.0925)	(0.2514)	(0.7343)
UAE	-0.4004%	-0.9137%	-0.4559%	-2.6117%	-0.9350%	-4.0230%**	-4.8674%*	3.2611%**	2.1162%***	3.3451%**
	(0.7290)	(0.7008)	(0.6006)	(0.1221)	(0.2352)	(0.0249)	(0.05603)	(0.0297)	(0.0050)	(0.0123)
CAAR	-0.5106%	-2.1683%	-3.1778%***	-3.3588%***	-7.1718%***	-20.9874%***	-5.6186%***	-6.2422%***	-3.0464%***	-4.6841%***
	(0.2575)	(0.1433)	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.0091)

Notes: (1) AR denotes abnormal return; (2) CAAR denotes cumulative average abnormal returns.

4.3.2 Stock Market Reactions to Domestic Lockdown Announcements

To assess the impact of domestic lockdown announcements on stock markets, I evaluated market responses to domestic lockdown announcements by examining abnormal returns on the event day and cumulative abnormal returns over different event windows.

Table 7 reports the detailed results of abnormal returns on the event date and cumulative abnormal returns of the sample countries over multiple event windows. Column (1) shows that the majority of the stock markets of the sample countries had significant and negative cumulative abnormal returns during the week before domestic lockdown announcements, with an average 13.53% drop. This result corresponds with previous findings in the panel data analysis, supporting that stock markets' slumps are not triggered by one's domestic lockdown announcement.

On the day when domestic lockdown was announced, almost all sample countries experienced negative and significant reactions to government announcement of lockdown (Column (2) in Table 7), except for Saudi Arabia and the United Arab Emirates (see footnote 8 for detailed explanation). Overall, the abnormal return of all sample markets on the event date had a negative response of approximately 4.46% to government announcements of lockdown. The finding of stock markets' significant and negative reactions to pandemic-related announcements aligns with Schell *et al*. (2020), who studied security markets' responses to Public Health Risk Emergency of International Concern announcements. The magnitudes of cumulative abnormal returns increased, on average, during the first five days after domestic lockdown announcements. This indicates that stock markets need time to internalise the negative shocks from such announcements. As time progressed, the cumulative abnormal return, on average, became insignificant on the tenth day following the event date, with a cumulative abnormal return of approximately -0.5%. this suggests that markets absorbed no new shocks from domestic lockdown announcements. It can be inferred that stock markets expected the lockdown to contain the spread of the pandemic and the market performance would improve in the long run.

Table 7: Results from the event study method

	(1)	(2)	(3)	(4)	(5)	(6)
Country	CAR [-7, -1]	AR Day 0	CAR [0, 1]	CAR [0, 2]	CAR [0, 5]	CAR [0, 10]
Australia	-17.1107%***	-5.76%***	-1.6418%*	3.7771%**	7.4571%***	9.6011%***
	(0.0000)	(0.0000)	(0.0329)	(0.0112)	(0.0020)	(0.0058)
Belgium	-33.8333%***	-0.32%*	1.4964%	3.7448%*	12.0251%***	12.9702%***
	(0.0000)	(0.0836)	(0.3014)	(0.0510)	(0.0005)	(0.0059)
Canada	-20.5218%***	-10.46%***	-7.9190%***	-15.8731%***	-20.3254%***	-5.6406%***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0037)
France	-13.5378%***	-12.95%***	-10.9870%***	-16.7635%***	-16.9909%***	0.1699%
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.9570)
Germany	-25.7974%***	-5.24%***	-2.8011%**	-8.3142%***	-4.1928%	8.4637%**
	(0.0000)	(0.0000)	(0.0422)	(0.0001)	(0.1024)	(0.0338)
Israel	-11.5146%***	-7.07%***	-3.1875%***	-7.2725%***	-2.6282%	-0.0815%
	(0.0028)	(0.0001)	(0.0089)	(0.0078)	(0.4731)	(0.9881)
Italy	-12.1180%***	-11.88%***	-15.2508%***	-14.9593%***	-33.0296%***	-29.4077%***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Japan	-12.3827%***	-6.22%***	-8.6617%***	-8.5538%***	-11.1833%***	2.8381%
	(0.0087)	(0.0004)	(0.0005)	(0.0032)	(0.0042)	(0.5565)
Netherlands	-10.5374%***	-11.26%***	-10.9799%***	-14.6542%***	-12.8957%***	0.9822%
	(0.0006)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.7651)

New Zealand	-16.5638%***	-8.18%***	-5.1191%***	3.0920%**	4.9865%**	6.1373%*
	(0.0000)	(0.0000)	(0.0005)	(0.0477)	(0.0374)	(0.0801)
Singapore	-16.7455%***	-3.80%***	11.8999%***	11.3867%***	11.7445%***	16.3541%***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0007)	(0.0013)
South Korea	-5.0956%	-4.19%**	-3.2518%*	-4.7734%	-9.1272%*	-12.7276%
	(0.3064)	(0.0255)	(0.0592)	(0.1142)	(0.0778)	(0.1108)
Spain	-31.0879%***	-3.81%***	-4.2459%***	2.1117%*	1.7007%	7.5002%**
	(0.0000)	(0.0000)	(0.0004)	(0.0855)	(0.3441)	(0.0121)
Sweden	-8.3040%***	-1.41%*	-12.5676%***	-10.7657%***	-13.5979%***	-5.6436%
	(0.0042)	(0.0905)	(0.0000)	(0.0000)	(0.0000)	(0.1081)
UK	-22.3172%***	-3.86%***	-0.8806%*	-4.7847%***	-5.8227%**	6.1212%
	(0.0000)	(0.0004)	(0.0511)	(0.0048)	(0.0181)	(0.1216)
US	-16.9819%***	-5.4416%***	-5.0914%***	-9.6435%***	-2.8597%	-3.6613%
	(0.0000)	(0.0000)	(0.0017)	(0.0001)	(0.2673)	(0.3446)
China[12]	-0.7335%	-3.7854%***	-3.7854%***	-3.7854%***	-3.7854%***	2.5558%
	(0.8531)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.4395)
India	-16.6627%***	-13.96%***	-11.1830%***	-4.2924%**	-4.1965%	-6.5102%
	(0.0002)	(0.0000)	(0.0000)	(0.0462)	(0.1817)	(0.1682)
Indonesia	-11.2802%***	-3.5286%**	-4.1191%***	-8.8331%***	-13.6829%***	-14.1554%***
	(0.0004)	(0.0043)	(0.0001)	(0.0000)	(0.0000)	(0.0001)
Mexico[13]	-12.5864%***	0.00%	0.0000%	0.0000%	-7.0855%***	-8.1177%**
	(0.0008)	(.)	(.)	(.)	(0.0012)	(0.0240)
Pakistan	-8.9235%**	-0.2501%*	-6.6089%***	-9.8720%***	-16.1585%***	-17.8884%***
	(0.0107)	(0.0804)	(0.0004)	(0.0001)	(0.0000)	(0.0002)
Philippines	-1.3606%	-6.90%***	-6.7156%***	-6.0682%**	-23.2385%***	-20.3864%***
	(0.7033)	(0.0000)	(0.0012)	(0.0113)	(0.0000)	(0.0002)
Poland	-8.2302%**	-5.59%***	-19.0132%***	-15.0379%***	-12.9598%***	-10.3319%**
	(0.0125)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0193)
Russia	-16.2923%***	-3.27%***	-7.3022%***	-12.4837%***	-5.1625%**	-6.2915%*
	(0.0000)	(0.0016)	(0.0000)	(0.0000)	(0.0443)	(0.0943)
Saudi Arabia	-2.9786%	3.76%	4.4285%***	6.7391%***	10.7909%***	20.0429%
	(0.2503)	(0.1400)	(0.0021)	(0.0004)	(0.0003)	(0.1036)
South Africa	-18.1698%***	-4.41%***	-3.6137%*	8.7737%***	9.7876%**	17.1228%***
	(0.0005)	(0.0048)	(0.0807)	(0.0027)	(0.0186)	(0.0077)
Turkey	-8.8238%*	-7.92%***	-6.2357%***	-15.0417%***	-19.3236%***	-14.1043%**
	(0.0547)	(0.0000)	(0.0073)	(0.0000)	(0.0002)	(0.0271)
Thailand	-8.5208%**	0.00%	-9.3024%***	-8.1328%***	-1.1769%	3.6060%
	(0.0425)	(.)	(0.0000)	(0.0005)	(0.7061)	(0.4683)
UAE	9.7713%	7.15%	-3.2485%**	3.2485%*	3.3071%**	7.5015%***

[12] The government announcement of lockdown in China was on January 23, 2020. From January 24, 2020, to February 2, 2020, the stock market in China was closed. The shutdown of Chinese stock market made the estimation result on the day following the event date unavailable and the estimation results over different cumulative event windows with the same value.

[13] The stock index data for Mexico on the event date and the day following the event date was unavailable.

	(0.2038)	(0.1023)	(0.0115)	(0.0015)	(0.0133)	(0.0012)
Group	-13.5306%***	-4.4645%***	-4.7641%***	-5.6357%***	-6.1028%***	-0.4705%
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2164)

Notes: (1) AR denotes abnormal return; (2) CAR denotes cumulative abnormal returns.

4.4 Discussions

The results from the event study method allows us to understand how stock markets are integrated and how they responded to big events with unprecedented occurrence, such as the COVID-19 pandemic. The evolution of stock market reactions to pandemic-enforced interventions suggests the learning behaviours of stock markets to novel events. From a Bayesian updating perspective, the learning behaviours of stock markets can be viewed as a process in which prior beliefs are updated in light of new information.

As China being the first global epicentre, the stock market's prior belief may have been that the economic impact would be limited to regional impacts in China or some Asian countries. This belief was reflected in stock prices, as the average reaction to China's lockdown announcement was not statistically significant. However, Italy's announcements of restrictive measures and national lockdown represented new and credible information about the contagiousness of the Coronavirus, as well as potential negative shocks on the economy due to halted operations and services. These announcements challenged market participants' prior belief of the inconsequentiality of the virus and led to a significant revision of expectations. Perceiving Italy's announcements as a signal that the economic impact of the pandemic would be significant, market participants withdrew from markets, resulting in sharp declines in stock prices. As more information about restrictive measures and potential impacts of the pandemic became available, market participants began to update their beliefs again. With lockdowns announced in several countries, the stock market response became relatively stabilised during the announcements of Germany and the US, reflecting that market participants had already expected such announcements and priced in the potential economic impacts of lockdowns. This updating process demonstrated the incorporation of new information into the market's prior beliefs, contributing to a gradual partial recovery in stock prices.

The finding of stock markets' learning behaviours provides empirical evidence for supporting the Adaptive Market Hypothesis (Lo, 2004; Lo, 2005) during the pandemic crisis. From information adaption to expectation adjustments, the learning process suggests that stock markets' responses to pandemic-enforced interventions during the initial stage of the pandemic are not entirely irrational, random, and sentiment-driven. Instead, the learning behaviours does not deny the rational component where market behaviours adjust to reflect the changing realities of the pandemic and pandemic-enforced interventions.

5. Conclusions

This chapter investigated stock market reactions to government announcements of lockdown and stringent restrictive measures. Adopting a combination of an event study method and panel data analysis, this research covered 29 developed and emerging countries and revealed that the stock market reacted significantly and negatively to the lockdown announcements and the increase in lockdown stringency. The development of global stock markets suggested adaptive learning behaviours, from initially overlooking China's lockdown announcement, to provoking panic in response to Italy's announcement of restrictive measures, to strongly reacting to Italy's lockdown announcement, to gradually stabilising in response to lockdown announcements of Germany and the US. From a Bayesian updating perspective, the overall "V-shaped" curves of the stock market returns demonstrate that the stock markets are adapting to novel events in the context of the pandemic. The learning process can be generally attributed to market participants' updates about their beliefs about incoming government responses of the German government and the US government to the pandemic based on prior information about Italy's announcements of restrictive measures and lockdown. It suggests that stock markets' responses to pandemic-enforced interventions were not entirely driven by sentiment, with the rational component playing a role.

The findings contribute to our understanding of the dynamics of stock market reactions to unprecedented events and the interplay between government interventions and investor sentiment. By examining a diverse range of developed and emerging countries, the adaptive learning behaviours in stock markets, indicating that while sentiment may affect market reactions, rational decision-making also plays a critical role. This finding highlights a nuanced interplay between emotion and reason in shaping market outcomes, advancing our knowledge of how financial markets respond to exogenous shocks. Furthermore, these insights provide valuable lessons for policymakers and investors as they navigate uncertain economic environments, emphasising the importance of balancing emotional responses with rational analysis in times of crisis.

This research recommends policymakers take a rational approach to managing significant health crises such as the COVID-19 pandemic. First, policymakers should consider the adaptive learning process of stock markets when implementing interventions in the context of managing public health crises and their economic consequences. As markets respond to new information and changing circumstances, policies should be flexible and responsive to evolving conditions. Secondly, policymakers are recommended to provide transparent and well-reasoned explanations for policy decisions to help investors make informed decisions, supporting rational decision-making by providing accurate information about the economic landscape. Thirdly, regular monitoring and assessment of market dynamics should be conducted to provide policymakers with timely information on how investors are processing and reacting to new information, informing more effective policy interventions and helping maintain market stability.

Although this chapter has attempted to demonstrate the stock market reactions to COVID-19 related government interventions, there are still other aspects that have not been fully examined. As the impacts of the COVID-19 pandemic and associated government interventions are sustained, future studies could investigate the impact of other interventions across a broader range of countries using newly composed datasets, which may provide valuable knowledge for the international community in the post-pandemic era.

Chapter 3 *Digitalisation and Resilience during the Initial Stage of the Pandemic: Evidence from European Countries*

1. Introduction

The COVID-19 pandemic has profoundly changed the operational conditions of industries on an unprecedented scale. Being restricted in their abilities to connect with customers and clients, industries have been forced to adapt and learn how to operate in a highly unstable and unpredictable environment by adjusting their productive capacities and growth expectations. Against this backdrop, resilience has been revealed and highlighted as one of the most fundamental characteristics of industries. According to Pike *et al*. (2013), resilience at the industry level is determined by the aggregate capacity of firms to ride out and adapt to disruptive changes, including recessions, crises, cyclical downturns, and radical innovations. Considered as a stress test for the resilience of different industries (Andreoni, 2021), the COVID-19 has affected industries' relationships with digitalisation by touting digitalisation as the principal path to resilience. According to Miceli *et al*. (2021), digitalisation enables the operations of significant business processes when unexpected events occur by allowing for remote collaboration and real-time connectivity, minimising the economic impact, and sustaining operational stability in both short- and medium-terms.

In light of the COVID-19 pandemic, researchers and practitioners have also become increasingly interested in the role of digitalisation in shaping the resilience of firms, sectors, and economies (Sheng *et al*. 2021; Bigot and Germon, 2021; Copestake *et al*., 2022). Despite the remarkable progress in theory and practice over the past few years, there remains considerable ambiguity about the role of digitalisation for resilience at the industry level. In this chapter, I investigated the role of the pre-pandemic digitalisation level in moderating the negative shocks from pandemic-induced lockdowns among European countries during the first and second waves of the COVID-19 pandemic (from 2020 Q1 to 2020 Q4). Both tangible and intangible aspects of digitalisation were covered to understand the moderating effect of digitalisation on the relationship between lockdown stringency and industry resilience. Additionally, I categorised industries based on their customer contact intensity to compare the differences in the moderating effect between non-contact-intensive and contact-intensive industries.

This chapter utilizes a comprehensive panel data approach combined with Instrumental Variables-Two Stage Least Squares (IV-2SLS) methodology to analyse the role of pre-pandemic digitalisation in moderating the effects of lockdown measures on industry resilience across various European countries. The data, drawn from multiple reliable sources, include industry-specific measures of digitalisation, lockdown stringency indices, and proxies for industry resilience during the initial stages of the pandemic. The empirical findings of this chapter suggest that digitalisation, in both tangible and intangible aspects, mitigate the negative impacts of lockdown stringency on industry resilience. Among contact-intensive industries, a higher level of investments in digitalisation coupled with lockdown stringency has a resilience-enhancing effect at a relatively stringent lockdown degree. The results are robust after using alternative indicators of digitalisation and industry resilience and accounting for endogeneity issues of lockdown stringency and digitalisation.

In this chapter, the role of digitalisation in fostering industry resilience during pandemic times was examined, contributing to the existing literature in several ways. Previous studies have mostly focused on firm-level evidence (e.g., Copestake *et al*, 2022; Abidi *et al*., 2021) and cross-country evidence (e.g., Comin *et al*., 2022), with limited analysis at the industry level. By investigating the role of the pre-pandemic digitalisation levels on industry resilience, this research offers valuable insights at the industry level. Additionally, this research contributes to this line of literature by using the real value of investments in digital technologies, rather than categorical variables, as proxies for digitalisation. This approach captures both the tangible and intangible aspects of digitalisation. Furthermore, the findings provide empirical evidence that the moderating effect of digitalisation on industry resilience is more profound for contact-intensive industries than for non-contact-intensive industries, highlighting the importance of tailoring policies to account for this distinction.

The remainder of this chapter is organised as follows. Section 2 provides a comprehensive review of the literature on digitalisation and resilience, identifying research gaps and presenting the hypotheses of this chapter. Section 3 discusses the methodology and data used in the empirical analysis. In Section 4, the empirical results are presented and discussed, with a specific focus on the role of digitalisation on the relationship between lockdown stringency and industry resilience, with a group of robustness checks elaborated upon in Section 5. This chapter concludes with a summary of main findings and their implications for future research on resilience and digitalisation.

2. Literature Review

2.1 Theoretical Concepts about Resilience

The COVID-19 pandemic has provided us with an opportunity to enhance our preparedness for future crises of various magnitudes. The pandemic reminds policymakers and researchers that shocks, either predictable or unexpected, are unavoidable. As a result, recent discourse has increasingly emphasized the importance of resilience as a means to withstand and recover from these interruptions (Walker, 2020). The emphasis involves investigations into how nations, societies, industries, and organisations can be shaped to develop the capacity to confront and adapt to severe and inevitable shocks, fostering resilience during the pandemic and beyond (Brunnermeier, 2021; Walker, 2020). Unlike robustness, which focuses on the ability to resist change when faced with disturbances, resilience refers to the capacity to rebound through adaptation and evolution in response to disruptions (Walker, 2020; Brunnermeier, 2021). Resilience is distinguished from robustness in its focus on flexible adaptation rather than structural unchanging resistance (Brunnermeier, 2021). Resilience encompasses technological, institutional, and behavioural dimensions, implying an active response to mitigate the impact of shocks (Laczkowski *et al*., 2019).

Digitalisation, defined as the use of digital technologies to modify business processes, culture, customer experiences, insights, and decision-making (speed and cost), is a crucial pillar enabling agility and resilience across multiple levels (Postolea and Bodea, 2021). By generating real-time data accessibility and insights, digitalisation facilitates rapid and informed adaptations to changing market conditions and unforeseen challenges (Postolea and Bodea, 2021). In times of uncertainty and disturbance, digitalisation empowers industries to cope with shocks brought by the pandemic and associated restrictive measures, by fostering remote working and operations and providing direct and constant access to clients and customers (Postolea and Bodea, 2021; Santos *et al*., 2023). Greater information velocity from digitalisation contributes to more flexible and resilient organizational and industry structures and strategies. Therefore, digital transformation and its data-driven capabilities are key enablers of adaptive resilience across operational and strategic dimensions.

2.2 Empirical Literature on Digitalisation and Resilience in the Global Pandemic Context

The COVID-19 pandemic has profoundly affected the way how various industries operate and react to business demands (Brodeur *et al.*, 2020; Abidi *et al.*, 2021). Recent research has identified factors that explain the heterogeneities in business performance resilience during the COVID-19 pandemic, with digitalisation touted as the principal pathway for facilitating economic resilience (Dabla-Norris *et al*., 2023; Abidi *et al*., 2021). By facilitating the absorption and response to shocks (Lopez-Gomez *et al*., 2021), digital technologies enable different industries to customize their services and rearrange business operations in accordance with relevant distancing guidelines and lockdown measures (Heredia *et al*., 2022; Santos *et al*., 2023). Recent evidence on the increased use of digital technologies in response to the global pandemic supports the notion that the pandemic reinforced the idea that the pandemic has amplified the value of digitalisation (Harasztosi and Savšek, 2022; Lavopa and Zagato, 2022). Apedo-Amah *et al*. (2022) investigated how firms had become increasingly relying on digital technologies to deal with the negative shocks brought on by the COVID-19 pandemic.

They argued that the mitigating effect of digitalisation was more substantial for large-sized firms than small- or medium-sized ones (Apedo-Amah *et al*., 2022).

Emerging studies have empirically extended our knowledge of the relationship between digitalisation and economic resilience during the global pandemic. Pierri and Timmer (2020) revealed the role of information technology adoption in shielding the US economy from the pandemic's impact of the. They documented that the unemployment rate was lower in areas with higher information technology adoption in response to social distancing measures (Pierri and Timmer, 2020).

In addition, much of the current literature on digitalisation and resilience in the backdrop of the global pandemic focuses on firm-level evidence. For instance, Comin *et al*. (2022) examined the positive impact of pre-pandemic technological sophistication on firms' sales performances in the manufacturing sector of Brazil, Senegal, and Vietnam during the COVID-19 pandemic. With a broader scope, Abidi *et al*. (2021) found that firms in manufacturing and service industries with a higher level of digitalisation adoption experienced fewer sales losses during the pandemic in 13 Middle Eastern and Central Asian economies. Shifting research scope to firms in a developed market, Burgel *et al*. (2023) concluded that the positive impact of pre-pandemic digitalisation on firm resilience among German entrepreneurial firms was conditional on a firm's exposure to globalisation, such as overseas competition and international trade, rather than universally applicable.

While these studies collectively indicate a positive relationship between digitalisation and resilience in general, they are subject to at least three limitations. First, their data collection exercises are country- or region-specific, failing to provide a consistent picture of the investments in and adoption of digital technologies across both developed, emerging, and developing economies. The findings would have been more convincing if these studies employed consistent measures of investments in digital technologies. Secondly, studies to date have primarily relied on binary or categorical measures of the tangible aspects of digital technologies, such as website use and communication tool use, while overlooking the intangible aspects of digital technologies, such as computer software and databases. Research on digitalisation and resilience might yield more accurate results by using true values of investments in both tangible and intangible aspects of digitalisation. Thirdly, a major drawback of the existing firm-level studies is the narrow focus on the general manufacturing and/or service industries. Despite digitalisation being considered as one of the key drivers of economic resilience, empirical evidence on its adoption and use by different industries in developed and emerging European countries remains limited. A more comprehensive study would adopt available data for all industries, with a meso-level scope, to investigate the association between digitalisation and resilience in response to the global pandemic. Employing available industry-level data, this research aims to investigate the moderating effect of digitalisation on the negative shocks brought by lockdown measures to foster industry resilience in the early stages of the COVID-19 pandemic.

The containment measures induced by the COVID-19 pandemic has impaired the abilities of industries making contributions to economic growth.

3. Data and Methodology

This section outlines the dataset and methods adopted. First, the sources of data and the construction of the used dataset are discussed. Secondly, the methodology adopted to conduct this empirical chapter is elaborated upon.

3.1 Data and Sources

Following Abidi *et al*. (2020), I used the quarterly changes in gross value added (as a percentage of gross domestic product) by industry in 2020, compared with the corresponding period in 2019, to characterise industry resilience. The quarterly gross value added were compiled from the National Statistical Institutes of sample countries, which was seasonally adjusted and working day adjusted. The industries covered in this study is listed in Appendix 3.2. As shown in Table 1, during the first two waves of the COVID-19 pandemic, resilience across industries varied significantly, driven by the inherent characteristics of each industry and their ability to adapt to the rapidly changing environment. Industries such as accommodations and hospitality encountered severe disruptions due to travel restrictions, mandatory closures, and reduced consumer spending, experiencing approximately 60% decline in gross value added, compared to the corresponding periods in 2019. On the other hand, industries like information and technology demonstrated high resilience as they were able to maintain or even increase their operations despite the challenging circumstances, as evidenced in the 5% increase in gross value added, compared to the corresponding periods in 2019. Additionally, the broad spectrum of resilience across industries, as demonstrated in the nearly 10% standard deviation in value added change, during the pandemic highlights the importance of industry-specific factors, such as the ability to continue operations under restrictions and the level of consumer demand, in determining how well different sectors could withstand the shocks of the pandemic.

I employed the stringency index from the Oxford COVID-19 Government Response Tracker to proxy for the strictness of lockdown measures implemented in each sample country. Aggregating the strictness of nine different containment measures, the stringency index computes the average intensity of school closures, workplace closures, public event cancellations, gathering restrictions, public transport closures, stay-at-home requirements, internal movement restrictions, international travel controls, and public information campaigns, with 100 denoting the most stringent government responses and 0 denoting the least stringent responses (OxCGRT, 2021). I computed the quarterly average of each sample country's stringency index to characterise the stringency level of lockdown measures. On average, sample European countries implemented relatively strict lockdown measures, with a mean of 53, during the early stages of the pandemic.

Given the substantial heterogeneities and nuances of each sample country's pre-pandemic level of digital adoption in both tangible and intangible aspects, I retrieved data of investment expenses in computing equipment, communication equipment, and computer software and databases from the EUKLEMS and INTANProd 2021 database. Widely used in industry-level analysis, the EUKLEMS data features original insights of industry growth and productivity based on the NACE rev. 2 classification (Stehrer, 2021). Computing equipment represents the physical hardware necessary for enabling remote work and maintaining digital operations. Industries with significant investments in computing equipment are better equipped to ensure business continuity through enhanced digital capabilities. Communication equipment, another tangible aspect of digitalisation, reflects the industry's capacity to maintain effective communication, both internally among employees and externally with customers and partners. High investments in communication equipment are indicative of an industry's ability to sustain operations and collaboration in a distributed work environment. As for intangible aspect of digitalisation, computer software and databases capture the industry's ability to manage, process, and utilise digital information effectively. Investments in software and databases are critical for data-driven decision-making, automation, and maintaining customer engagement, which are vital for resilience during periods of disruption. Together, these three proxies provide a comprehensive measure of digitalisation, capturing the physical, communicative, and data-driven capabilities that are critical for assessing the extent to which digitalisation has been integrated into industry operations and how well-prepared industries were to withstand the shocks induced by the pandemic.

Considering the differences in investment expenses in these digital adoptions, I constructed the shares of these digitalisation investments in capital stock net. For tangible assets, I constructed the share of computing equipment in net capital stock and the share of communications equipment in net capital stock, respectively. For intangible assets, I constructed the share of computer software and databases in net capital stock. In general, industries with the greatest investments in both tangible and intangible digitalisation are distributed in information and communication, financial and insurance activities, and professional, scientific, and technical activities across the sample European countries. Detailed information about the industries whose investments in digitalisation are among the top 10% are reported in Appendix 3.3.

Although the shocks from COVID-19-induced lockdown are exogenous to industry conditions, an industry's pre-pandemic investment level of digitalisation adoption is not an orthogonal process. Therefore, industry-level factors that simultaneously impact value added by industry and the decision to invest in digital technologies were controlled. These industry-level factors include the size of capitals, innovation, formal training for employees, and the skill composition of workers. In terms of the size of capitals, one can conjecture that high levels of investments in digital technologies require a non-negligible number of capitals that could be allocated principally through investments (Abidi *et al*., 2021). To account for this factor, the variable of total assets by industry as a proxy for the size of capitals by industry is introduced, transformed into natural logarithms. Previous empirical evidence indicates that adoptions of digital technologies coincided with innovation as well (Harasztozi *et al*., 2023; Bloom *et al*., 2014; Bartel *et al*., 2007). To estimate the effects of innovation, I included the share of research and development expenditures in net capital stock by industry as a proxy variable for innovation. As in Abidi *et al*. (2021), the promising performances of industries depend on workers or employees with proper digital skills at work, which requires investments in formal training and labour with good education qualifications. Therefore, I incorporated the variables for the share of formal training in capital stock net for employees and the share of labour with high education qualifications to account for these effects. These variables were collected and compiled from the EUKLEMS and INTANProd 2021 database as well.

The lagged form of quarterly value added by industry (in natural logarithms) was included to account for dynamic effects. Country-level macroeconomic variables, including GDP per capita at constant prices (in natural logarithms), debt-to-GDP ratio, and inflation rate were controlled in the specifications as well.

To evaluate how pre-pandemic digital technology adoption influences industry-level resilience among European countries, this research covers twenty European countries with available data. These countries include Austria, Belgium, Czechia, Denmark, Estonia, Finland, France, Germany, Hungary, Ireland, Italy, Latvia, Malta, the Netherlands, Poland, Portugal, Slovakia, Slovenia, Sweden, and the United Kingdom.

Following Copestake *et al*. (2022) and Wu *et al*. (2024), the variables had been winsorized at the 1st and 99th percentiles to eliminate outliers, with descriptive statistics and definitions of the variables reported in Table 1 and Appendix 3.1, respectively. Appendix 3.4 reports the correlations between each pair of variables. With no multicollinearity issues are diagnosed at the 0.10 significance level, these variables retained in the following analysis. Additionally, I computed the Variance Inflation Factors, yielding a value of 6.64. According to a rule of thumb (6.64<10.00), no significant multicollinearity issue was detected. Considering the test power implications for our analysis, which involves a relatively large number of panels and relatively small number of time dimensions (Hlouskova and Wagner, 2005), I conducted the Harris–Tsavalis test on the variables to examine stationarity, with results reported in Appendix 3.5. The extremely small p-values allow for the rejection of the null hypothesis of a unit-root and therefore the tested variables are stationary.

Table 1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max

Country-industry level					
Resilience (%)	1022	-4.315	9.956	-64.4	4.867
Computing equipment	872	0.043	0.033	0	0.143
Communication equipment	872	0.046	0.035	0	0.199
Computer software and databases	886	0.116	0.123	0	0.622
Capitals	908	9.312	2.117	4.892	15.184
Research & development	888	0.072	0.109	0	0.479
Training	924	0.099	0.08	0	0.436
Education	990	0.036	0.006	0.012	0.051
Value added of 2019	1022	9.64	2.1	4.92	14.578
Country level					
Lockdown	1022	53.41	15.76	18.948	82.152
GDP	1022	10.329	0.521	9.218	11.355
Inflation	1022	0.009	0.012	0.004	0.034
Debt	1022	0.953	0.525	0.243	1.908

3.2 Empirical Methods

Following Pierri and Timmer (2021), I used the following regression specification to evaluate the impact of pre-pandemic digitalisation levels on industry resilience to the COVID-19 pandemic in the context of government response:

$$\begin{aligned} Industry\ resilience_{c,i,t} &= lockdown_{c,i,t} + digitalisation_{c,i,t} + lockdown_{c,i,t} * digitalisation_{c,i,t} \\ &+ Z_{c,i,t} + \mu_{c,i} + \mu_t + \epsilon_{c,i,t} \end{aligned}$$

where c, i, and t index country, industry, and time, respectively. $Industry\ resilience_{c,i,t}$ denotes the quarterly changes in value added of a country (as a per centage of GDP) by industry. $stringency\ index_{c,i,t}$ is the quarterly average of the stringency index that an industry of a country adheres to. $digitalisation_{c,i,t-1}$ includes the measures of the share of computing equipment in capital stock net, the share of communication equipment in capital stock net, the share of computer software and database in capital stock net of industry i in country c in 2019. $Z_{c,i,t}$ is an array of control variables, including the size of capitals, the share of research and development activities in capital stock net, the share of investments in formal training for employees, the share of labour with high education qualifications, and the gross value added in 2019 (in natural logarithms) of industry i in country c. Macroeconomic variables including inflation rate, debt to GDP ratio, GDP per capita (in natural logarithms) are controlled as well. $\mu_{c,i}$ and μ_t represent the country-industry fixed effects and time fixed effects, respectively. Specifically, I opted for country-industry fixed effects over industry fixed effects[14] due

[14] I ran the specification with pure industry fixed effects and time fixed effects as well. The directions of the coefficients of our main variables remained the same as specification with country-industry fixed effects and time fixed effects.

to established heterogeneities in country-industry competitive advantages, such as hourly intensity between western and central European industries, that may potentially affect industry performance (Giordano and Lopez-Garcia, 2019). I employed a Hausman test to determine the suitability of a fixed effects model versus a random effects model as well. With a p-value of 0.0312, I rejected the null hypothesis that the difference in coefficients is not systematic and adopted the model with fixed effects.

The conventional panel data approach was employed in the analysis for the following reasons. First, adopting panel data analysis enables the examination of lockdown stringency and the interaction effects between lockdown stringency and digitalisation over an intended period, properly corresponding to the development and evolvement of the pandemic-enforced interventions. Secondly, applying panel data analysis allows for the appropriate identification of the time-varying relationship between dependent variable and independent variables (Wooldridge, 2010). Thirdly, panel data analysis helps to control and alleviate issues such as individual heteroscedasticity, multicollinearity issues, and estimation bias (Baltagi, 2008).

4. Estimation Results and Empirical Analysis

This section presents estimation results of the relationship between lockdown stringency and industry resilience conditional on different digitalisation investments during the early stages of the COVID-19 pandemic. The baseline results in Table 2will be discussed first, followed by a group of robustness checks.

4.1 Baseline Estimation Results

Lockdown stringency enters significantly and negatively on industry resilience during the first and second waves of Coronavirus spread, see Column (1) of Table 2. Significant at 1%, this result suggests that industries experience decreased resilience as lockdown measures intensified.

Table 2: Estimation results of baseline analysis

	(1)	(2)	(3)	(4)
VARIABLES	Resilience	Resilience	Resilience	Resilience
Lockdown	-0.0577***	-0.230***	-0.220***	-0.213***
	(0.0218)	(0.0629)	(0.0755)	(0.0503)
IT		164.5***		
		(60.67)		
Lockdown#IT		0.259***		
		(0.097)		

CT			117.6*	
			(65.33)	
Lockdown#CT			0.212*	
			(0.109)	
DB				90.56
				(93.02)
Lockdown#DB				0.341*
				(0.184)
Capitals	1.241*	0.430	0.123	1.429***
	(0.651)	(0.589)	(0.536)	(0.279)
RD	2.452	0.304	0.667	2.185
	(3.076)	(4.565)	(4.841)	(3.970)
Training	-5.114	-38.66	-40.69	-31.01
	(8.727)	(27.64)	(28.46)	(22.27)
Education	7.779	0.966	11.419	20.805**
	(6.583)	(7.744)	(8.211)	(10.196)
Inflation	-366.0***	-731.3***	-798.9***	-650.0***
	(72.90)	(149.9)	(156.9)	(112.5)
Debt	-7.886***	-8.886***	-8.622***	-9.516***
	(2.609)	(2.345)	(2.372)	(2.241)
GDP	-6.158***	-8.512***	-8.293***	-11.58***
	(1.752)	(1.911)	(1.913)	(2.551)
VA_2019	-0.569	-0.454*	-0.414*	-0.100
	(0.657)	(0.267)	(0.243)	(0.523)
Constant	71.35***	117.8***	118.0***	141.2***
	(18.25)	(22.18)	(23.86)	(28.81)
Observations	904	852	852	864
R-squared	0.314	0.663	0.692	0.616
Country_Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Notes: (1) Robust standard errors in parentheses; (2) *** p<0.01, ** p<0.05, * p<0.1.

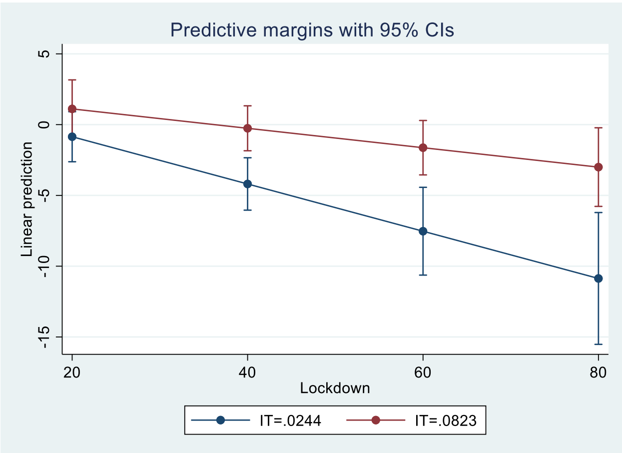
4.2 Introducing Interactions between Lockdown Stringency and Digitalisation

Considering the adverse impacts of the lockdown measures induced by the pandemic on industry performance, it is expected that industries with advanced levels of pre-pandemic digitalisation would be less affected by the negative shocks brought by lockdown measures. I evaluated industry resilience to lockdown measures as functions of these pre-pandemic digitalisation traits.

With the interaction term between lockdown stringency and the share of computing equipment in capital stock net, the coefficient of the interaction term is positive and statistically significant on industry resilience, see Column (2) of Table 2. The coefficient indicates that a one standard deviation increase in the share of computer equipment (0.033) would reduce the negative resilience response to lockdown stringency (with a mean of 53.41) by 0.456 percentage points (0.259*0.033 *53.41=0.456). This suggests a moderating effect of investments in computing equipment on the relationship between lockdown stringency and industry resilience, indicating that industries with greater investments in computing equipment are more resilient to negative effects brought by lockdown measures, compared with those with fewer investments in computing equipment.

Figure 1 visualises the moderating effect of investments in computing equipment on the relationship between lockdown stringency and industry resilience. With a 95% confidence interval, a higher level of investments in computing equipment coupled with lockdown stringency has a resilience-enhancing effect at stringency levels at and above 40.

Figure 1: The relationship between lockdown stringency and industry resilience conditional on the share of computing equipment

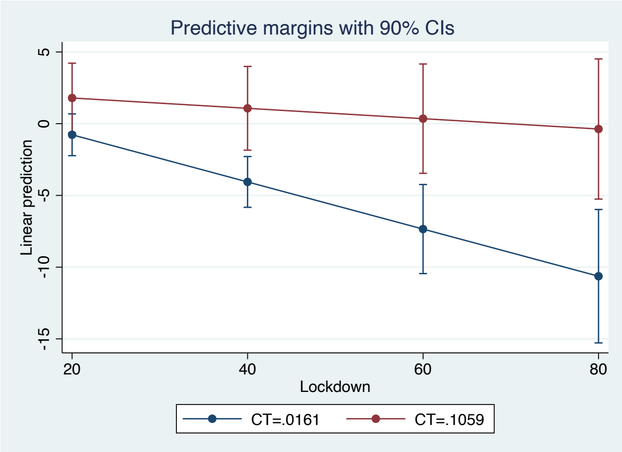


Notes: the values of IT (the share of computing equipment in capital net stock) are taken at the 10th and 90th centile of the variable's distribution.

The coefficient of the interaction between lockdown stringency and the share of communication equipment in capital stock net is positive and statistically significant at 10%, see Column (3) of Table 2. This result shows that the negative effect of lockdown stringency on resilience is lower in industries with greater investments in communication equipment. With a one standard deviation increase in the share of communication equipment (0.035), the negative resilience response to lockdown stringency (with a mean of 53.41) reduces by 0.396 percentage points (0.212* 0.035*53.41=0.396).

Figure 2 graphically demonstrates the relationship between lockdown stringency and industry resilience, which is conditional on investments in communication equipment. The difference in industry resilience between industries of high-digital intensity and low-digital intensity is marginally significant with a confidence interval of 90%, when lockdown stringency is at and above 40.

Figure 2: The relationship between lockdown stringency and industry resilience conditional on the share of communication equipment

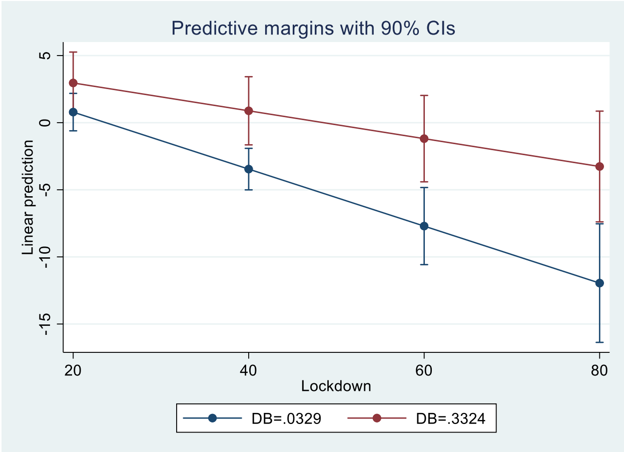


Notes: the values of CT (the share of communication equipment in capital net stock) are taken at the 10th and 90th centile of the variable's distribution.

Column (4) of Table 2 reveals how the effect of lockdown stringency on industry resilience varies with the level of investments in computer software and databases. The positive and significant coefficient of the interaction term indicates that a one standard deviation increase in the share of computer software and databases (0.123) would reduce the negative resilience response to lockdown stringency (with a mean of 53.41) by 2.368 percent points (0.341*0.123*53.41=2.368). This suggests that industries with greater investments in computer software and databases suffer less from lockdown measures than those with fewer investments in computer software and databases.

The positive interaction effect is illustrated in Figure 3. With relatively stringent lockdown measures (at and above 40), we observe that industries with greater investments in intangible digitalisation experience less pronounced negative effect of lockdown than those with fewer investments.

Figure 3: The relationship between lockdown stringency and industry resilience conditional on the share of computer software and databases



Notes: the values of DB (the share of computer software and databases in capital net stock) are taken at the 10th and 90th centile of the variable's distribution.

In summary, the estimation results in Table 2 reveal that industries with greater pre-pandemic digitalisation investments, both in tangible and intangible aspects, are more resilient to negative shocks brought by lockdown measures during the early stages of the COVID-19 pandemic. Lockdown-induced drops in industry value added have been milder among industries with greater pre-pandemic investments in computing equipment, communication equipment, and computer software and databases.

4.3 Differences between Contact-Intensive Industries and Non-Contact-Intensive Industries

Compared with non-contact-intensive industries, contact-intensive industries with digitalisation constraints are expected to face increasing difficulties in responding to their customers and clients, which would adversely affect industry total outputs. I c categorised industries into contact-intensive industries and non-contact-intensive industries based on industry contact intensity classification published by the International Monetary Fund (2022), see more details in Appendix 3.2. I constructed a dummy variable of industry group to classify the sample, with 1 denoting contact-intensive industries and 0 denoting non-contact-intensive industries. From a statistical standpoint, I also conducted Chow tests to examine whether there is structural difference between non-contact-intensive industries and contact-intensive industries with the three digitalisation indicators. The extremely small p-values of the Chow F statistics[15] led to the rejection of the null hypothesis of equal coefficients between these two industry groups for these three digitalisation indicators. The results demonstrate the presence of structural differences between these two industry groups.

[15] The Chow F statistics for IT, CT, and DB as digitalisation indicators were found to be 9.23 (with a p-value of 0.0000), 9.42 (with a p-value of 0.0000), and 5.59 (with a p-value of 0.0000), respectively.

By introducing the three-way interaction terms of lockdown stringency, investments in digitalisation, and industry group, I investigated whether the moderating effect of digitalisation on the relationship between lockdown stringency and industry resilience varies between contact-intensive industries and non-contact-intensive industries. Estimation results with three-way interaction terms are reported in Table 3.

Table 3: Estimation results by industry group

	(1)	(2)	(3)
VARIABLES	IT	CT	DB
Lockdown	-0.0710	-0.104	-0.0530
	(0.0605)	(0.0674)	(0.0462)
IT	-67.23		
	(49.21)		
Lockdown#IT	0.827		
	(0.793)		
Industry_group	118.7*	43.50*	5.303
	(64.82)	(25.75)	(7.456)
Industry_group#Lockdown	-3.571**	-1.329**	-0.263
	(1.487)	(0.587)	(0.174)
Industry_group#IT	-2.762*		
	(1,501)		
Industry_group#Lockdown#IT	8.135**		
	(3.404)		
CT		-75.68	
		(56.95)	
Lockdown#CT		1.489	
		(0.982)	
Industry_group#CT		-779.1*	
		(453.0)	
Industry_group#Lockdown#CT		2.297**	
		(1.019)	
DB			9.481
			(88.78)
Lockdown#DB			0.509
			(1.296)
Industry_group#DB			-540.8
			(454.3)
Industry_group#Lockdown#DB			13.42
			(8.960)
Capitals	2.125	1.146	-1.804
	(1.463)	(1.719)	(3.294)
RD	18.09*	7.405	11.46

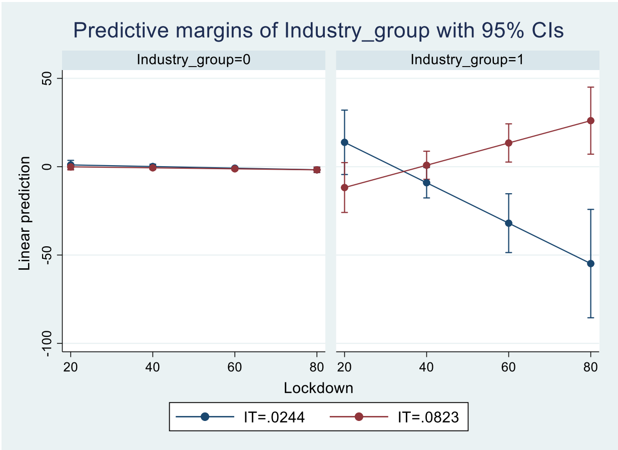
	(10.06)	(9.783)	(7.039)
Training	69.47	22.72	67.86**
	(44.71)	(38.33)	(32.61)
Education	313.405	183.672	497.915**
	(189.812)	(239.065)	(235.037)
Inflation	-822.3***	-494.1**	-324.7***
	(229.6)	(213.8)	(89.12)
Debt	-4.508	-6.020**	-8.768**
	(3.067)	(2.986)	(3.392)
GDP	-6.233*	-4.639*	-7.820***
	(3.230)	(2.570)	(2.522)
VA_2019	-4.358*	-1.969	2.258
	(2.193)	(1.985)	(3.464)
Constant	85.60***	63.30**	67.80***
	(30.75)	(25.87)	(23.57)
Observations	852	852	864
R-squared	0.719	0.732	0.555
Country-Industry FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: (1) Robust standard errors in parentheses; (2) *** p<0.01, ** p<0.05, * p<0.1.

In Column (1) of Table 3, the coefficient of the three-way interaction term of lockdown stringency, investments in computing equipment, and industry group is positive and significant, at the 5% significance level. This result indicates that the moderating effect of investments in computing equipment is significantly greater for contact-intensive industries than for non-contact-intensive industries.

Figure 4 illustrates this three-way interaction effect by showing how the lockdown slope changes from negative to positive as increasing investments in computing equipment for both non-contact-intensive industries and contact-intensive industries. For contact-intensive industries, the lockdown slope with greater investments in computing equipment is statistically different from the one with fewer investments in computing equipment when lockdown measures are relatively stringent (at and above 60, as shown in the x-axis of with industry group denoting 1). For non-contact-intensive industries, the lockdown slopes are not statistically different with changes in investments in computing equipment regardless of lockdown stringency. These observations reveal that the moderating effect of computing equipment on the relationship between lockdown stringency and industry resilience varies between contact-intensive industries and non-contact-intensive industries.

Figure 4: The relationship between lockdown stringency and industry resilience conditional on the share of computing equipment by industry group

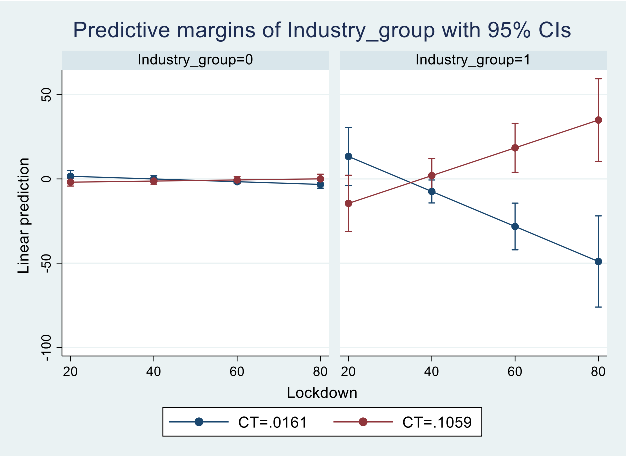


Notes: the values of IT (the share of computing equipment in capital net stock) are taken at the 10th and 90th centile of the variable's distribution.

The coefficient of the three-way interaction term of lockdown stringency, investments in communication equipment, and industry group, as reported in Column (2) of Table 3, is positive at a significance level of 5%. This result suggests that the effect of lockdown stringency on industry resilience as a function of investments in communication equipment is significantly greater for industries of high contact intensity than the others.

Figure 5 depicts the lockdown impacts on industry resilience as a function of investments in communication equipment by dimension of industry group. A moderating effect of investments in communication equipment on lockdown slopes for both contact-intensive industries and non-contact-intensive industries can be observed. For contact-intensive industries, there is a statistically significant difference in the relationship between lockdown stringency and industry resilience when comparing scenarios with higher and lower investments in communication equipment under strict lockdown measures (at and above 60, as shown on the X-axis with industry group denoted as 1). This finding suggests that the moderating effect of communication equipment on the relationship between lockdown stringency and industry resilience varies among industries based on the level of contact intensity.

Figure 5: The relationship between lockdown stringency and industry resilience conditional on the share of communication equipment by industry group

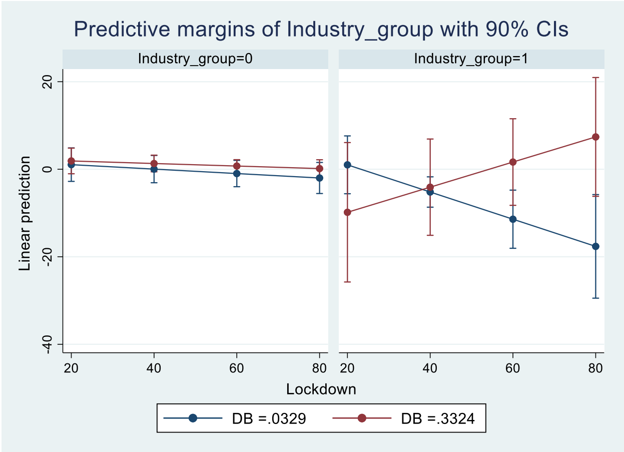


Notes: the values of CT (the share of communication equipment in capital net stock) are taken at the 10th and 90th centile of the variable's distribution.

As reported in Column (3) of Table 3, although the three-way interaction term of lockdown stringency, investments in computer software and databases, and industry group is positive, the interaction is statistically significant.

While the average effect is not significant, Figure 6 visualises the moderated relationship between lockdown stringency and industry resilience by comparing high- and low-digital intensities in computer software and databases between non-contact-intensive industries and contact-intensive industries. Given the overlaps between confidence intervals when plotting the conditional effect of investments in computer software and databases on the lockdown stringency-resilience relationship, the differences in the impact of this digitalisation measure are not statistically significant for low- and high-digital intensity industries. Nevertheless, it can be observed that investments in computer software and databases exhibit a mitigating effect on the negative shocks from lockdown stringency in both non-contact-intensive and contact-intensive industries.

Figure 6: The relationship between lockdown stringency and industry resilience conditional on the share of computer software and databases by industry group



Notes: the values of DB (the share of computer software and databases in capital net stock) are taken at the 10^{th} and 90^{th} centile of the variable's distribution.

While the concept of resilience is crucial for understanding how industries responded to the COVID-19 pandemic, it is essential to acknowledge that the pandemic's impact on various sectors was not solely a function of their resilience. The pandemic induced sector-specific shocks that were largely independent of pre-existing resilience levels. For example, the healthcare sector experienced a dramatic surge in demand for services and products, leading to an unprecedented boom, while other sectors, such as travel and hospitality, were almost entirely shut down by government restrictions and public health concerns, rendering traditional resilience measures less effective. This divergence in sectoral/industrial experiences across countries raises questions about the limitations of resilience as a singular explanatory variable. In some industries, like information and communication as well as human health and social work activities, the pandemic created favorable conditions that allowed these industries to thrive, driven by a significant increase in demand. Conversely, in industries like accommodation, where operations were severely curtailed due to lockdowns and travel bans, no level of pre-pandemic digitalisation or other resilience investments could have prevented the massive losses incurred.

While it is important to acknowledge that sector-specific demand shocks could have significantly influenced industry outcomes during the pandemic, this study primarily focuses on resilience as captured by digitalisation and its interaction with lockdown measures. Although these shocks are a critical factor in understanding the broader landscape of pandemic-induced sectoral shifts, the current analysis is constrained by the lack of relevant data to effectively incorporate these variables. Therefore, the research maintains its focus on digitalisation and lockdown stringency as key determinants of resilience, recognizing that future studies may benefit from a more comprehensive dataset to explore the complex relationship between resilience, sector-specific shocks, and overall economic performance during the pandemic.

5. Robustness Checks

In this section, I conducted three robustness checks to ensure the validity of the previous empirical arguments. First, I replaced the indicators of digitalisation with an alternative digitalisation index by using Principal Component Analysis (PCA). Secondly, I alternatively used resilience deviation to characterise resilience. Thirdly, I addressed the endogeneity issues in lockdown stringency and digitalisation by using the Instrumental Variable – Two Stage Least Squares (IV-2SLS) approach.

5.1 Using an Alternative Proxy for Pre-Pandemic Digitalisation Level

5.1.1 The Moderating Effect of Digitalisation on the Relationship between Lockdown Stringency and Industry Resilience

Digitalisation is a multidimensional process (Abidi *et al*., 2021). In this sense, one may believe that analysing the effects of investments in computing equipment, communication equipment, and software and database separately in specifications do not fully reflect the picture of digitalisation. I used the PCA to construct an alternative indicator of digitalisation that features the pre-pandemic investment level of assorted digital technologies, with detailed results of PCA reported in Appendix 3.7. As a widely used dimensionality-reduction method (Abdi and Williams, 2010; Bro and Smilde, 2014), PCA is employed to transform the previously adopted digitalisation variables into an index that contains most of the information about investments in different categories of digitalisation. Estimation results using this alternative digitalisation index are reported in Column (1) of Table 4. As in the baseline results, lockdown stringency enters significantly and negatively on industry resilience. The coefficient of the interaction term between lockdown stringency and the alternative digitalisation index is positive at a 5% significance level.

Table 4: Estimation results by using an alternative indicator of digitalisation

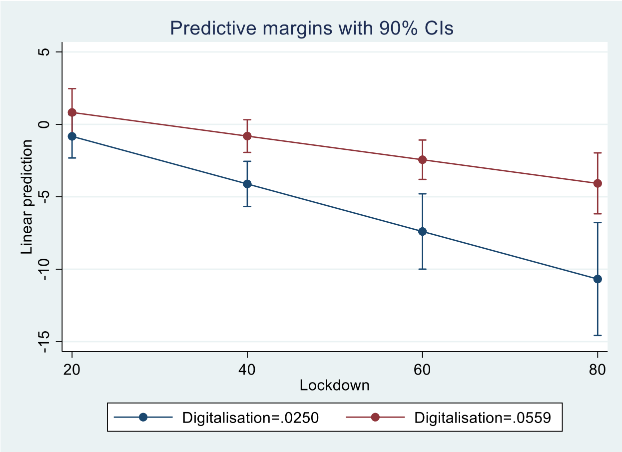
	(1)	(2)
VARIABLES	Industry resilience	Industry resilience
Lockdown	-0.231***	0.00948
	(0.0654)	(0.0308)
Digitalisation	170.7**	58.07
	(66.14)	(45.78)
Lockdown#Digitalisation	2.674**	0.977
	(1.075)	(0.683)
Industry_group		-9.880

		(6.875)
Industry_group#Lockdown		0.269*
		(0.137)
Industry_group#Digitalisation		-969.2*
		(554.5)
Industry_group#Lockdown#Digitalisation		29.00**
		(12.51)
Capitals	0.438	1.678
	(0.591)	(1.306)
RD	0.199	11.95
	(4.642)	(12.59)
Training	38.62	43.20
	(27.60)	(46.83)
Education	0.911	201.1
	(0.755)	(210.1)
Inflation	-725.4***	-625.4***
	(149.0)	(216.7)
Debt	-8.845***	-5.313*
	(2.356)	(2.717)
GDP	-8.570***	-5.161*
	(1.934)	(2.856)
VA_2019	-0.368	-3.127
	(1.213)	(1.915)
Constant	121.922***	66.70**
	(18.744)	(28.20)
Observations	828	828
R-squared	0.654	0.638
Country_Industry FE	Yes	Yes
Time FE	Yes	Yes

Notes: (1) Robust standard errors in parentheses; (2) *** p<0.01, ** p<0.05, * p<0.1

Figure 7 demonstrates the moderating effect of the alternative digitalisation index on the relationship between lockdown stringency and industry resilience. When lockdown stringency is at and above 40, there is a significant difference in lockdown slopes with different levels of digitalisation investment. Industries with greater investments in digitalisation have a higher resilience than those with lower investments in digitalisation, supporting the previous conclusion about the moderating effect of digitalisation on the relationship between lockdown stringency and industry resilience.

Figure 7: The relationship between lockdown stringency and industry resilience conditional on an alternative digitalisation index



Notes: the values of Digitalisation are taken at the 10th and 90th centile of the variable's distribution.

5.1.2 Differences between Contact-Intensive Industries and Non-Contact-Intensive Industries

With this alternative digitalisation index derived from PCA, I investigated potential differences in the moderating effect of digitalisation on the lockdown-resilience relationship between industries of different contact intensities. The extremely small p-value of the Chow F statistic (11.85)[16] suggests that there are structural differences between non-contact-intensive industries and contact-intensive industries when using the alternative digitalisation index derived from PCA. Following a similar estimation strategy, I used a three-way interaction term of lockdown stringency, the alternative digitalisation index, and an industry group dummy in the specification, with results reported in Column (2) of Table 4.

The coefficient of the three-way interaction term is positive and significant at 5%, suggesting that the interacting effect of lockdown stringency and digitalisation is different across different industry groups. Figure 8 illustrates the relationship between lockdown stringency and industry resilience conditional on this alternative digitalisation indicator by industry group. For non-contact-intensive industries, there is no statistical difference in industry resilience between industries with low- and high-digitalisation investments at different levels of lockdown stringency. Among contact-intensive industries, resilience is significantly higher for industries with greater digitalisation investments than those with lower digitalisation investments under relatively strict lockdowns (at and above 60). The results are consistent with earlier findings regarding the disparities in the moderating effect of digitalisation on the relationship between industry resilience and lockdown stringency in contact-intensive and non-contact-intensive industries.

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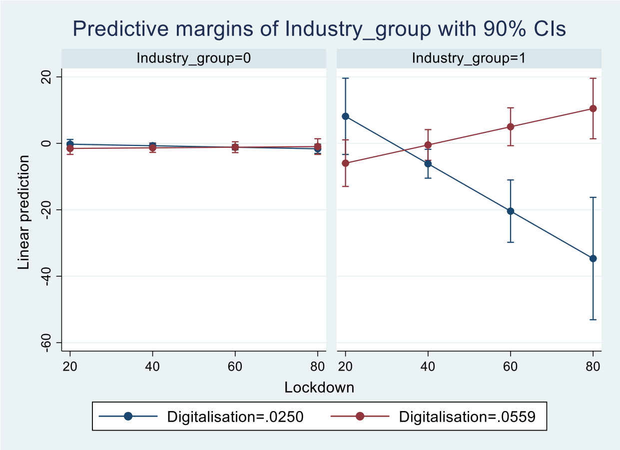
[16] With this alternative indicator of digitalisation, the Chow F statistic is 11.85, with a p-value of 0.0000.

Figure 8: The relationship between lockdown stringency and industry resilience conditional on an alternative digitalisation index by industry group



Notes: the values of Digitalisation are taken at the 10th and 90th centile of the variable's distribution.

5.2 Using an Alternative Proxy for Industry Resilience

5.2.1 The Moderating Effect of Digitalisation on the Relationship between Lockdown Stringency and Resilience Deviation

According to Markman and Venzin (2014), the level of variation in industry performance over a period of time is another validated indicator to quantify business performances used in economics empirical research. Considering sudden drops and increases experienced by some industries in sample countries during the early stages of the pandemic, I replaced the previous indicator of industry resilience in the specification by generating the deviation from the mean of industry resilience in 2019, with regression results reporting in Table 5. With a positive coefficient of lockdown stringency, industry resilience becomes more volatile as the increase of lockdown stringency after controlling for other factors, see Column (1) of Table 5.

Table 5: Estimation results by using an alternative indicator of resilience

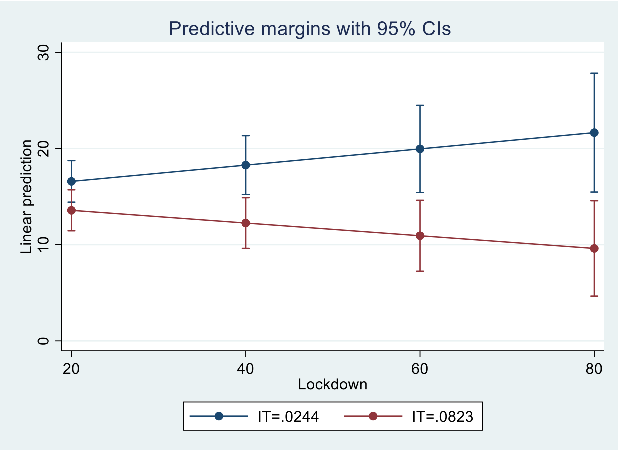
	(1)	(2)	(3)	(4)
VARIABLES	Deviation	Deviation	Deviation	Deviation
Lockdown	0.0817***	0.0792*	0.0340	0.0802*
	(0.0209)	(0.0421)	(0.0226)	(0.0410)
IT		1.068*		
		(0.592)		
Lockdown#IT		-0.0238**		
		(0.0106)		
CT			-4.189	

			(4.220)	
Lockdown#CT			-0.131*	
			(0.0653)	
DB				0.548
				(0.386)
Lockdown#DB				-0.0138**
				(0.00568)
Capitals	-0.132	-0.477	-0.590	-0.599*
	(0.321)	(0.442)	(0.441)	(0.346)
RD	-3.519	-4.742	-6.202**	-4.812**
	(2.419)	(2.829)	(2.673)	(2.095)
Training	-20.69**	-19.42*	-19.69*	-17.47**
	(9.297)	(10.77)	(9.851)	(7.560)
Education	10.36	25.20	75.14	38.86
	(44.43)	(45.25)	(45.82)	(35.75)
Inflation	93.36	723.1	659.1	160.0
	(110.3)	(504.2)	(504.4)	(109.2)
Debt	4.966	27.84	28.53*	8.978
	(6.512)	(16.74)	(16.80)	(6.381)
GDP	0.908*	0.801*	0.719*	1.193*
	(0.527)	(0.466)	(0.413)	(0.663)
VA_2019	0.268	0.117*	0.00465	0.164*
	(0.491)	(0.068)	(0.621)	(0.096)
Constant	-7.12	-22.57	-19.76	-8.48
	(11.89)	(19.65)	(18.91)	(10.70)
Observations	904	852	852	864
R-squared	0.301	0.467	0.548	0.478
Country_Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Notes: (1) Robust standard errors in parentheses; (2) *** p<0.01, ** p<0.05, * p<0.1

The interaction between lockdown stringency and investments in computing equipment is negative and statistically significant at 5% level of significance, as reported in Column (2) of Table 6. This result indicates that the positive effect of lockdown stringency on resilience deviation becomes smaller with increased investments in computing equipment for all industries. Figure 9 demonstrates the moderating effect of investments in computing equipment on the relationship between lockdown stringency and resilience deviation. With a confidence interval of 95%, industries with greater investments in computing equipment are less volatile than the those with lower investments under relative stringent lockdowns (at and above 40).

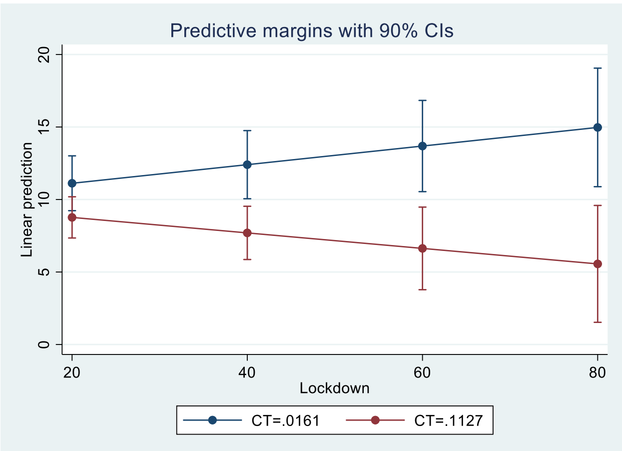
Figure 9: The relationship between lockdown stringency and resilience deviation conditional on the share of computing equipment



Notes: the values of IT (the share of computing equipment in capital net stock) are taken at the 10th and 90th centile of the variable's distribution.

As reported in Column (3) of Table 6, the negative and significant coefficient of the interaction term between lockdown stringency and investments in communication equipment indicates that the positive effect of lockdown stringency on resilience deviation weakens as industries invest more in communication equipment. This result is illustrated in Figure 10, which demonstrates the weakening effect of investments in communication equipment on the relationship between lockdown stringency and resilience deviation. With a confidence interval of 90%, industries with greater investments in communication equipment experience less volatility than the those with lower investments when lockdown measures are relatively stringent (at and above 40).

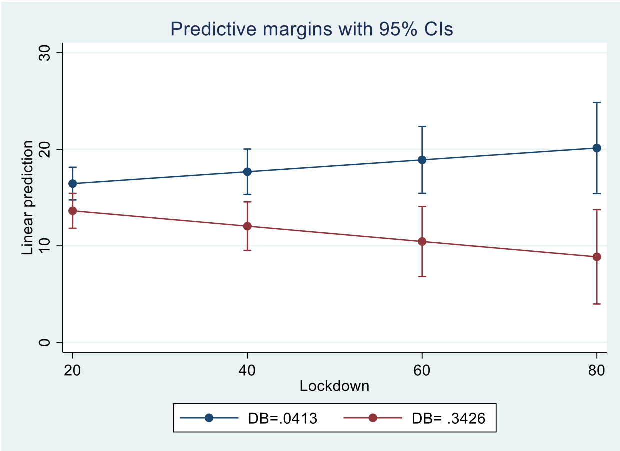
Figure 10: The relationship between lockdown stringency and resilience deviation conditional on the share of communication equipment



Notes: the values of CT (the share of communication equipment in capital net stock) are at 10% and 90% of the variable in the regression

Column (4) of Table 6 reports a negative and significant coefficient of the interaction term between lockdown stringency and investments in computer software and databases. This result suggests a moderating effect of investments in intangible digitalisation on the relationship between lockdown stringency and resilience deviation. Figure 11 reveals that investments in computer software and databases reduce the positive relationship between lockdown stringency and resilience deviation. When lockdown measures are relatively stringent (at and above 40), industries with fewer investments in computer software and databases experience larger resilience deviation than those with greater investments.

Figure 11: The relationship between lockdown stringency and resilience deviation conditional on the share of computer software and databases



Notes: the values of DB (the share of computer software and databases in capital net stock) are taken at the 10^{th} and 90^{th} centile of the variable's distribution.

With resilience deviation as the alternative indicator of industry resilience, it can be concluded that deviations of resilience are smaller for industry with greater digitalisation than those with lower digitalisation in relatively strict lockdown conditions. This finding supports the main conclusion that the pre-pandemic digitalisation has a moderating effect on the relationship between lockdown stringency and industry resilience.

5.2.2 Differences between Contact-Intensive Industries and Non-Contact-Intensive Industries

Replacing industry resilience with resilience deviation in the three-way interaction terms, I investigated whether the interacting effects of lockdown stringency and digitalisation vary across non-contact-intensive industries and contact-intensive industries. From a statistical point of view, the extremely small p-values of the Chow F statistics[17] indicate that there are structural differences between non-contact-intensive industries and contact-intensive industries for each digitalisation indicator, when resilience deviation is employed as the alternative resilience indicator. Table 6 reports

[17] When resilience deviation is used as the alternative resilience indicator, the Chow F statistics for IT, CT, and DB as digitalisation indicator are 4.25 (with a p-value of 0.0001), 6.18 (with a p-value of 0.0000), 4.49 (with a p-value of 0.0000), respectively.

the estimation results with this alternative resilience indicator.

Table 6: Estimation results by industry group of using an alternative indicator of resilience

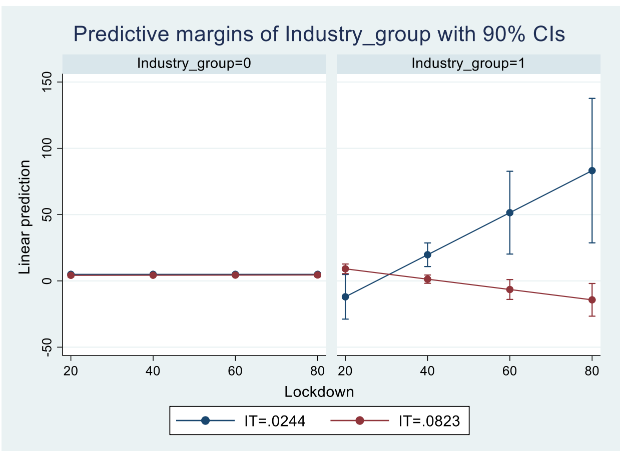
	(1)	(2)	(3)
VARIABLES	IT	CT	DB
Lockdown	0.00451	-0.0143	-0.00397
	(0.0230)	(0.0171)	(0.0252)
IT	-13.61		
	(12.58)		
Lockdown#IT	0.0713		
	(0.288)		
Industry_group	13.00**	-28.77*	5.396
	(5.304)	(14.92)	(5.562)
Industry_group#Lockdown	-0.401**	0.971*	-0.119
	(0.158)	(0.506)	(0.104)
Industry_group#IT	1,020**		
	(485.5)		
Industry_group#Lockdown#IT	-32.88**		
	(14.36)		
CT		-1.323**	
		(0.658)	
Lockdown#CT		0.0121	
		(0.00896)	
Industry_group#CT		827.8**	
		(407.7)	
Industry_group#Lockdown#CT		-28.75**	
		(14.48)	
DB			0.780
			(3.444)
Lockdown#DB			-0.00945
			(0.0596)
Industry_group#DB			151.6
			(178.2)
Industry_group#Lockdown#DB			-3.271
			(3.701)
Capitals	-0.577	-0.328	-0.167
	(0.608)	(0.449)	(0.567)
R&D	4.371	0.116	3.752
	(2.904)	(2.441)	(2.814)
Training	-1.883	-20.97**	-2.377
	(12.81)	(9.151)	(12.68)
Education	8.050	43.51	30.22

	(61.00)	(67.49)	(64.22)
Inflation	32.27	24.24	31.12
	(31.72)	(34.41)	(31.54)
Debt	8.978	9.753	8.362
	(6.381)	(7.904)	(8.145)
GDP	1.507	2.429**	1.276
	(1.092)	(0.978)	(0.807)
VA_2019	-0.739	-0.0534	-0.249
	(0.628)	(0.498)	(0.611)
Constant	-11.22	-16.63*	-9.078
	(9.870)	(9.389)	(9.070)
Observations	852	852	864
R-squared	0.452	0.545	0.496
Country-Industry FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: (1) Robust standard errors in parentheses; (2) *** p<0.01, ** p<0.05, * p<0.1

As reported in Column (1) of Table 6, the three-way interaction term is negative and statistically significant at 5%. The average interacting effect of lockdown stringency and investments in computing equipment on resilience deviation is significantly lower for contact-intensive industries than for non-contact-intensive industries. Visualising this interacting effect by industry group in Figure 12, there is no statistically significant difference in resilience deviation across the levels of digitalisation among non-contact-intensive industries. For contact-intensive industries, highly digitised industries in terms of investments in computing equipment, compared with inadequately digitised industries, experience lower resilience deviation under strict lockdowns (at and above 40).

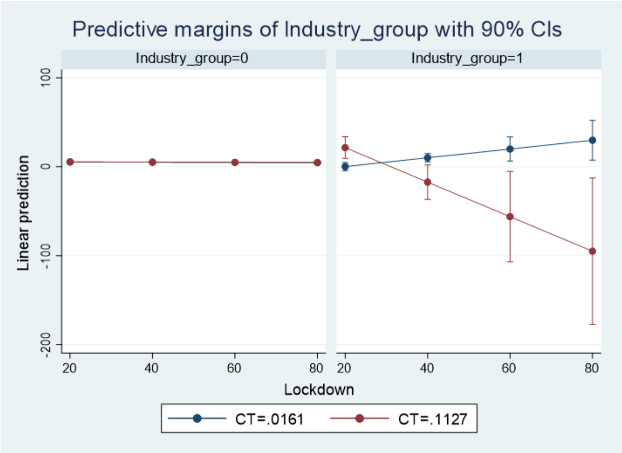
Figure 12: The relationship between lockdown stringency and resilience deviation conditional on the share of computing equipment by industry group



Notes: the values of IT (the share of computing equipment in capital net stock) are taken at the 10th and 90th centile of the variable's distribution.

A negative and significant triple interaction occurs when using investments in communication equipment as the digitalisation indicator, see Column (2) of Table 6. This result suggests that the interacting effect of lockdown stringency and investments in communication equipment on resilience deviation is significantly lower for contact-intensive industries than for non-contact-intensive industries. After classifying industries based on their contact intensity, as shown in Figure 13, the impact of investments in communication equipment on resilience deviation is not statistically significant for low- and high-digital intensity industries among the non-contact group. For the contact-intensive group, there is a significant difference in resilience deviation for low- and high-digital intensity industries when the stringency of lockdown measures is at and above 40.

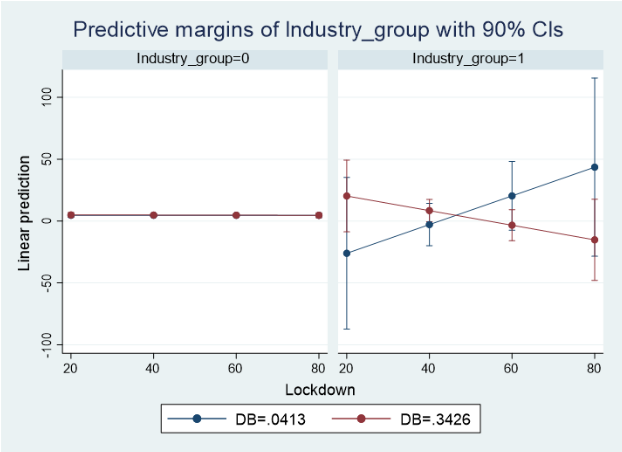
Figure 13: The relationship between lockdown stringency and resilience deviation conditional on the share of communication equipment by industry group



Notes: the values of CT (the share of communication equipment in capital net stock) are taken at the 10th and 90th centile of the variable's distribution.

Although the three-way interaction term is negative in Column (3) of Table 6, the coefficient is not significant, suggesting that the average interacting effect of lockdown stringency and investments in computer software and databases does not significantly vary across industries of different contact intensities. Figure 14 demonstrates the moderating effect of investments in computer software and databases on the relationship between lockdown stringency and resilience deviation by industry group. For non-contact-intensive industries, there is no significant difference in resilience deviation among industries with low- and high-investments in intangible digitalisation. For contact-intensive industries, the differences in the impact of investments in intangible digitalisation are not statistically significant for low- and high-digital intensity industries, given the overlaps between confidence intervals. Nevertheless, a mitigating effect of investments in computer software and databases on the relationship between lockdown stringency and industry resilience can be observed.

Figure 14: The relationship between lockdown stringency and resilience deviation conditional on the share of computer software and databases by industry group



Notes: the values of DB (the share of computer software and databases in capital net stock) are taken at the 10th and 90th centile of the variable's distribution.

With resilience deviation portraying industry resilience, the moderating effect of digitalisation is more pronounced for contact-intensive industries than for non-contact-intensive industries, aligning with the previous finding.

5.3 Accounting for the Endogeneity Issue

5.3.1 Addressing the Endogeneity Issue with the IV-2SLS Technique

Accounting for potential endogeneity issues in the baseline analysis, I re-estimated the baseline results by using the Instrumental Variable-Two-Stage Least Square technique (IV-2SLS) approach (Bascle, 2008; Wooldridge, 2010). In this endogeneity robustness check, I followed the estimation strategy used in the baseline analysis, using the quarterly changes in gross value added between 2020 and 2019 as the indicator of industry resilience. I treated lockdown stringency, digitalisation, and the interaction between lockdown stringency and digitalisation as endogenous variables.

I used two instrumental variables to instrument lockdown stringency. The decision to deploy stringent lockdown measures is not random; therefore, one can conjecture that time-invariant country characteristics may affect economic outcomes. For instance, economies with greater social trust may not require stringent lockdowns, as people are likely to take greater precautions against infecting others and could also better withstand the economic impact of the pandemic (Caselli *et al*., 2020). Economies with lower trust are likely to suffer from citizens' scepticisms about governments' portrayal of the situation, resulting in governments' stricter lockdown measures in anticipation of citizens exhibiting a weaker behavioural response (Spiliopoulos, 2022). Besides, low-trust countries tend to have inadequate public health systems; therefore, governments of these low-trust countries may impose more stringent lockdown measures, compared with high-trust countries, to prevent intensive care units from filling to capacity (Spiliopoulos, 2022). In this sense, I adopted the time-invariant variable of generalized trust developed by Bekkers and Sandberg (2018) from the European Social Survey as the first instrument for lockdown stringency. I used the quarterly average of the quotient of the daily log growth rate of COVID-19 confirmed cases and the number of hospital beds per thousand people as another instrument for lockdown stringency. This second instrument can only affect industry performance by influencing the stringency of lockdown measures.

For variables of digitalisation investments, I used the predetermined variable of the share of computing equipment (communication equipment / computer software and databases) in capital stock net of the year 2018 as the instrument for the share of computing equipment (communication equipment / computer software and databases) in capital stock net of the year 2019. This instrument can be considered exogenous, as it is unlikely to be affected by any exogenous shocks in 2019 and 2020.

According to Wooldridge (2010), an interaction between endogenous variables renders the interaction term endogeneity. The natural procedure to instrument the interaction term is to use the instruments of endogenous regressors to construct the instruments for the interaction term (Wooldridge, 2010; Balli and Sorensen, 2013). Therefore, I treated the interaction terms between lockdown stringency and digitalisation investments as endogenous. To create the instruments for the endogenous interactions, I developed interaction terms between the two instruments representing lockdown stringency and the instrument capturing digitalisation.

Table 7 reports the estimation results with the IV-2SLS approach. The coefficients of the interaction terms in Column (1) to (3) remain positive and significant, after accounting for endogeneity issues. Both tangible and intangible digitalisation has moderating effects on the relationship between lockdown stringency and industry resilience. The regression results support the previous argument in baseline analyses that digitalisation mitigates the negative shocks from pandemic-enforced lockdown on industry resilience. Comparing with the results from the baseline model, the moderating effects of tangible and intangible digitalisation on the relationship between lockdown stringency and industry resilience remain positive and significant in the IV-2SLS specifications, with the magnitude of the effects becoming smaller. The endogeneity of lockdown stringency and these digitalisation investments causes an upward bias in the baseline model.

Table 7: Estimation results addressing the endogeneity issue

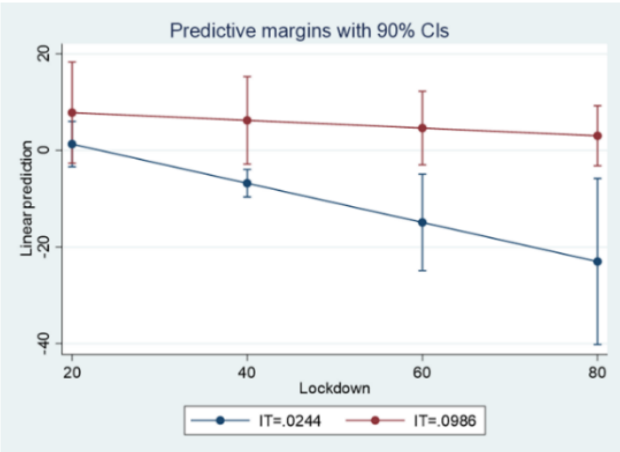
	(1)	(2)	(3)
VARIABLES	IT	CT	DB
Lockdown	-0.179	-0.144	-0.0849**

	(0.153)	(0.117)	(0.0369)
IT	130.57**		
	(65.98)		
Lockdown#IT	0.196*		
	(0.107)		
CT		129.03	
		(87.52)	
Lockdown#CT		0.382*	
		(0.227)	
DB			132.19*
			(71.78)
Lockdown#DB			0.572*
			(0.317)
Capitals	1.405***	1.723***	0.336
	(0.491)	(0.571)	(0.443)
R&D	3.422	7.132	6.542**
	(4.909)	(5.602)	(2.679)
Training	-45.04***	-45.29***	-41.544
	(15.18)	(15.43)	(5.297)
Education	27.52*	26.41*	26.37
	(15.45)	(15.98)	(39.28)
Inflation	-258.5***	-225.2**	-86.34*
	(98.29)	(90.75)	(52.31)
Debt	-7.985***	-8.350**	-9.016***
	(3.965)	(4.047)	(3.444)
GDP	-8.033***	-6.557***	-3.591***
	(1.373)	(1.285)	(0.868)
VA_2019	-0.136	-0.194	-0.209
	(0.277)	(0.186)	(0.563)
Constant	-32.03***	-30.50***	-41.41***
	(12.22)	(11.04)	(9.322)
Observations	794	788	804
IV tests			
Kleibergen-Paap rk LM statistic	40.326	44.113	23.260
p-value	0.0000	0.0000	0.0003
Cragg-Donald Wald F statistic	14.792	15.727	15.406
Stock-Yogo 5% maximal IV relative bias	13.95	13.95	13.95
Stock-Yogo10% maximal IV relative bias	8.50	8.50	8.50
Hansen J statistic	3.972	4.067	4.695
p-value	0.2645	0.3971	0.1955

Notes: (1) Robust standard errors in parentheses; (2) *** p<0.01, ** p<0.05, * p<0.1; (3) Stock-Yogo 5% maximal IV relative bias and Stock-Yogo 10% maximal IV relative bias are Stock and Yogo (2005) weak identification test with critical values for 5% and 10%, respectively. According to Stock and Yogo (2005), when Cragg-Donald F statistic > 5% maximal IV relative bias, instruments are very powerful; when 10% maximal IV relative bias <Cragg-Donald F statistic <5% maximal IV relative bias, instruments are powerful.

Figure 15 demonstrates the moderating effect of investments in computing equipment on the relationship between lockdown stringency and industry resilience after accounting for endogeneity issues, as reported in Column (1) of Table 7. When lockdown stringency is no less than 40, a higher level of investment in computing equipment coupled with lockdown stringency has a resilience-enhancing effect.

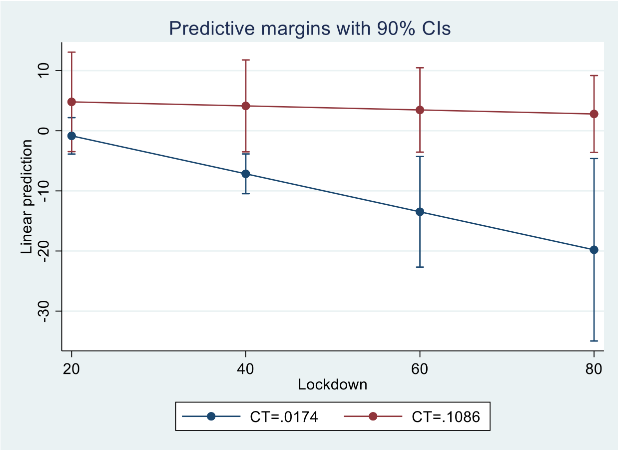
Figure 15: The relationship between lockdown stringency and industry resilience conditional on the share of computing equipment accounting for endogeneity issues



Notes: the values of IT (the share of computing equipment in capital net stock) are taken at the 10th and 90th centile of the variable's distribution.

The moderating effect of investments in communication equipment on the relationship between lockdown stringency and industry resilience conditional on the share of communication equipment, after accounting for endogeneity issues, is illustrated in Figure 16. In relatively stringent lockdown situations (at and above 40), industries with greater investments in communication equipment are more resilient than industries with fewer investments in communication equipment.

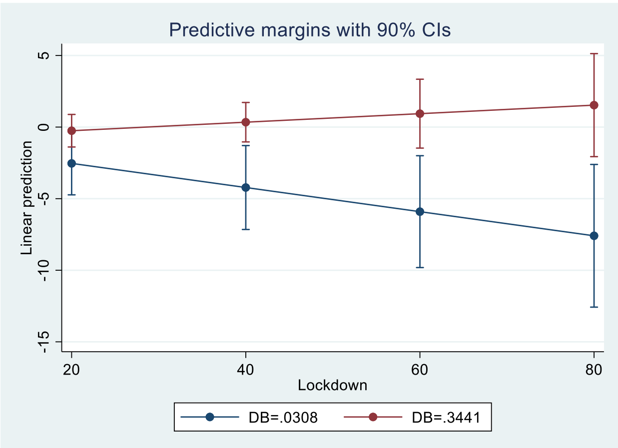
Figure 16: The relationship between lockdown stringency and industry resilience conditional on the share of communication equipment accounting for endogeneity issues



Notes: the values of CT (the share of communication equipment in capital net stock) are taken at the 10th and 90th centile of the variable's distribution.

Figure 17 illustrates the moderating effect of investments in computer software and databases on the relationship between lockdown stringency and industry resilience after addressing endogeneity issues. A greater level of investments in computer software and databases coupled with lockdown stringency has a resilience-enhancing effect for conditions with lockdown measures at and greater than 40.

Figure 17: The relationship between lockdown stringency and industry resilience conditional on the share of computer software and databases accounting for endogeneity issues



Notes: the values of DB (the share of computer software and databases in capital net stock) are taken at the 10th and 90th centile of the variable's distribution.

Comparing Figure 17 (with investments in the intangible aspect as the indicator of digitalisation) with Figures 15 and 16 (with investments in tangible aspects as the indicator of digitalisation), a pattern of increasing lockdown slopes as investments in digitalization rise can be observed. Notably, the rate of growth appears to be greater when intangible digitalization is used as the indicator (Figure 17) compared to tangible aspects (Figures 15 and 16). One may wonder why intangible digitalisation exerts a greater impact on the relationship between lockdown stringency and industry resilience than tangible digitalisation. Tangible digitalisation, in terms of computing equipment and communication equipment, forms the foundation of digital infrastructure and creates a minimum condition for organisations to engage in digitalisation strategies. Therefore, tangible digitalisation contributes to mitigating negative shocks from lockdown measures but is not sufficient yet to increase industry resilience. By contrast, intangible digitalisation, in terms of computer software and databases, increases digital capabilities by bypassing lockdown restrictions and reaching out to more customers via making effective use of data and responding to customers in a tailored way to serve them with personalised offerings through real-time data analytics and tailored promotion. Therefore, intangible digitalisation not only helps to survive this pandemic with lockdown restrictions but also boosts resilience.

5.3.2 Postestimation Tests for the IV-2SLS Approach

I conducted three postestimation tests to ensure the validity of the estimation results produced by the selected instruments. First, I conducted the under-identification test and report the statistics of the Kleibergen-Paap rk LM for the three specifications. With p-values smaller than 0.01 for these three specifications, the null hypothesis of instruments' insufficient explanatory power to predict endogenous variables can be rejected. Therefore, the instruments are confirmed to be correlated with the endogenous regressors. Secondly, the Cragg-Donald Wald F-statistics for the weak instrument test are all greater than the threshold of the Stock-Yogo 5% maximal IV relative bias for these three specifications; therefore, the selected instruments can be considered very powerful (Stock and Yogo, 2005) and do not suffer from the weak instrument issue. Thirdly, with the p-values of the Hansen over-identification tests greater than 0.1, the null hypothesis that instruments are correctly excluded from the estimated equation cannot be rejected. Therefore, the selected instruments do not have a direct effect on the dependent variables.

Drawing on the outcomes of these three post-estimation tests, it can be concluded that that the selection of instrumental variables is both reasonable and appropriate. The instruments meet the relevance condition, indicating that they are significantly correlated with the endogenous variables. Additionally, no weak instrumental variable issues were detected, which means that the instruments are strongly correlated with the endogenous variables and provide meaningful estimates. Lastly, the exclusion conditions are satisfied, ensuring that the instruments are uncorrelated with the error terms and thus do not introduce bias into the estimation.

With an IV-2SLS approach addressing the endogeneity issue, the estimation results support previous findings that the pre-pandemic digitalisation level has a moderating effect on the relationship between lockdown stringency and resilience.

5.3.3 Differences between Non-Contact-Intensive Industries and Contact-Intensive Industries

Accounting for endogeneity issues, I adopted the three-way interaction terms to investigate whether the interacting effect of lockdown stringency and digitalisation varies across industries of different contact intensities, with estimation results reported in Table 8. The coefficients of the three-way interactions in Column (1) to (3) are positive and significant, suggesting that the average interacting effect of lockdown stringency and digitalisation are different across non-contact-intensive industries and contact-intensive industries. This indicates that the lockdown and digitalisation interaction is significantly higher for industry resilience in contact-intensive industries than in non-contact-intensive industries.

Table 8: Estimation results by industry group accounting for the endogeneity issue

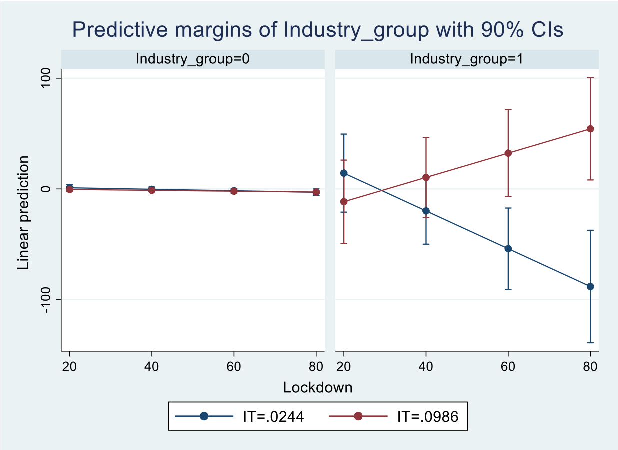
	(1)	(2)	(3)
VARIABLES	IT	CT	DB
Lockdown	-0.0968	-0.129**	-0.0763
	(0.0592)	(0.065)	(0.0485)
IT	-80.75		
	(59.12)		
Lockdown#IT	1.087		
	(0.689)		
Industry_group	132.4	33.75	19.79*
	(87.70)	(23.00)	(11.73)
Industry_group#Lockdown	-4.643***	-1.364***	-0.578**
	(1.686)	(0.527)	(0.256)
Industry_group#IT	-313.9		
	(213.1)		
Industry_group#Lockdown#IT	1.091***		
	(0.394)		
CT		-148.5	
		(102.2)	
Lockdown#CT		1.922*	
		(1.020)	
Industry_group#CT		-591.3	
		(422.6)	
Industry_group#Lockdown#CT		1.831*	
		(1.029)	
DB			5.124
			(8.539)
Lockdown#DB			0.111

			(0.133)
Industry_group#DB			-102.9
			(64.26)
Industry_group#Lockdown#DB			2.976**
			(1.274)
Capitals	5.411	1.146	1.038
	(6.409)	(1.503)	(3.697)
RD	44.44	7.405	7.110
	(38.18)	(8.555)	(10.87)
Training	175.2	22.72	64.45
	(116.2)	(33.52)	(48.97)
Education	9.478	183.7	51.21**
	(744.3)	(209.1)	(23.50)
Inflation	-1,937	-494.1***	-104.1
	(1,475)	(187.0)	(184.6)
Debt	-5.938	-6.020**	-7.954*
	(15.03)	(2.611)	(4.616)
GDP	-3.519	-4.639**	-8.418
	(4.771)	(2.247)	(7.664)
VA_2019	-12.51	-1.969	-4.085
	(13.81)	(1.736)	(4.908)
Constant	67.40	63.30***	-135.8
	(84.57)	(22.62)	(90.57)
Observations	794	788	804
R-squared	0.743	0.732	0.648
IV Tests			
Kleibergen-Paap rk LM statistic	24.223	28.987	13.294
p-value	0.0000	0.0000	0.0000
Cragg-Donald Wald F statistic	13.906	14.179	13.724

Notes: (1) Robust standard errors in parentheses; (2) *** p<0.01, ** p<0.05, * p<0.1

Graphing the three-way interaction effect of lockdown stringency, investments in computing equipment, and industry group in Figure 18, there is no significant difference in industry resilience can be observed among industries of low- and high-digital intensity in the non-contact-intensive group. In the contact-intensive group, a significantly higher industry resilience can be observed among industries of high-digital intensity than those of low-digital intensity when lockdown is stringent (at and above 60).

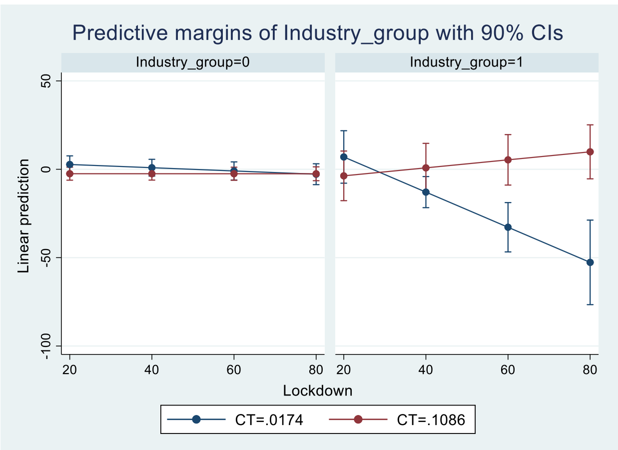
Figure 18: The relationship between lockdown stringency and industry resilience conditional on the share of computing equipment by industry group accounting for endogeneity issues



Notes: the values of IT (the share of computing equipment in capital net stock) are taken at the 10th and 90th centile of the variable's distribution.

Figure 19 presents the three-way interaction effect of lockdown, investments in communication equipment, and industry group on the relationship between lockdown stringency and industry resilience, after addressing endogeneity issues. There is no significant difference in industry resilience between industries with high and low intensity in communication equipment within the non-contact-intensive industries, as indicated by the overlapping confidence intervals. Within the contact-intensive industry group, a contrasting pattern emerges. Industries with high intensity in communication equipment exhibit significantly higher resilience than those with low intensity when lockdown measures are relatively stringent (at and above 60).

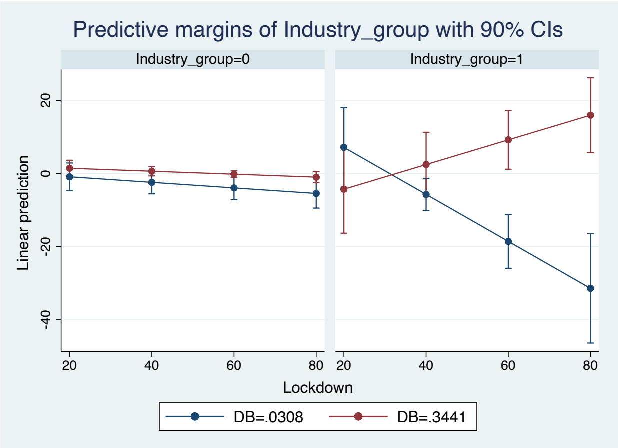
Figure 19: The relationship between lockdown stringency and industry resilience conditional on the share of communication equipment by industry group accounting for endogeneity issues



Notes: the values of CT (the share of communication equipment in capital net stock) are taken at the 10th and 90th centile of the variable's distribution.

Figure 20 demonstrates the corresponding three-way interacting effect with investments in computer software and databases being the digitalisation indicator. There is no significant difference in industry resilience between industries with high and low intensity in computer software and databases among non-contact-intensive industries, given the overlapping confidence intervals. Despite this, one can observe the moderating effect of investments in computer software and databases on the relationship between lockdown stringency and industry resilience within this group. In the case of contact-intensive industries, higher levels of investments in computer software and databases, combined with increased lockdown stringency, contribute to enhanced industry resilience under strict lockdowns (at and above 60).

Figure 20: The relationship between lockdown stringency and industry resilience conditional on the share of computer software and databases by industry group accounting for endogeneity issues



Notes: the values of DB (the share of computer software and databases in capital net stock) are taken at the 10th and 90th centile of the variable's distribution.

Applying the IV-2SLS approach addressing the endogeneity issues of lockdown, digitalisation, and their interactions, the results reaffirm the previous argument about the moderating effect of digitalisation on the relationship between lockdown stringency and industry resilience is robust. In addition, the results are consistent with the finding that the average moderating effect of digitalisation on the relationship between lockdown stringency and industry resilience varies across non-contact-intensive industries and contact-intensive industries. The mitigating effects of digitalisation on negative shocks from pandemic-enforced lockdowns are more pronounced for contact-intensive industries than for non-contact-intensive industries.

6. Conclusions

In this chapter, I investigated how pre-pandemic digitalisation affects the economic losses arising from lockdown measures in European countries. Distinguished from previous studies, I evaluated the pre-pandemic digitalisation level from both tangible and intangible aspects by using true values of investments in computing equipment, communication equipment, and computer software and databases. The results demonstrate that digitalisation has a moderating effect on the relationship between lockdown stringency and industry resilience in the early stages of the pandemic (from 2020 Q1 to 2020 Q4). In general, industries with greater digital-intensity, in terms of investments in computing equipment, communication equipment, and computer software and databases, are more resilient than those with lower digital-intensity when lockdown measures are relatively stringent. Pre-pandemic investments in digitalisation could act as an important mitigating factor for negative economic shocks under strict lockdown conditions. In addition, the moderating effect of digitalisation on the relationship between lockdown stringency and industry resilience is more pronounced in industries of high contact intensity than those of low contact intensity among these European countries. These findings are robust against using alternative indicators of key variables and addressing endogeneity issues.

Echoing Abidi *et al*. (2020) focusing on firm-level evidence, this research reveals that that digitalisation strengthens resilience to the COVID-19 pandemic on an industry level. The dampening effect of digitalisation on negative economic shocks has important implications for the implementation of lockdown policies. The findings suggest that industries with greater investments in both tangible and intangible digitalisation experience lower economic costs associated with lockdown measures. This insight serves to mitigate a potential trade-off between public health and the economy, as it provides robust evidence that digitalisation can help industries remain resilient during times of crisis without compromising public health concerns.

With lockdown and social distancing measures forcing businesses of different industries online, the global pandemic has reinforced the importance of communication infrastructures and database services. Ensuring the resilience of industry performance in this digital age requires investments in both tangible and intangible digital technologies. As countries across the world struggle to lessen the prolonged economic losses from the global pandemic, a better understanding of industry resilience would be relevant to economic decisions for worldwide digitalisation development. Based on empirical results derived at meso-level analysis, the results emphasize the need for industries in European countries, particularly contact-intensive industries, to invest in both tangible and intangible aspects of digitalisation to bolster their preparedness for future crises involving unconventional lockdown restrictions.

Despite the contributions to relevant literature, this research has limitations. One primary constraint was the availability of data, which restricted the analysis to the role of pre-pandemic digitalisation in mitigating economic losses resulting from pandemic-enforced lockdowns at the time of drafting this chapter. Consequently, the findings provide short-term evidence of the relationship between digitalisation and resilience in the context of the pandemic. Future studies could incorporate longer sample periods to further validate the role of digitalisation in shaping industry resilience in response to lockdown measures by using the change in digitalisation between 2020 and 2019 as a potential indicator for digital transformation. Another limitation of this study is the potential oversight of sector-specific demand shocks, which were not explicitly controlled for in the analysis. While the study focused on the role of digitalisation and its interaction with lockdown stringency in determining industry resilience, it did not account for the differential impacts of the pandemic across sectors. For instance, some sectors, like online retail, experienced a significant surge in demand due to the pandemic, which may have led to an overestimation of the role of digitalisation in enhancing resilience. Conversely, sectors such as tourism, which faced unique challenges and severe operational restrictions, might have their resilience underestimated if these demand shocks are not considered. This limitation suggests that the results could be biased if the differential sectoral impacts are not adequately controlled for. To address this limitation in future research, it is recommended that sector-specific demand shocks be incorporated as additional explanatory variables when relevant variables are available. One approach could involve introducing interaction terms between the lockdown stringency index and industry-specific indicators of demand changes during the pandemic. Such indicators might include changes in consumer spending patterns, shifts in service delivery modes (e.g., from in-person to online), or variations in sectoral employment levels. By including these variables, future analyses could better isolate the effects of resilience from those of pandemic-induced demand shifts, leading to a more accurate understanding of how different industries responded to the crisis.

Chapter 4 *The Gendered Impacts of the COVID-19 Pandemic on Labour market Outcomes: Evidence from the U.K.*

1. Introduction

The COVID-19 pandemic has exerted profound impacts on employment around the world, especially among women and marginalised groups. As Alon *et al*. (2020) argued, the COVID-19 pandemic differs from prior crises in its effects on women's employment. According to the Women's Budget Group (2020), women are five percentage points more likely than men to have been made unemployed in the UK during the pandemic lockdown in 2020, with the gender pay gap increasing by 15 percentage points in 2020 April alone. Previous research has mainly attributed the stronger impacts on female employment than male employment to two aspects. First, unlike regular recessions that disproportionately affect male-dominated sectors such as construction and manufacturing, the pandemic recession had a greater impact on sectors like hospitality and tourism, which have a higher proportion of female employees. Second, pandemic-enforced school closure has disproportionately increased women's household production in education and childcare services, as women on average perform the larger part of these tasks than men.

The impact of the COVID-19 pandemic on the labour market outcomes of women is complex and multifaceted. On the one hand, women are disproportionately represented in service industries that have been subject to lockdown or social distancing measures, potentially affecting their employment prospects. On the other hand, women are also more likely to be employed in sectors considered essential to the COVID-19 response and in occupations that can be performed remotely, which may offset certain adverse effects on their employment prospects. Therefore, it is unclear whether women's labour market prospects have been more severely affected than men's (Hupkau and Petrongolo, 2020). Another important consideration is the impact of increased childcare responsibilities on female employment penalties. Women typically perform a greater share of household tasks, including childcare, and they often bear the brunt of earning penalties associated with childbearing. Due to closures of schools and childcare centres, heightened childcare responsibilities, especially concerning the care of school-aged children, amidst the pandemic may amplify this inequality, resulting in enduring impacts on women's career prospects.

By using the Understanding Society: COVID-19 Study dataset, this chapter aims to examine intersectional gendered effects of the COVID-19 pandemic on labour market outcomes for diverse groups of women in the UK in the initial stage of the pandemic. Focusing on the working-age population of the UK labour market, this research investigates the effect of negative labour market shocks borne by females with school-aged children, and the factors that moderate the "motherhood penalty" on employment outcomes. With an intersectional approach, this research also identifies combinations of traits associated with the greatest employment vulnerability among females.

The research reaches the following key findings. First, the persistence of the motherhood penalty is evidenced in the UK labour market in the initial stage of the pandemic. In contrast to males, cohabitation, employment in non-contact-intensive industries, and being a white native are factors mitigating unemployment risk for mothers with school-aged children. Among other factors, ethnic migrant status emerges as the most influential factor affecting female's likelihood of transitioning from paid employment to unemployment during the early stages of the pandemic. In addition, disproportionately high pandemic job loss was found among Black, Asian, and minority ethnic (BAME) migrant women, compared to white native women with similar occupational skills. Among BAME migrant females in blue-collar roles, those with health vulnerabilities and lack of family support in childcare are the most vulnerable groups in job displacement.

This research contributes to the existing literature in several aspects. First, while existing studies have pointed out the disparities in employment outcomes across binary categorisations such as gender and occupations, insufficient attention has been dedicated to examining intersectional penalties on individual employment outcomes, especially among females with school-aged children. This research bridges the gap by providing a comprehensive understanding of the complex interplay between gender, childcare duties, and other socioeconomic factors in shaping employment outcomes during the pandemic. Secondly, this research provides evidence of the motherhood penalty in the initial stage of the pandemic, shedding light on the factors that moderate the motherhood penalty on employment outcomes. Thirdly, the intersectional approach adopted in this research highlights the interconnected nature of various factors that contribute to employment disparities, particularly for marginalised groups such as BAME migrant mothers. Fourthly, this research documents the differences in employment outcomes between female and male subgroups, offering evidence-based recommendations for gender-based policy development in the UK labour market.

The remaining parts of this chapter are structured as follows. Section 2 reviews literature on the economics of fertility, the overarching gendered impacts on the labour market, and the various lenses through which the gender gap in labour market outcomes have been examined. Section 3 presents the data and methodology adopted in this study. Section 4 and Section 5 present and discuss the findings from empirical estimations, respectively. This chapter finalises with some concluding remarks.

2. Literature Review

The COVID-19 pandemic has exacerbated existing inequalities in the labour market along gender and other identity lines (Power, 2020). Intersectional analysis examining these uneven effects and their multidimensional interactions is vital for policy interventions in the post-pandemic recovery. This section reviews theoretical models of childbearing and relevant literature on pandemic employment outcomes in the UK and other developed markets like the US across gender, occupations, childcare responsibility, marital status, ethnicity and migrant status, and education attainment, with an objective to identify critical gaps in current research.

2.1 The Economics of Fertility

The economics of fertility represents a major research area examining choices regarding childbearing through economic models of utility maximisation and cost-benefit calculations. By modelling parents as deriving utility from child quantity and quality, Becker (1960) proposed the "new home economics" approach to fertility decisions, in which rational actors make optimising choices about family size based on wages, childrearing costs, and preferences. The Becker model assumes household production functions, with parents allocating time between market labour and child services. It predicts fertility falls as women's wages rise, as the opportunity cost of childrearing time increases. Subsequent extensions incorporate marital bargaining, considering fertility as an outcome of bargaining power related to each partner's wages and outside options (Lundberg and Pollak, 1996; Rasul, 2008).

In addition to Becker's foundational fertility model, Easterlin (1975) proposed the relative income hypothesis and theorised that fertility decisions are not only driven by absolute income, but by income relative to aspirations. Assuming that people's aspirations are shaped by the standard of living they experienced growing up, this theory proposes that people are likely to delay marriage and childbearing if their earning potential falls short of these aspirations. Easterlin (1975) also argued that material aspirations outgrow income growth. Economic development, therefore, tends to depress fertility through rising material aspirations.

Friedman *et al*. (1994) integrated economic models of fertility with sociological perspectives by incorporating social norms. In the theory of value of children, they claimed that individuals derive value from having socially accepted numbers of children. Social norms define the optimal family size, and deviation from these norms is penalised through social stigma. However, these norms evolve based on the changing costs and benefits associated with having children. As the economic value of children decreased with industrialisation, the optimal family size decreased as well. Children were no longer necessary as labour on farms, and the social acceptance value of children also decreased as parents focused more on "quality"—raising educated and successful children, rather than "quantity"—simply having many children. This model recognizes that fertility decisions involve both economic costs and benefits, as well as social costs and benefits. It helps explain demographic transitions, in which social norms co-evolve with economic incentives as society modernizes.

Overall, while Becker's models were foundational, later theories, such as the relative income hypothesis and value of children, enrich the economics of fertility by incorporating bargaining dynamics, social influences, and relative income effects. These economic theories of fertility retain the premise that childbearing stems from rational choices weighing costs against benefits.

2.2 Overall Gendered Impacts on the Labour Market

The COVID-19 enforced interventions such as social distancing measures and stay-at-home orders have severely affected economic activities of both males and females. Emerging evidence has suggested that the associated impacts are not gender neutral, with pre-existing gender inequalities in labour markets being exacerbated (Wenham *et al*., 2020). Although previous economic downturns often witnessed males' greater job losses, the COVID-19 induced recession has resulted in a stark reversal. Studies by Alon *et al*. (2020) and Landivar *et al*. (2020), focusing on the US labour market, highlighted this shift, revealing the gender gaps where more females experienced job loss compared to males during this initial phase. Further studies confirmed that this gender imbalance in employment outcomes remains consistent at least until June 2020, despite some slight estimation variations across studies (Cajner *et al*., 2020; Montenovo *et al*., 2022; Adams-Prassl *et al*., 2020a).

To better understand the factors underlying this reversal in gendered employment impacts, the following section examines the impacts of the pandemic through multiple dimensions including occupational segregation, childcare responsibilities, and other socioeconomic factors.

2.3 Exploring the Gender Gap in Labour Market Outcomes through Multiple Lenses

In response to the evidenced adverse impacts on female's labour market outcomes, emerging studies have attempted to understand the differential labour market outcomes of the pandemic by occupational segregation, childcare responsibility, marital status, ethnic migrant status, and levels of skills.

2.3.1 Occupational Segregation

One possible explanation of this gender gap in employment disparity stems from the variation in industry impacts, along with industrial gender segregation, which mirrors the trends seen in prior economic downturns (Kim *et al*., 2021). However, the unique nature of the pandemic-induced recession has significantly affected industries reliant on face-to-face interactions, with female-dominated service-oriented industries experiencing the most substantial job losses (Cajner *et al*., 2020; Montenovo *et al*., 2022). In contrast, industries facilitating remote work witnessed fewer job displacements (Adams-Prassl *et al*., 2020b; Papanikolaou and Schmidt, 2020). As males are more likely to hold positions that allow for remote work, they have been comparatively less impacted in terms of employment outcomes than females (Alon *et al*., 2020; Montenovo *et al*., 2022).

2.3.2 Childcare Responsibility

The increase in childcare responsibilities disproportionately shouldered by females is conjectured as another reason for the gendered disparities in employment outcomes during the initial stage of the pandemic. Research by Joshi *et al*. (2021) and Costa Dias *et al*. (2018) pointed out that the gender wage gap significantly widens after the birth of the first child, leading to females' transition to part-time roles with lower pay rates. The advent of the COVID-19 pandemic has amplified these pre-existing gendered inequalities in labour markets, intensifying pressures from domestic responsibilities resulting from prolonged school closures and the expectation for parents to undertake home schooling duties.

Emerging evidence suggests that increased childcare responsibilities have played a significant role in exacerbating gender gaps within labour market outcomes, particularly during the COVID-19 pandemic. Employing real-time collected data within the UK, Sevilla and Smith (2020) concluded that mothers with dependent children aged below 12 devoted more time in childcare responsibilities, compared with their male counterparts. These mothers' additional hours of childcare were less influenced by their employment status compared to males, resulting in adverse effects on females' career developments (Sevilla and Smith, 2020). Focusing on the U.S. labour market, Furman *et al*. (2021) revealed that that mothers with young children experienced a disproportionately negative impact on their employment status, while fathers with children of similar ages were less likely to encounter job displacements compared to other men. Landivar *et al*. (2020) highlighted that mothers experienced a more pronounced reduction in working hours than fathers did during the pandemic, leading to a substantial increase in the gender hours gap, estimated between 20% to 50%. In addition, there is evidence indicating a 'fatherhood premium' that shields fathers from post-pandemic layoffs, highlighting employers' favouritism toward fathers during economic downturns (Correll *et al*., 2007; Dias *et al*., 2020). This phenomenon was evident in April 2020, where fathers demonstrated the lowest likelihood of experiencing layoffs compared to both mothers and individuals without children (Dias *et al*., 2020). In Italy, working mothers with young children aged 0 to 5 suffered the most from job losses due to pandemic-induced changes in housework division and childcare responsibilities during the early stages of the pandemic (Del Boca *et al*., 2020). In Spain, females experienced a higher likelihood of job loss than males in May 2020, and those who managed to retain their employment were more likely to work from home (Farré *et al*., 2020). Adopting a cross-country perspective, Adams-Prassl *et al*. (2020a) found that individuals involved in alternative work arrangements or occupations that do not allow for remote work faced a heightened vulnerability to job loss or reduced earnings in the US, the UK, and Germany. Notably, this risk was more distinct among individuals with lower educational attainment and women.

In terms of work productivity, Fuchs-Shundeln (2020) revealed a decline in the percentage of female authors of research papers submitted during lockdowns. Similar gender gap in research production has been observed among mid-career economists engaging in early research on COVID-19 as well (Amano-Patino *et al*., 2020). The multifaceted evidence suggests that increased childcare responsibilities during the pandemic significantly contributed to gender gaps in labour market outcomes.

2.3.3 Marital Status

A growing number of studies have highlighted the role of marital status in shaping the changes in gender gaps in employment outcomes during the pandemic. In past economic recessions, females tended to enter the labour market to sustain their families' income when their partners experienced job loss (Pruitt and Turner, 2020). Serving as a with-in family insurance, this "added worker effect" is argued to shape the gender disparities in employment outcomes during lockdowns. On the one hand, pandemic-induced "stay-at-home" shifts may have facilitated an internal support system within families. For partnered parents, these shifts enabled one parent to manage sudden childcare needs while the other maintained employment. Conversely, single parents shouldered the entire burden alone unless they had support from extended family or informal caregivers. During the pandemic recession, marriage could serve as a buffer for parents, offering a degree of protection from increased childcare responsibilities rather than serving as insurance in case of job loss. On the other hand, the with-in family insurance might work differently during the pandemic from previous economic recessions. Families grappling with escalated childcare demands might face difficulties in compensating for a partner's layoff by expanding their labour supply, as these additional childcare responsibilities might curtail their ability to increase work hours or explore employment prospects (Alon *et al*., 2020).

Empirical evidence suggests fathers have become more involved in childcare due to increased flexibility in balancing caregiving tasks and work (Sevilla and Smith, 2020; Carlson *et al*., 2022; Alon *et al*., 2020; Lyttelton *et al*., 2020). Research has indicated a more balanced division of housework and childcare among partnered parents during the onset of the pandemic, especially among those engaged in remote working (Carlson *et al*., 2022). Studies focusing on married parents have highlighted the impact of remote work on the gendered allocation of childcare responsibilities (Collins *et al*., 2021; Petts *et al*., 2021; Calarco *et al*., 2020; Landivar *et al*., 2020). This shift might have affected single mothers differently, possibly making them more vulnerable to increased childcare burdens as they may have had reduced adaptability in managing childcare losses during the pandemic compared to their partnered counterparts (Alon *et al*., 2020). Consequently, the intensified childcare demands during the pandemic might have notably influenced labour market outcomes for single mothers, potentially more so than for married or partnered mothers.

2.3.4 Ethnicity and Migrant Status

Previous studies confirm persistent disparities in employment and wages among different ethnic and migrant groups, compounding the gendered impact on labour market outcomes. Women within migrant populations encounter heightened challenges in securing stable employment due to factors such as health conditions, language proficiency, cultural norms, and limited access to networks (Longhi and Brynin, 2017; Nandi and Platt, 2023). Furthermore, significant disparities in employment rates among ethnic minority groups have been concluded, with women experiencing comparatively lower rates than their male counterparts (Platt and Warwick, 2020a). In addition, Montenovo *et al*. (2022) found that black individuals in the US experienced disproportionately high rates of job loss during the early stages of the COVID-19 pandemic. Research also shows that ethnic minority women often faced segregation in low-paying sectors, leading to employment precarity and limited career advancement (Rajan *et al*., 2020). These findings provide evidence for how intricate interplay of gender, ethnicity, and migrant status accentuate the gender gap in employment outcomes faced by migrant and ethnic minority women.

2.3.5 Health Conditions

Emerging research indicates that pre-existing health conditions amplified the adverse labour market impacts of the COVID-19 pandemic for women relative to men in the UK. Studies reveal women were more likely to experience job loss and shortened working hours due to pandemic health risks (Sevilla and Smith, 2020; Hupkau and Petrongolo, 2020). These effects were exacerbated for women with health risks such as diabetes and heart disease that increase COVID-19 mortality risks (Joyce and Xu, 2020; Blundell *et al*., 2022).

While there is limited research specifically examining the intersection of health conditions and gender in the UK labour market during the pandemic, existing literature suggests that women with health conditions may face unique challenges. Analysis of

UK labour data revealed women with long-term health conditions had a greater increase in economic inactivity during the pandemic compared to healthy women and men (Hupkau and Petrongolo 2020). Disabled and chronically ill women were also disproportionately furloughed or absent from work due to health shielding requirements and care duties (Office for National Statistics, 2020).

2.3.6 Education / Levels of Skills

As the disproportionate impact on female-dominated industries, the pandemic has significantly affected sectors primarily employing individuals with lower levels of education and occupational skills (Kim *et al*., 2022). Persistent occupational segregation by gender has long been a prominent issue, particularly among non-college-educated individuals (England, 2010). As in Goldin (2022) and Moen *et al*. (2020), unemployment surged more prominently among those without college degrees and white-collar skills across various age, gender, occupations, and racial groups during the initial phase of the pandemic.

Sectors reliant on face-to-face interactions typically employ a higher proportion of non-college-educated workers, while individuals with college degrees are more inclined to occupy tele-commutable roles (Montenovo *et al*., 2022). This dynamic likely renders mothers without college degrees more vulnerable to involuntary job loss during the pandemic. Among those who remained employed, the adaptation to heightened childcare duties posed greater challenges, especially for less-educated mothers unable to engage in remote work in the US (Montenovo *et al*., 2022). These findings indicate that gendered disparities in labour market outcomes may be more pronounced among individuals with lower educational qualifications or occupational skills compared with their counterparts, after controlling for essential industries and non-essential industries.

In summary, previous literature points to the need for investigating the interplay between various factors, such as marital status, ethnic migrant status, health conditions in explaining a surge in gendered labour market disparities during and aftermath of the pandemic.

3. Data and Methodology

3.1 Data Source and Sample Construction

This chapter uses microdata from the Understanding Society: COVID-19 Study[18] to investigate the intersectional impacts of the pandemic on employment outcomes in the UK. The Understanding Society COVID-19 Study (USoc COVID-19 Study) leverages Understanding Society: the UK Household Longitudinal Study as its foundation and employs regular web surveys or telephone surveys to capture the experiences and behaviours of the participants of the past waves of the Understanding Society (USoc) surveys throughout the COVID-19 pandemic. As the largest longitudinal household panel study in the UK with large and representative sample, the USoc datasets provide comprehensive information on personal and family-related characteristics in life changes and stability (University of Essex, 2021). The USoc COVID-19 Study has been increasingly used for investigating pandemic impacts on individuals in the UK, i.e. the labour market shocks that individuals experienced, the economic outcomes of the pandemic on different groups of workers, and the impacts of the pandemic on parents' relationship with their children (Crossley *et al*., 2021; Benzeval *et al*., 2020; Perelli-Harris and Walzenbach, 2020).

To investigate individuals' labour marker outcomes during the early stages of the pandemic, this study employs data from the first and second waves of the USoc COVID-19 Study, which was fielded in April and May 2020[19], respectively, alongside contextual information from Wave 9 of the main USoc dataset in 2019. This timeframe of the early stage of the pandemic was chosen because it captures the initial impacts of the COVID-19 pandemic in the UK, a period marked by the most stringent lockdown measures. Although the pandemic began affecting the UK in March 2020, the earliest available data for analysis begins in April 2020. As a result, March 2020 is not included in the analysis due to the lack of available data, which limits our ability to capture the very first responses to the pandemic. April 2020 marks the first full month of data collection, during which the UK government had already implemented widespread restrictions, including mandatory closures of non-essential businesses, social distancing protocols, and a nationwide stay-at-home order. The data from April and May 2020 therefore provide a crucial snapshot of the labour market and economic conditions during the most acute phase of the pandemic, before any significant policy adjustments or economic recovery efforts took place. The decision to limit the analysis to the end of May 2020 is because, by this time, the UK began to gradually lift the strictest

[18] Understanding Society, conducted by the University of Essex's Institute for Social and Economic Research, is the UK's primary longitudinal household survey and one of the world's largest household panel studies. Launched in 2009, it continues the work of the earlier British Household Panel Survey, which ran from 1991 to 2008. Understanding Society aims to interview all adults in sample households annually, employing a mixed-mode design that involves face-to-face interviews and web-based questionnaires.

[19] The first web survey was fielded on April 24th and the second on May 27th. Further information on the Understanding Society COVID-19 Study can be found via https://www.understandingsociety.ac.uk/topic/covid-19.

restrictions, allowing some businesses to reopen and certain economic activities to resume. Focusing on this early period allows us to isolate the immediate impacts of the pandemic, avoiding the confounding effects of later recovery phases, which were influenced by various factors such as the easing of restrictions and the adaptation of businesses to new operating conditions. By concentrating on the data from April and May 2020, this study aims to provide a focused analysis of the initial response to the pandemic and the direct consequences on labour market outcomes, particularly for vulnerable groups such as women and ethnic minorities.

The USoc dataset was chosen for this research over other than other UK surveys for several main reasons. First, the USoc dataset provides comparable reliable population inferences both before and during the COVID-19 pandemic, allowing for a controlled comparison of employment outcomes. The dataset includes detailed information on family, sociodemographic groups, occupation, and industry, allowing for controls of these confounding factors (University of Essex, 2021). Additionally, the USoc dataset critically incorporates gender related information about employment outcomes adhering to an established definition aligned with legislation, ensuring a consistent and reliable basis for analysis. Furthermore, the dataset provides a sufficiently large sample size, which allows for robustness checks and enhances the validity of findings (University of Essex, 2021).

The analytical sample for this study was derived from the April and May 2020 USoc datasets, specifically referencing data from the previous main wave to ensure continuity and reliability. In constructing the sample, I restricted individuals aged 16 to 64—the commonly recognized working-age population in the UK[20]—who had taken part in at least one of the COVID-19 waves, had previously participated in USoc Wave 9, and reported being employed during pre-pandemic period as of January-February 2020. Next, I adhered to the criteria to keep those respondents for whom complete data was available across key variables of interest. As a result, 1,276 observations were necessarily excluded from the analysis due to missing or incomplete data on key variables of gender, age, education qualifications, and ethnic migrant status. It is important to note that these exclusions were not due to selection bias but were purely a consequence of the unavailability of data in the previous main wave of the dataset. This approach ensures that the remaining sample is robust and reflective of the population under study, although it does mean that certain groups with incomplete data are underrepresented. To be noted, over 86% of the excluded cases did not report having school-aged children, which is a central focus of this research. The exclusion of these cases, particularly those without school-aged children, could potentially lead to an underrepresentation of broader labour market experiences during the pandemic. While this does not severely bias the results for the key focus group, it may limit the generalisability of the findings to the wider population, particularly in understanding

[20] According to the UK Office for National Statistics, the working age population mainly refers to labour aged 16 to 64 years. (Detailed information can be accessed at: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/timeseries/lf2o/lms)

employment dynamics among those without school-aged children. Nonetheless, the current analytical sample remains robust and well-suited for analysing the specific research questions at hand, particularly those related to the impact of the pandemic on individuals with school-aged children. The comprehensive data available for this group ensures that the key variables of interest are adequately represented, allowing for meaningful and accurate analysis. Descriptive statistics by gender and ethnic migrant status for this analytical sample are reported in Table 1.

While the main USoc waves employ face-to-face interviews supplemented by mixed-mode techniques for data collection, the USoc COVID-19 Study employs web-based self-completed questionnaires to gather relevant data. To counter potential sample selection biases stemming from divergent data collection methods, the following analysis incorporates sampling weights and stratification provided by the USoc team to adjust for any discrepancies between the sample and the overall population. These adjustments are crucial to correct for any under- or over-representation of certain groups within the sample and ensure the validity and reliability of the findings.

Table 1: Descriptive statistics by gender and ethnic migrant status of the analytical sample

Subgroups	*Employment status during the pandemic*				
	Paid employment	Self-employment	Both	Unemployment	Total
Gender					
Male	5585	1012	239	838	7674
	72.78%	13.19%	3.11%	10.92%	100.00%
Female	8510	916	294	1672	11392
	74.70%	8.04%	2.58%	14.68%	100.00%
Total	14095	1928	533	2510	19066
	73.93%	10.11%	2.79%	13.70%	100.00%
Ethnic migrant status					
White native	13280	1801	518	2316	17915
	74.13%	10.05%	2.89%	12.93%	100.00%
Others (BAME native, BAME migrant, and white migrant)	711	158	57	225	1151
	61.77%	13.73%	4.95%	19.55%	100.00
Total	13991	1959	575	2541	19066
	73.38%	10.27%	3.01%	13.33%	100.00

Notes: (1) First row has *frequencies*; second row has *column percentages;* (2) Row percentages show how a particular category (row) is composed of various groups.

3.2 Variables

3.2.1 Dependent Variable - Employment Status

A categorical variable is used to capture four types of employment statuses during the early stage of the pandemic period, which includes paid employment, self-employment, both paid employment and self-employment, and unemployment. Among these four categories, paid employment is selected as the baseline group.

Table 2A summarises the key transitions among different employment statuses of the sample. In the sample, 12.89% of individuals transitioned from paid employment to unemployment during the pandemic, while 0.93% moved from paid employment to both paid employment and self-employment. To further illustrate the scale and direction of employment transitions, Tables 2B and 2C present transition matrices for males and females, respectively. Notably, the data reveals that a higher percentage of women transitioned from paid employment to unemployment (14.97%) compared to men (9.54%). This could indicate that women faced greater employment instability or were more affected by the economic conditions during this pandemic time. In contrast, the transition rates from self-employment to unemployment among females are lower than that of males. The differences in transition rates suggests that factors affecting employment stability during the pandemic may have different impacts depending on both the type of employment and gender.

Table 2A: Employment transition matrix for the entire sample

Pre-pandemic period: Jan Feb 2020	Pandemic period: April and May 2020				
	Employed	Self-employed	Both	No	Total
Paid employment	12932	499	144	2009	15584
	82.98%	3.20%	0.93%	12.89%	100.00%
Self-employment	994	1306	156	305	2761
	36.00%	47.30%	5.65%	11.05%	100.00%
Both	169	123	233	196	721
	23.44%	17.06%	32.32%	27.18%	100.00%
Total	14095	1928	533	2510	19066
	73.93%	10.11%	2.79%	13.70%	100.00%

Notes: (1) First row has *frequencies*; second row has *column percentages;* (2) Row percentages show how a particular category (row) is composed of various groups.

Table 2B: Employment transition matrix for males

Pre-pandemic period: Jan Feb 2020	Pandemic period: April and May 2020				
	Paid employment	Self-employment	Both	Unemployment	Total
Paid employment	5014	311	63	568	5956
	84.18%	5.22%	1.06%	9.54%	100.00%
Self-employment	511	665	115	195	1486

	34.39%	44.75%	7.74%	13.12%	100.00%
Both	60	36	61	75	232
	25.86%	15.52%	26.29%	32.33%	100.00%
Total	5585	1012	239	838	7674
	72.78%	13.19%	3.11%	10.92%	100.00%

Notes: (1) First row has *frequencies*; second row has *row percentages;* (2) Row percentages show how a particular category (row) is composed of various groups.

Table 2C: Employment transition matrix for females

Pre-pandemic period: Jan Feb 2020	Pandemic period: April and May 202				
	Paid employment	Self-employment	Both	Unemployment	Total
Paid employment	7,918	188	81	1441	9628
	82.24%	1.95%	0.84%	14.97%	100.00%
Self-employment	483	641	41	110	1275
	37.88%	50.27%	3.22%	8.63%	100.00%
Both	109	87	172	121	489
	22.29%	17.79%	35.17%	24.75%	100.00%
Total	8510	916	294	1672	11392
	74.70%	8.04%	2.58%	14.68%	100.00%

Notes: (1) First row has *frequencies*; second row has *column percentages;* (2) Row percentages show how a particular category (row) is composed of various groups.

3.2.2 Independent Variables and Moderators

Gender and the presence of school-aged children are included as the main independent variables to investigate the persistence of motherhood penalty during the initial stage of the pandemic with the entire analytical sample. Additionally, moderators, such as ethnic migrant status (white native (86.1%) or others-including white migrant (3.74%), BAME native (5.57%), and BAME migrant (4.59%)), de facto marriage (cohabitating with a partner or not), industry contact intensity (contact-intensive or non-contact-intensive), and furlough status (furloughed or not) during the pandemic, are included to understand how they interact with the main independent variables, influencing employment outcomes during the early stage of the pandemic.

For the variable of ethnic migrant status, I used an interaction between ethnicity (white or BAME) and migrant status (born in the UK or not), rather than analysing these factors separately, to capture the compounded effects of these intersecting identities on labour market outcomes. Ethnic migrant status was determined based on participants' self-reported ethnicity and whether they were born in the UK. Participants were categorised into two main groups: white natives and BAME (Black, Asian, and Minority Ethnic) migrants. White natives are individuals who are white and born in the UK, while the BAME migrant group encompasses a more nuanced classification, including white individuals not born in the UK, BAME individuals born in the UK, and BAME individuals not born in the UK. This combined classification enabled a more detailed examination of the intersectionality affecting employment outcomes. Existing research has demonstrated that the intersection of race and migrant status significantly influences employment experiences and outcomes. By using the interaction between ethnicity and migrant status, this analysis aims to investigate these intersectional penalties more comprehensively, particularly during the COVID-19 pandemic. For example, while BAME mothers already encounter substantial challenges in the labour market, the additional factor of migrant status can intensify these challenges, leading to greater vulnerabilities. This approach allows for a more nuanced understanding of specific subgroup dynamics that might otherwise be overlooked when ethnicity and migrant status are analysed separately. Within the sample, white natives constituted 86.1% of the population, while BAME migrants accounted for 13.9%, further broken down into 3.74% white migrants, 5.57% BAME natives, and 4.59% BAME migrants.

With a comparative analysis between gender sub-samples, the investigation extends to examine the interplay between ethnic migrant status, presence of school-aged children, self-reported health conditions (clinically vulnerable to Coronavirus or not), and access to family support in childcare (having family support in childcare or not) on individual's employment outcomes during the early stages of the pandemic.

3.2.3 Control Variables

To address the risk of omitted variable bias, a comprehensive set of control variables was included in the regression models. A group of variables capturing individual sociodemographic features, employment related features, and financial conditions are controlled in the empirical analysis as well. These controls account for various factors that could influence employment outcomes independently of gender and its interactions with other demographic factors. Personal sociodemographic features include gender, age, age square, education qualification, and urban residency. Employment related features cover the remote working frequency of one's employment and occupational class. Regarding financial conditions, a categorical variable of household income level is included. Table 3 reports the summary statistics of these variables, with detailed information about variable constructions and descriptions elaborated in Appendix 4.1.

Table 3: Summary statistics of independent categorical variables

Variables	Obs	Categories	Percentage
Gender	19,066	Male	41.4%
		Female	58.6%
Education	19,066	Bachelor's degree and above	32.9%
		Below bachelor's degree	50.7%
		No qualification	16.4%
School-aged children	19,066	No	79.8%
		Yes	20.2%
Ethnic migrant status	19,066	White native	86.1%

		Others	13.9%
Occupational class	18,993	Higher managerial, administrative, and professional	27.1%
		Lower managerial, administrative, and professional	13.2%
		Intermediate	18.9%
		Small employers and own account worker	5.8%
		Lower supervisory and technical	16.7%
		Others	18.3%
Urban	18,420	Rural	19.4%
		Urban	80.6%
Work at home	17,929	Never	64.6%
		Sometimes	21.7%
		Often	7.6%
		Always	6.1%
Household income (qnt)	18,242	Low	23.6%
		Middle	37.9%
		High	38.5%
Cohabitation	16,370	No	31.9%
		Yes	68.1%
Furlough	15,111	No	86.3%
		Yes	13.7%
Family support in childcare	15,344	No	38.8%
		Yes	61.2%
Health conditions	15,903	Not clinically vulnerable to Coronavirus	85.8%
		Clinically vulnerable to Coronavirus	14.2%
Baseline employment status (pre-pandemic)	19,066	Paid employment	84.7%
		Self-employment	11.8%
		Both paid employment and self-employment	3.5%

Notes: Detailed information about these variables can be found in Appendix 4.1.

3.3 Model Specification

This study uses a dynamic multinomial logistic model (DMNL model) to investigate how the pandemic has affected individual's labour market outcomes during the early stages of the outbreaks. A DMNL model was selected for the following main reasons. First, the DMNL model is widely used to model categorical outcome variables that lack a natural ordering of categories (Hartzel *et al.*, 2001), which in this case is the employment status of individuals during the global pandemic[21]. Secondly, the DMNL model recognises that individual's choices may be influenced by their own past behaviours and allows for modelling state dependence (Cowling and Wooden, 2021), which in this case is the influence of individual's employment status in January-February 2020 before the outbreaks of the pandemic on the current employment status

[21] A Brant test was conducted to examine the parallel regression assumption, determining the suitability of either ordinal logistic regression or multinomial logistic regression for this analysis. With a p-value of 0.000, the multinomial logistic regression is considered as the more appropriate choice over the ordinal logistic regression.

during the pandemic period. By including lagged variables or individual-specific effects, the DMNL model enables to account for temporal dimension (Lechmann and Wunder, 2017). In addition, the model allows for capturing heterogeneities in choice patterns of different individuals over time (Cowling and Wooden, 2021).

The DMNL model used in this study is as follows:

$$\text{Prob}\left(y_{it} = \text{j} \mid x_{it}, y_{i,t-1}, \alpha_{ij}\right) = \frac{\exp\left(\beta_j' x_{it} + \gamma_j' y_{i,t-1} + \alpha_{ij}\right)}{\sum_{k=1}^{4} \exp\left(\beta_k' x_{it} + \gamma_k' y_{i,t-1} + \alpha_{ik}\right)}$$

where yit represents the individual's employment status j at time t during the covid period, $yi,\ t{-}1$ captures one's pre-pandemic employment status in Jan-Feb 2020, xit is a vector of observed individual characteristics, and αij is a robust random error component intended to capture individual-specific unobserved heterogeneity. The examination of the motherhood penalty is conducted using the entire sample. The analyses of intersectional penalties associated with having school-aged children, ethnic migrant status, other relevant factors are concentrated on gender sub-samples.

A random effects logistic regression model is selected for the following main reasons. First, as individuals were randomly sampled from the population, any unobserved heterogeneity in employment outcomes is considered randomly distributed rather than systematic, which favours modelling heterogeneity via random effects. Additionally, a random effects model allows better for generalization than a fixed effects model (Woodridge, 2010). Furthermore, estimating a large number of fixed effects for each individual would substantially overfit the model given the extensive sample, while the parsimonious random effects specification avoids this issue (Bell and Jones, 2015). The random-effects estimators yield valid estimates in the presence of unobserved heterogeneity at the panel level as well (Hartzel *et al*., 2001).

4. Empirical Analysis

This section examines how the COVID-19 pandemic has affected individual economic outcomes in the labour market within the UK context. I first examined the existence of a motherhood penalty during the pandemic, based on I which investigated the gender gaps in the probability of employment transition during the pandemic, conditional on ethnic migrant status, de facto marital status, industry contact intensity, and furlough status. Second, I focused on the female sample, in comparison with the male sample, to identify combinations of traits associated with the greatest economic vulnerability by estimating interaction effects between sociodemographic characteristics.

4.1 Motherhood Penalty during the Initial Stage of the Pandemic

4.1.1 Motherhood Penalty among the Entire Sample

An interaction term between gender and the presence of school-aged children was introduced to examine the motherhood penalty, as reported in Table 4A. In Column (3), the positive coefficient of 0.934 for the interaction term between gender and the presence of school-aged children indicates that the log-odds of transitioning into unemployment increase by 0.934 unit for individuals who are females and have school-aged children, relative to individuals who are males and do not have school-aged children. The gender barriers in remaining employed during the crisis are intensified by having school-aged children for females, relating to a higher probability of becoming unemployed relative to retaining work for mothers.

While the coefficients from the multinomial logistic regression model indicate the direction and significance of relationships between predictors and employment outcomes, their interpretation in terms of log-odds can be challenging due to the nonlinearity inherent in the model. To provide a more intuitive understanding of these relationships, average marginal effects (AMEs) are reported in this chapter. AMEs overcome the interpretive limitations of log-odds by providing the averaged effect of a one-unit change in each predictor on the probability of an outcome across the sample. This approach offers clearer insights into the practical significance of key factors, such as gender, the presence of school-aged children, and ethnicity, in shaping employment probabilities during the pandemic. For instance, Table 4B reports the AME of gender on the probability of transitioning from paid employment to unemployment, conditional on the presence or absence of school-aged children. The AME indicates the average change in unemployment probability associated with being female, compared to male, in each subgroup. The results show that, for individuals without school-aged children, being female is associated with a statistically significant 2.57 percentage point decrease in the probability of unemployment. In contrast, for individuals with school-aged children, the effect of gender is not statistically significant, with an AME of 0.69 percentage points. This suggests that the presence of caregiving responsibilities may reduce the likelihood of employment stability associated with gender.

Table 4A: Estimation results predicting changes in employment status with interaction between gender and the presence of school-aged children

VARIABLES	(1) Self-employment vs paid employment	(2) Both vs paid employment	(3) No employment vs paid employment
Gender (ref.=male)	-0.611	-0.355	-0.802***
	(0.398)	(0.345)	(0.264)

Children (ref.=no)	-0.769*	-0.504	-0.362*
	(0.449)	(0.355)	(0.218)
Gender#Children	0.365	0.417	0.934***
	(0.532)	(0.418)	(0.345)
Education (ref.=Bachelor's degree and above)			
Below Bachelor's degree	0.886	1.452	1.188***
	(0.817)	(1.154)	(0.450)
No qualification	0.855	1.530	1.543***
	(0.807)	(1.163)	(0.478)
Age	-0.243***	-0.106	-0.275***
	(0.0891)	(0.0843)	(0.0433)
Age_squared	0.00296***	0.00137	0.00319***
	(0.00102)	(0.000978)	(0.000507)
Ethnic_migrant (ref.=white native)	-0.314	-0.556	0.935***
	(0.950)	(0.521)	(0.252)
Urban	-0.106	-0.201	-0.157
	(0.248)	(0.223)	(0.275)
Work at home (ref.=never)			
Sometimes	-0.805	-0.174	0.334
	(0.689)	(0.435)	(0.363)
Often	-0.969	-0.0938	-0.707*
	(0.672)	(0.435)	(0.402)
Always	-1.703**	-1.197***	-0.779**
	(0.754)	(0.414)	(0.279)
Household income (ref.=low)			
Middle	0.132	0.127	-0.127
	(0.361)	(0.292)	(0.195)
High	-0.324	0.188	-0.552
	(0.289)	(0.271)	(0.553)
Occupational class (ref.=managerial, administrative, and technical)			
Intermediate	-0.653	-0.683	-0.541
	(0.503)	(0.591)	(0.674)
Small employers and own account workers	1.349***	1.162**	1.489***
	(0.365)	(0.461)	(0.318)
Lower supervisory and technical occupation	0.682	-0.211	0.633**
	(0.774)	(0.393)	(0.276)
Semi-routine and routine	0.110	0.234	0.612**
	(0.420)	(0.278)	(0.240)
Not applicable (others, inactive, etc.)	0.233	-0.243	0.710
	(0.538)	(0.359)	(0.637)

Baseline employment status (ref.=paid employment)			
Self-employment	9.177***	4.628***	3.732***
	(0.523)	(0.369)	(0.285)
Both paid and self-employment	4.922***	6.669***	2.135***
	(0.531)	(0.253)	(0.453)
Observations	17,350	17,350	17,350

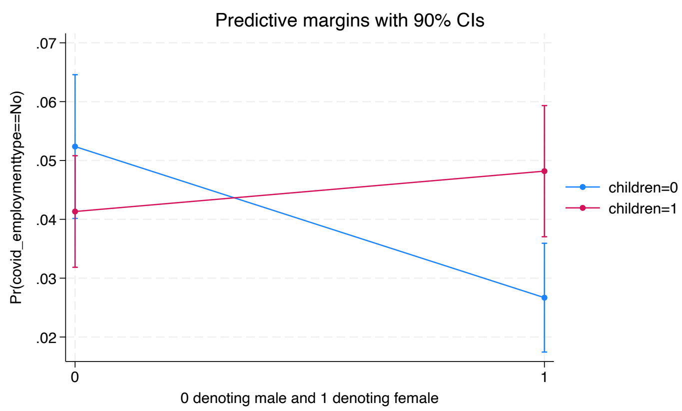
Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

Table 4B: Average marginal effects (AMEs) of gender and the presence of school-aged children

Variable	Condition	AME (%)	p-value	95% Confidence Interval
Gender (Female)	With school-aged children	+0.69	0.434	-1.03, 2.40
Gender (Female)	Without school-aged children	-2.57	0.003	-4.27, -0.86

Figure 1A visualizes the relationship between gender and the probability of transitioning from paid employment to unemployment conditional on the presence of school-aged children during the early stage of the pandemic. For males, having school-aged children is associated with an insignificant increase in the probability of becoming unemployed, given the overlapping confidence intervals. In contrast, for females, the presence of school-aged children increases the probability of switching from paid employment to unemployment by approximately 2%. This result supports the motherhood penalty hypothesis (Correll *et al.*, 2007; Kelley *et al.* 2020) that mothers with school-aged children face greater barriers to employment participation, compared with females without school-aged children.

Figure 1A: The relationship between gender and probability of transitioning to unemployment conditional the presence of school-aged children



From the estimation results, it is evident that the coefficients of the interaction terms of interest are not statistically significant in the regressions estimating the probabilities of transitioning from paid employment to self-employment and from paid employment to both paid employment and self-employment, whereas those in the regressions estimating the probabilities of transitioning from paid employment to unemployment are statistically significant. The probabilities of transitioning from paid employment to self-employment or a combination of paid employment and self-employment consistently lack statistical significance in the following sections focusing on different time periods/subgroups. Therefore, for the simplicity of presentation, I will report the estimation results focused on the probabilities of transitioning from paid employment to unemployment. Detailed results of the probabilities of other employment transitions, including transitions to self-employment and combined employment, in the following analyses can be found in the Appendix 4.2. The observed differences in the statistical significance of the probabilities can be attributed to the nature of employment transitions and sample sizes.

The shift from paid employment to unemployment during economic crises, such as the COVID-19 pandemic, is primarily involuntary and heavily driven by external factors like layoffs, business closures, and widespread labour market contractions. Given the profound economic impact of the pandemic, these involuntary transitions became widespread, naturally resulting in the statistically significant findings presented in this chapter. The high volume of job losses during this period amplified the statistical power of the analysis, enhancing the ability to detect meaningful effects. In contrast, transitions from paid employment to self-employment, or a combination of both, tend to be more nuanced and generally voluntary. These career changes are often shaped by individual preferences, risk tolerance, and personal circumstances, leading to smaller sample sizes and higher variability in outcomes. This complexity likely accounts for the observed lack of statistical significance in these transitions, as such voluntary changes inherently lack the uniformity and frequency seen in involuntary unemployment shifts during crises. Therefore, the absence of statistical significance in these specific cases does not undermine the robustness of the findings but rather reflects the distinct nature of voluntary versus involuntary employment transitions.

4.1.2 Comparative Analysis of Motherhood Penalty in April and May 2020

To ensure the robustness of the findings on employment status changes, analogous regressions were conducted as robustness checks using samples of individuals in the first wave of survey (April 2020) and individuals of the second wave of the survey (May 2020), respectively. This approach examined whether the observed changes in employment status remained consistent across different time points, considering the rapid evolution of the socioeconomic circumstances during the pandemic. This rigorous approach can identify and account for potential biases specific to a particular period, enhancing the validity and reliability of the study, as it takes into consideration the dynamic nature of the pandemic context. To appropriately estimate the interacting effects of time-invariant variables between gender and the presence of school-aged children on employment outcomes with the April sample and the May sample, I implemented specifications with random effects to control for cross-sectional heterogeneity and estimate coefficients on the time-constant interacting factors.

In both April and May 2020, the coefficients of the interaction term between gender and the presence of school-aged children remain positive and significant on the probability of transitioning to unemployment, as reported in Column (1) and (2) of Table 5. The results suggest that mothers with school-aged children have a higher probability of transitioning from paid employment to unemployment compared to those without school-aged children in both April 2020 and May 2020, indicating the persistence of motherhood penalty during the initial stage of the pandemic.

Table 5B presents the AMEs of gender on the probability of unemployment, conditional on the presence or absence of school-aged children in April and May 2020, respectively. The results indicate that, although the effective of being female is associated with an increase in the probability of becoming unemployed, the effect is not statistically significant in both April and May 2020. In contrast, for individuals without school-aged children, the AME for gender shows that being female is associated with a statistically significant decrease in the probability of unemployment in both April and May 2020. The results corroborate with that of the entire sample and suggest that the presence of caregiving responsibilities influence the probability of employment stability associated with gender.

Table 5A: Estimation results predicting changes in employment status with interaction between gender and the presence of school-aged children in April and May 2020

	(1) First wave	(2) Second wave
VARIABLES	No vs paid employment	No vs paid employment
Gender (ref.=male)	-1.003***	-1.099***
	(0.283)	(0.270)
Children (ref.=no)	-0.446**	-0.352
	(0.213)	(0.215)
Gender#Children	1.058***	1.170***
	(0.356)	(0.337)
Controls	Yes	Yes
Observations	8,549	8,801

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

Table 5B: Average marginal effects (AMEs) of gender and the presence of school-aged children in April and May 2020

Variable	Condition	AME (%)	p-value	95% Confidence Interval
April 2020				
Gender (Female)	With school-aged children	+1.11	0.614	-0.09, 2.13
Gender (Female)	Without school-aged children	-3.31	0.000	-5.13, -1.49
May 2020				
Gender (Female)	With school-aged children	+0.65	0.471	-1.12, 2.43
Gender (Female)	Without school-aged children	-3.54	0.000	-5.29, -1.79

Figures 1B and 1C illustrate the relationship between the probability of transitioning from paid employment to unemployment and gender, conditional on the presence of school-aged children in April and May 2020, respectively. The results across both April and May samples are overall consistent with the result in the entire sample observed in Figure 1A. Specifically, in April 2020, mothers with school-aged children exhibit a 2.2% higher probability of transitioning to unemployment compared to those without school-aged children. In May 2020, this percentage change increases to nearly 3% for mothers with school-aged children compared to their counterparts. The marginally greater percentage change observed in May as opposed to April could be attributed to the prolonged impact of the pandemic. This extended duration might have facilitated shifts in employment dynamics, resulting in more pronounced observed percentage changes.

Figure 1B: The relationship between gender and probability of transitioning to unemployment conditional on the presence of school-aged children in April 2020

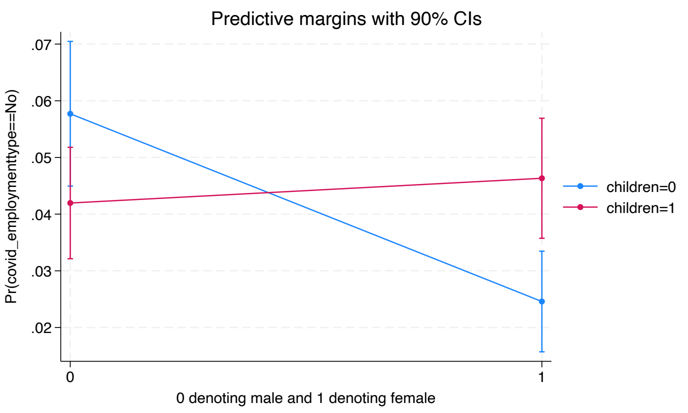
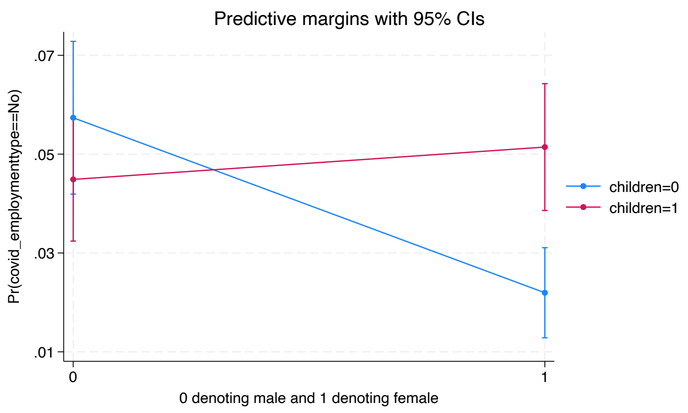


Figure 1C: The relationship between gender and probability of transitioning to unemployment conditional on the presence of school-aged children in May 2020



4.2 Intersectional Penalties

Previous literature has argued that gender intersects with other factors such as ethnic origin and socioeconomic class, creating complex and interactive relations that shape economic outcomes during the pandemic (Ryan and El Ayadi, 2020). Applying an intersectional approach, this section examined gender gaps in employment transitions during the pandemic, conditional on ethnic migrant status, de facto marital status, industry contact intensity, and furlough status among individuals of different occupational skills, in light of the motherhood penalty.

4.2.1 The Interplay of Gender, School-Aged Children, and Moderating Factors

To comprehensively investigate the dynamics of employment transitions during the pandemic, I conducted interaction analyses between gender, the presence of school-aged children, and relevant moderating factors such as ethnic migrant status, de facto marriage (cohabitation), contact intensity within the employment industry, and furlough status, on one's employment status. Table 6A reports estimation results predicting changes in employment status with interactions between gender, the presence of school-aged children, and these moderating factors, including ethnic migrant status, de facto marriage, contact intensity of the employment industry, and furlough status, respectively.

The coefficient of the three-way interaction between gender, the presence of school-aged children, and ethnic migrant status, as reported in Column (1), is positive at a significance level of 10%. Gender, the presence of school-aged children, and ethnic migrant status has a three-way interaction effect on one's probability of transitioning from paid employment to unemployment, suggesting that the relationship between gender and the likelihood of job displacement due to the presence of school-aged children is moderated by an individual's ethnic migrant status. This finding indicates that the effect of being a woman with school-aged children on the probability of losing a job during the pandemic is not uniform across all individuals, but rather varies depending on their ethnic migrant status.

In addition, the three-way interaction between gender, the presence of school-aged children, and cohabitation (industry contact intensity) enters negatively on one's transition from paid employment to unemployment during the pandemic, as shown in Column (2) and (3). The results indicate that the effect of gender on the likelihood of job displacement as a function of cohabitation (industry contact intensity) is significantly influenced by having school-aged children.

Column (4) reports the estimation results with a three-way interaction between gender, the presence of school-aged children, and furlough status, predicting the transition from paid employment to both paid employment and self-employment. The Coronavirus Job Retention Scheme, commonly known as furlough, was introduced by the UK government in March 2020 as a temporary economic support measure in response to the COVID-19 pandemic. Under the furlough scheme, employees' working hours or payment are reduced but their jobs are retained by employers. This three-way interaction term enters positively and significantly on one's probability of transitioning to both paid employment and self-employment.

The AME results in Table 6B provide insights into how gender affects unemployment probability under various conditions. For individuals without school-aged children, being female has an insignificant effect on unemployment probability, regardless of ethnic migrant status. However, among individuals who are not white natives and with school-aged children, being female is associated with a 4.69% increase in unemployment probability. Additionally, for those in couples (in non-contact-intensive industries) with children, the AME shows a significant 2.74% (2.34%) decrease in unemployment probability for females, suggesting that partnership dynamics (the contact intensity of working industry) interact with caregiving to influence employment outcomes. These results highlight the intersectional impacts of gender, caregiving responsibilities, and ethnic migrant status/relationship status/working industry on employment stability, suggesting the importance of considering intersecting demographic factors when analysing labour market vulnerabilities.

Table 6A: Estimation results predicting changes in employment status with three-way interaction between gender, the presence of school-aged children, and relevant moderating factors[22]

VARIABLES	(1) No employment vs paid employment	(2) No employment vs paid employment	(3) No employment vs paid employment
Gender (ref.=male)	0.0244	0.383	-0.111
	(0.148)	(0.512)	(0.209)
Children (ref.=no)	-0.231	-0.904	-0.408
	(0.267)	(0.744)	(0.436)
Gender#Children	-0.107	1.991**	0.347*
	(0.334)	(0.803)	(0.192)
Ethnic_migrant (ref.=white native)	1.024***		
	(0.330)		
Gender#Ethnic_migrant	-0.779*		
	(0.470)		
Children#Ethnic_migrant	0.222		
	(0.565)		
Gender#Children#Ethnic_migrant	1.131*		
	(0.673)		
Cohabitation (ref.=no)		0.684	
		(0.480)	
Gender#Cohabitation		-0.330	
		(0.583)	
Children#Cohabitation		1.069	

[22] The full table for relevant regression results of Table 6A can be found in Appendix 4.2.1, 4.2.2, and 4.2.3.

		(0.861)	
Gender#Children#Cohabitation		-2.719***	
		(0.944)	
Industry (ref.=contact-intensive)			0.0129
			(0.279)
Gender#Industry			-0.439
			(0.366)
Children#Industry			0.349
			(0.593)
Gender#Children#Industry			-0.966*
			(0.551)
Controls	Yes	Yes	Yes
Observations	17,348	16,370	15,567

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

Table 6B: Average marginal effects (AMEs) of gender, the presence of school-aged children, and relevant moderating factors

Variable	Condition	AME (%)	p-value	95% Confidence Interval
Gender (Female)	With school-aged children, White native	-0.23	0.650	-1.23, 0.77
Gender (Female)	With school-aged children, BAME migrant	+4.69	0.094	-0.79, 10.18
Gender (Female)	With school-aged children, Not cohabitation	-0.49	0.704	-3.02, 2.47
Gender (Female)	With school-aged children, Cohabitation	-2.74	0.002	-4.52, -0.98
Gender (Female)	With school-aged children, Contact-intensive	+0.87	0.461	-1.45, 3.20
Gender (Female)	With school-aged children, Non-contact-intensive	-2.34	0.075	-4.92, 0.23

Figures 2A-C illustrate the relationship between gender and the probability of employment transition conditional on one's ethnic migrant status, de facto marriage, and industry contact intensity, respectively. As shown in Figures 2A-C, there is no statistically significant difference in the probability of transitioning to unemployment between genders for individuals without school-aged children, irrespective of their ethnic migrant status, cohabitation, and industry contact intensity, given the overlapping confidence intervals.

Contrastingly, significant effects of these moderating factors on the probability of employment transition can be observed among females with school-aged children. As demonstrated in Figure 2A, BAME migrant mothers with school-aged children have an approximately 7% higher probability of becoming unemployed than white native mothers. This finding aligns with prior research by Bambra *et al*. (2020), which highlighted the disparities in employment outcomes experienced by different ethnic groups during the pandemic. Several factors contribute to this difference in the probability of transitioning from paid employment to unemployment between white native and BAME migrant mothers with school-aged children. First, existing research shows that BAME individuals often face systemic barriers and discrimination in the labour market, which may render them more vulnerable to job displacement during economic downturns (Heath and Di Stasio, 2019). This vulnerability may be further exacerbated for BAME migrant women with school-aged children, as they navigate the additional challenges of balancing work and childcare responsibilities. In addition, white native women may have stronger social networks and support systems that provide access to information, resources, and job opportunities, helping them maintain employment during challenging economic times (McDonald *et al*., 2009). In contrast, BAME migrant women might face greater social isolation and have more limited access to these support systems, making it harder for them to secure alternative employment when needed (Datta *et al*., 2007).

Figure 2B demonstrates that cohabitating with a partner significantly mitigates the probability of transitioning into unemployment by approximately 2%, among mothers of school-aged children. The result indicates that for mothers with school-aged children, cohabitation offers a form of within-family insurance during the early stage of the pandemic. Previous research has shown that some couples reported more egalitarian divisions of labour, indicating increased involvement of fathers in childcare (Carlson *et al*., 2022; Shockley *et al*., 2021; Sevilla and Smith, 2020). According to Kim *et al*. (2022), cohabitation forms the “added caregiver effect”, which serves as a principal mechanism of within-family insurance, allowing multiple caregivers to share caregiving tasks and subsequently reducing stress and burnout among individual caregivers. To be noted, I do not argue that cohabitation (de facto marriage) inherently alleviates the disproportionate burden of childcare faced by females. However, the presence of a partner can provide flexible support as necessitated by emergencies or illness, a benefit unavailable to single females (Petts *et al*., 2021). This flexibility became especially critical during the pandemic when adhering to physical distancing guidelines significantly restricted the availability of external emergency caregivers outside the household. Despite persistent gender imbalances in the division of labour, partnered mothers could call on spouses for child supervision or sick care when crises arose. Therefore, cohabitation (de facto marriage) can serve as a safety net conferring flexibility and reliability of care at a time when few alternatives existed during lockdowns.

Figure 2C provides evidence that employment in non-contact-intensive industries is associated with a significantly reduced likelihood of transitioning to unemployment, with an estimated decrease of approximately 1.5% among mothers of school-aged children. The moderating effect between gender and employment transition can be attributed to the nature of industries. With widespread lockdowns and location-dependent hours constraints, contact-intensive industries face sharper activity declines (Del Rio-Chanona *et al*., 2020), catalysing job losses especially for women balancing parental duties. In contrast, non-contact-intensive with greater flexibility around remote-work and schedule variability exhibit resilience maintaining employment levels. According to Goldin (2021), certain industries were able to narrow the divide between professional and personal realms by allowing mothers' space-time flexibility through remote work and schedule adjustments, possibly mitigating unemployment risks in these non-contact-intensive industries during the lockdowns. The time-space flexibility sparked by the pandemic could bridge work-family conflicts that previously led to mothers' employment displacement due to unmet caretaking needs.

In summary, Figures 2A-C emphasize the complex interplay between gender, the presence of school-aged children, and various moderating factors in influencing employment transitions during the pandemic. Among these moderating factors, ethnic migrant status emerges as the most impactful factor on an individual's transition from paid employment to unemployment. These findings emphasize the importance of considering the unique challenges faced by specific demographic groups, particularly BAME migrant mothers with school-aged children, when investigating intersectional penalties on employment.

Figure 2A: The relationship between gender and probability of transitioning to unemployment conditional on ethnic migrant status by the presence of school-aged children

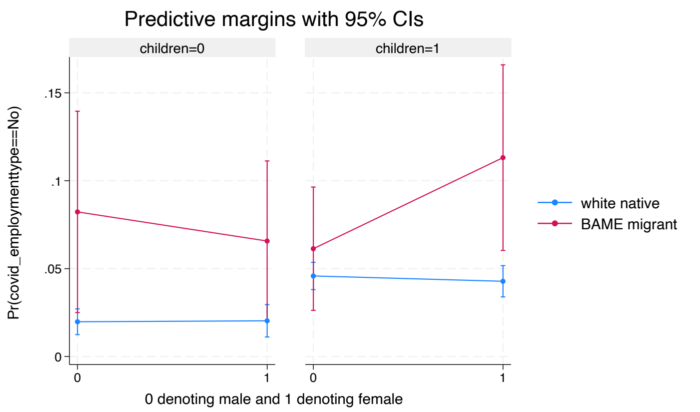


Figure 2B: The relationship between gender and probability of transitioning to unemployment conditional on cohabitation by the presence of school-aged children

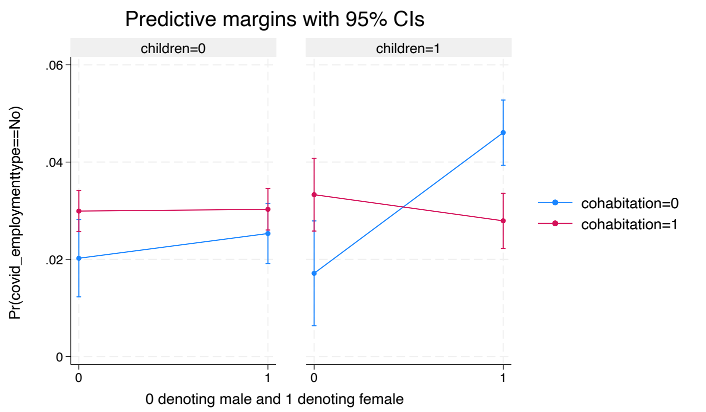
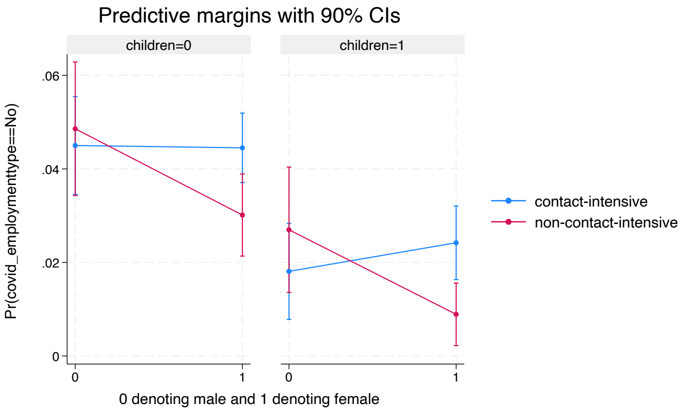


Figure 2C: The relationship between gender and probability of transitioning to unemployment conditional on industry contact intensity by the presence of school-aged children



4.2.2 Gender, School-Aged Children, and Moderating Factors: April and May 2020

I conducted parallel analyses using data from the April and May surveys to explore gender disparities in the probability of employment transition during April and May 2020, respectively. This investigation serves as robustness checks to validate the consistency of the findings across different survey waves. Table 7A presents the estimation results predicting changes in employment status, incorporating interactions between gender, the presence of school-aged children, and moderating factors such as ethnic migrant status, de facto marriage, industry contact intensity, and furlough status in April (Column (1) to (4)) and May (Column (5) to (8)), respectively.

Consistent with the findings from the entire sample, the three-way interaction between gender, the presence of school-aged children, and ethnic migrant status (cohabitation/ low contact intensity of employment industry) is positively (negatively) and significantly associated with the probability of transitioning to unemployment in both April and May 2020. Additionally, the three-way interaction effect of gender, the presence of school-aged children, and furlough status remains positive and significant on the likelihood of taking additional self-employment activities in both time periods. The relatively stable results corroborate the previous findings within the entire sample, evidencing the moderating effects of ethnic migrant status, cohabitation, contact intensity of employment industry, and furlough status on employment transitions during the pandemic.

As in Table 7B, the corresponding AMEs reveal consistent findings with the results derived from the entire sample. The AMEs indicate that gender effects on unemployment probability are nuanced by caregiving responsibilities, ethnic migrant status, relationship dynamics, and the contact intensity of employment industry. For example, in the analyses for both April and May 2020, being female among non-white, non-native individuals with school-aged children are associated with a higher probability of unemployment. Similarly, women in couples (in non-contact-intensive industries) with children show a reduced likelihood of becoming unemployed.

Table 7A: Estimation results predicting changes in employment status with three-way interaction between gender, the presence of school-aged children, and moderating factors in April and May 2020

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	April 2020				May 2020			
VARIABLES	No employment vs paid employment	No employment vs paid employment	No employment vs paid employment	Both vs paid employment	No employment vs paid employment	No employment vs paid employment	No employment vs paid employment	Both vs paid employment
Gender (ref.=male)	0.0537	0.577	0.0935	1.186*	0.0762	0.341	-0.0367	1.200*
	(0.300)	(0.529)	(0.231)	(0.635)	(0.298)	(0.503)	(0.163)	(0.627)
Children (ref.=no)	0.300	-1.131	-0.205	0.319	0.272	-0.296	-0.111	0.262
	(0.222)	(0.739)	(0.446)	(0.562)	(0.222)	(0.754)	(0.284)	(0.611)
Gender#Children	-0.0585	2.079***	0.121	-2.180**	-0.00861	1.499*	-0.0389	-2.094**
	(0.332)	(0.804)	(0.508)	(0.861)	(0.331)	(0.821)	(0.347)	(0.905)
Ethnic_migrant (ref.=white native)	1.564***				1.638***			
	(0.442)				(0.441)			
Gender#Ethnic_migrant	-0.174				-0.412			
	(0.626)				(0.647)			
Children#Ethnic_migrant	-1.312**				-1.266**			
	(0.555)				(0.553)			
Gender#Children#Ethnic_migrant	1.114*				1.140*			
	(0.618)				(0.633)			
Cohabitation (ref.=no)		0.702				0.877*		
		(0.484)				(0.459)		
Gender#Cohabitation		-0.630				-0.363		
		(0.599)				(0.575)		
Children#Cohabitation		1.309				0.468		
		(0.818)				(0.849)		
Gender#Children#Cohabitation		-2.723***				-2.190**		
		(0.914)				(0.952)		
Industry (ref.=contact-intensive)			0.102				0.225	
			(0.306)				(0.234)	
Gender#Industry			-0.521*				-0.621*	

			(0.287)				(0.321)	
Children#Industry			0.171				-0.182	
			(0.606)				(0.476)	
Gender#Children#Industry			-0.785*				-0.656*	
			(0.439)				(0.351)	
Furlough (ref.=no)					0.298			0.247
					(0.434)			(0.428)
Gender#Furlough					-0.864			-0.839
					(0.773)			(0.764)
Children#Furlough					-0.678			-0.569
					(0.616)			(0.681)
Gender#Children#Furlough					2.453**			2.343**
					(0.986)			(1.027)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,557	8,015	7,643	7398	8,879	8,355	7,924	7,713

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

Table 7B: Average marginal effects (AMEs) of gender, the presence of school-aged children, and relevant moderating factors in April and May 2020

Variable	Condition	AME (%)	p-value	95% Confidence Interval
April 2020				
Gender (Female)	With school-aged children, White native	-0.23	0.649	-1.24, 0.78
Gender (Female)	With school-aged children, BAME migrant	+4.66	0.090	-0.72, 10.05
Gender (Female)	With school-aged children, Not cohabitation	-0.64	0.533	-2.67, 1.38
Gender (Female)	With school-aged children, Cohabitation	-2.19	0.001	-3.44, -0.93
Gender (Female)	With school-aged children, Contact-intensive	+0.87	0.392	-1.12, 2.85
Gender (Female)	With school-aged children, Non-contact-intensive	-2.47	0.063	-5.08, 0.14
May 2020				
Gender (Female)	With school-aged children, White native	-0.35	0.491	-1.34, 0.64
Gender (Female)	With school-aged children, BAME migrant	+4.83	0.094	-0.82, 10.47
Gender	With school-aged children, Not cohabitation	-0.71	0.450	-2.55, 1.13

(Female)				
Gender (Female)	With school-aged children, Cohabitation	-2.32	0.001	-3.64, -0.99
Gender (Female)	With school-aged children, Contact-intensive	+0.84	0.482	-1.51, 3.19
Gender (Female)	With school-aged children, Non-contact-intensive	-2.37	0.070	-4.94, 0.19

Figures 3A-C and 4A-C illustrate the relationship between gender and the probability of employment transition conditional on one's ethnic migrant status, cohabitation, industry contact intensity, and furlough status in April and May 2020, respectively.

The results in Figure 3A demonstrate a notable disparity in unemployment rates, with BAME migrant mothers of school-aged children having a roughly 6.9% higher probability of becoming unemployed compared to white native mothers. Observing the three-way interacting effects in Figure 3B and 3C, cohabitation and working in non-contact-intensive industries lowers the likelihood of unemployment by approximately 1.8% and 1.5% among women with school-aged children, respectively. Regarding the probability of taking additional self-employment activities in April, the difference between mothers who were furloughed and those who were not is approximately 1.3%. The estimation results in Figures 3A-C are consistent with the previous findings of the significant moderating effects of ethnic migrant status, de facto marriage, and contact intensity of employment industry on one's employment transition during the pandemic.

Figure 3A: The relationship between gender and probability of transitioning to unemployment conditional on ethnic migrant status by the presence of school-aged children in April 2020

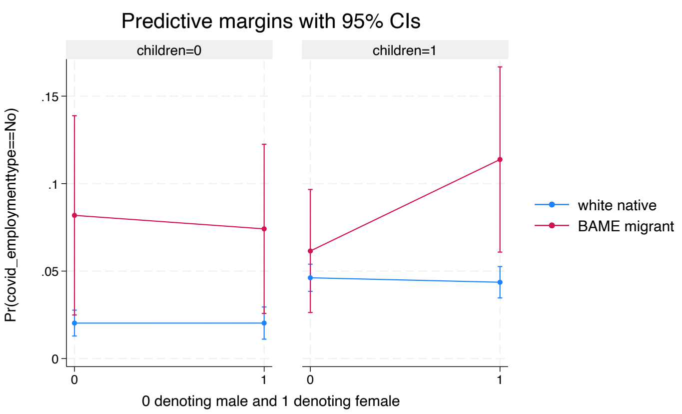


Figure 3B: The relationship between gender and probability of transitioning to unemployment conditional on cohabitation by the presence of school-aged children in April 2020

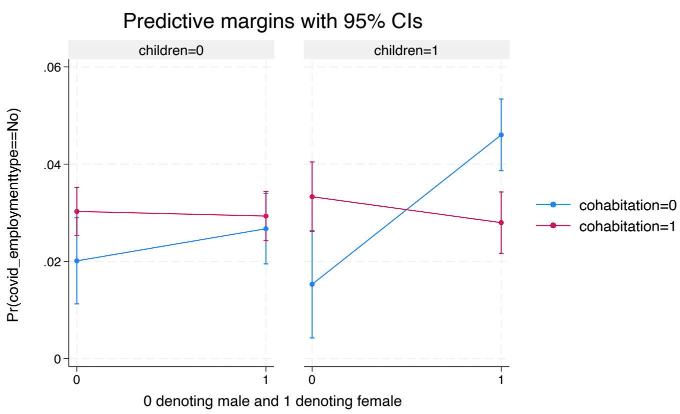
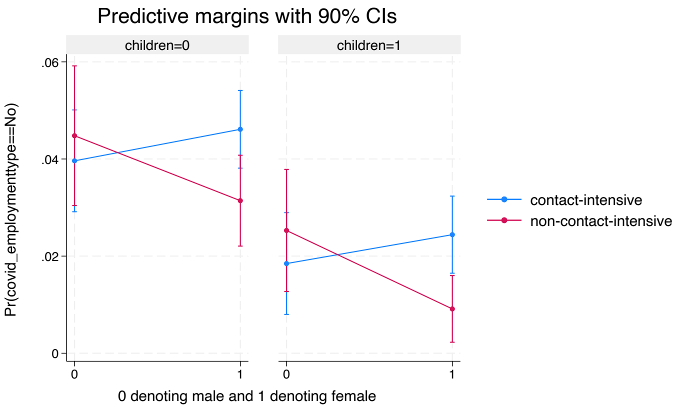


Figure 3C: The relationship between gender and probability of transitioning to unemployment conditional on industry contact intensity by the presence of school-aged children in April 2020



Focusing on May's analysis in Figures 4A-C, ethnic migrant status, de facto marriage, contact intensity of employment industry, and furlough status remain significant in moderating one's employment transitions, consistent with findings from the entire sample. Comparing Figures 4A-C with Figures 3A-C, the moderating effects of ethnic migrant status, marital status, contact intensity of employment industry, and furlough status are slightly greater on employment transition in May 2020 compared to April 2020. Figures 4A-C indicate that BAME migrant mothers with school-aged children had a roughly 7.5% higher likelihood of becoming unemployed compared to white native mothers in May. Figures 4B and 4C demonstrate that cohabitation and working in non-contact-intensive industries decreased the likelihood of unemployment by approximately 2% and 1.7%, respectively, among women with school-aged children.

The slightly greater moderating effects of these factors in comparison to April can be attributed to time-lag effects. The full impact of the pandemic on employment transitions may not have been entirely unfolding in April 2020, as individuals and businesses of various industries were still adjusting to the new circumstances. By May 2020, individuals had more time to adjust to the prolonged impacts of the pandemic, leading to changes in employment dynamics and larger shifts in employment transitions compared to April.

The estimation results from the April and May wave samples altogether reaffirm the previous findings of the significant moderating effects of ethnic migrant status, cohabitation, industry contact intensity, and furlough status on employment transition. These results again highlight the significance of ethnic migrant status as a key factor in shaping employment transitions during the initial stage of the pandemic.

Figure 4A: The relationship between gender and probability of transitioning to unemployment conditional on ethnic migrant status by the presence of school-aged children in May 2020

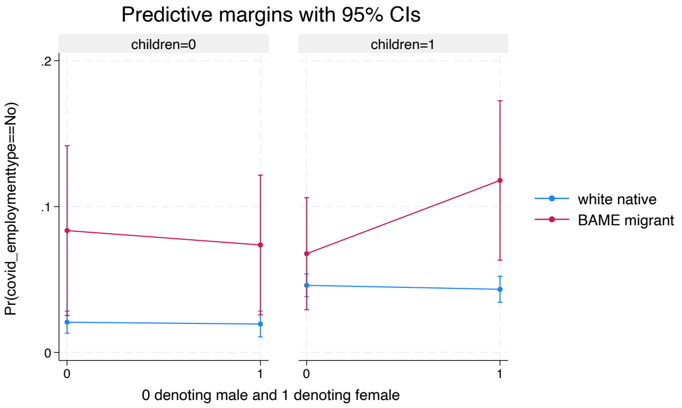


Figure 4B: The relationship between gender and probability of transitioning to unemployment conditional on cohabitation by the presence of school-aged children in May 2020

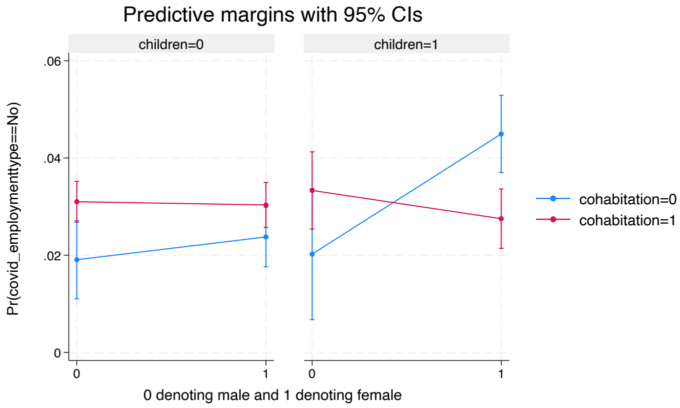
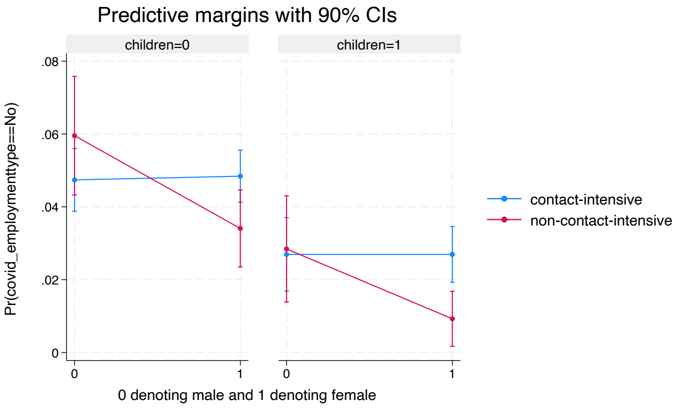


Figure 4C: The relationship between gender and probability of transitioning to unemployment conditional on industry contact intensity by the presence of school-aged children in May 2020



4.3 Intersectional Penalties on Labour Market Outcomes across Gender Sub-Samples

Dimensions of gender, ethnic origins, and occupational class are intricately intertwined and mutually reinforcing in shaping individual's employment outcomes (Berkhout and Richardson, 2020; Maestripieri, 2021). Studies have revealed that women of ethnic origins face heightened challenges in securing stable employment due to a range of factors, including health conditions, language proficiency, and limited access to networks (Longhi and Brynin, 2017; Nandi and Platt, 2023; Platt and Warwick, 2020a; 2020b). This trend is particularly concerning during times of economic hardship, as it exacerbates inequalities and further marginalises the already vulnerable populations. Considering the impactful effects of ethnic migrant status on employment transition evidenced in Section 4.2, I examined the intersectional dimensions of employment outcomes among various ethnic migrant groups. By comparing disparities between white native and BAME migrant individuals, this analysis aims to quantify the variations in employment outcomes based on ethnic migrant status.

To further investigate the intersectional penalties from an ethnic migrant perspective, I split the whole sample into female and male subsamples. This approach enables analyses of the complex interrelationship between childcare responsibilities and other influential factors, such as health conditions and family support in childcare. This intersectional lens allows for a better understanding of how these variables may compound or mitigate employment penalties experienced by individuals from different ethnic migrant groups.

To complement the theoretical considerations above, I employed proportion tests to rigorously examine potential disparities in health conditions and family support for childcare between white native and BAME migrant groups within both female and male samples. The results of these tests, as detailed in Appendix 4.2, demonstrated significant differences at the 5% significance level in the proportions of health conditions and family support in childcare between white native female s and BAME migrant females. Among the male sample, significant differences were found in health conditions between white native males and BAME migrant males at the 5% significance level. Additionally, family support for childcare significantly differed between these groups at the 10% significance level.

4.3.1 The Interplay of the Presence of School-Aged Children and Ethnic Migrant Status

4.3.1.1 The Interplay of the Presence of School-Aged Children and Ethnic Migrant Status across the Female Sample

This section further explores the interaction between the presence of school-aged children and ethnic migrant status on females' employment outcomes during the initial stage of the pandemic, as reported in Table 8A. In Column (1), the positive and significant interaction term at the 5% significance level suggests that being a BAME migrant female exacerbates the negative impact of having school-aged children on employment outcomes, leading to an increase probability of job displacement.

The AME results in Table 8B highlight significant variations in unemployment probability by ethnicity and occupation among female samples. In the entire female sample, being either a BAMR or a migrant is associated with a 6.98% increase in unemployment probability, though this effect is marginally significant, while being a white native shows no significant effect. In the blue-collar sample, BAME or migrant females experience a notable 28.06% increase in unemployment probability, indicating heightened vulnerability in job loss during the pandemic, whereas white native females in this group show no significant effect. For the white-collar sample, ethnic migrant status exhibits insignificant effects on one's employment transition. These findings suggest the intersectional influences of ethnic migrant status and occupation on female employment outcomes.

Table 8A: Estimation results predicting changes in employment status with interaction between the presence of school-aged children and ethnic migrant status across the female sample[23]

	(1) All females	(2) Blue-collar females	(3) White-collar females
VARIABLES	No vs paid employment	No vs paid employment	No vs paid employment
Children (ref.=no)	-0.145	-0.274	-0.0938
	(0.234)	(0.554)	(0.260)
Ethnic_migrant (ref.=white native)	0.233	-0.340	0.285
	(0.342)	(0.819)	(0.393)
Children#Ethnic_migrant	1.282**	2.364**	0.886
	(0.556)	(1.172)	(0.693)
Controls	Yes	Yes	Yes
Observations	9,803	4,313	5,490

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

Table 8B: Average marginal effects (AMEs) of ethnic migrant status and the presence of school-aged children across the female sample with school-aged children

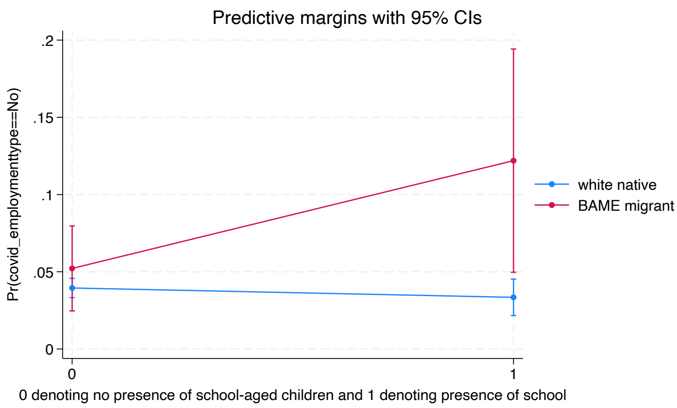
Variable	Condition	AME (%)	p-value	95% Confidence Interval
Entire Female Sample				
Children (with school-aged children)	BAME migrant	+6.98	0.088	-1.04, 14.99
Children (with school-aged children)	White native	-0.63	0.415	-2.05, 0.85
Blue-Collar Female Sample				
Children (with school-aged children)	BAME migrant	+28.06	0.050	+0.01, 56.12
Children (with school-aged children)	White native	-1.91	0.645	-10.08, 6.24
White-Collar Female Sample				
Children (with school-aged	BAME migrant	-5.55	0.167	-13.42, 2.33

23 The full table of the regression results can be found in Appendix 4.2.4 and 4.2.5.

children)				
Children (with school-aged children)	White native	-1.20	0.199	-3.03, 0.63

Figure 5A illustrates the relationship between the probability of transitioning from paid employment to unemployment and having school-aged children conditional on one's ethnic migrant status during the first wave of coronavirus outbreaks. For females without school-aged children, there is no statistically significant difference in the probability of job displacement between different ethnic migrant groups, given the overlapping confidence intervals. In contrast, BAME migrant females with school-aged children have a roughly 9% higher likelihood of transitioning to unemployment compared to white native mothers.

Figure 5A: The relationship between having school-aged children and probability of transitioning to unemployment conditional ethnic migrant status across the female sample



Several factors contribute to this disparity in employment outcomes between BAME migrant mothers and white native mothers during the COVID-19 pandemic. First, previous studies have indicated that white natives often have more social capitals and stronger ties within influential networks that facilitate employment opportunities compared to ethnic minority communities (Gilchrist and Kyprianou, 2011). These networks can act as a resource for finding employment or receiving referrals for staying employed, potentially offering an advantage over BAME migrant individuals who might have smaller influential networks. In addition, pre-existing structural inequalities and discrimination against ethnic minority groups in labour market practices continue to hinder their ability to secure jobs, exacerbating unemployment rates among BAME females (Li and Health, 2020; Rajan *et al.*, 2020). The intersectionality of gender and ethnic immigrant status magnifies the impact, as BAME females often encounter multiple barriers in career advancement and face higher risks of employment instability due to discriminatory practices (Rajan *et al.*, 2020).

4.3.1.2 The Interplay of School-Aged Children and Ethnic Migrant Status Across Different Levels of Occupational Skills Across the Female Sample

As previous research indicating that the effects of childbearing differ based on females' skills or wage levels (England *et al*., 2016; Wilde *et al*., 2010), I aimed to examine the differences in employment outcomes across various occupational skills categories. Following established conventions of occupational skill levels (Deming, 2017; Hu and Kaplan, 2010), occupations requiring manual and mechanical skills, physical abilities, and procedural focus were classified as blue-collar, while those emphasizing interpersonal, analytical, technological skills, and creativity were categorized as white-collar.

Employing the established classifications of occupational skills, the re-estimated results demonstrated a positive interaction effect between the presence of school-aged children and ethnic migrant status on the likelihood of displacement out of employment. As in Column (2) of Table 7, this relationship is statistically significant only for blue-collar workers at the 1% level. This empirical evidence demonstrates that the effect of ethnic migrant status on the likelihood of job displacement is significant among blue-collar mothers of school-aged children but not among their white-collar counterparts.

Figures 5B and 5C demonstrate the interacting effects on the probability of transitioning to unemployment within blue-collar and white-collar females, respectively. Among blue-collar females, the probability of job displacement is approximately 30% higher within BAME migrant mothers with school-aged children than their white native counterparts. However, there is no statistical difference in the probability of employment displacement between BAME migrant mothers and white native mothers among the white-collar group, given the overlaps between 90% confidence intervals.

Figure 5B: The relationship between having school-aged children and probability of transitioning to unemployment conditional on ethnic migrant status among blue-collar females

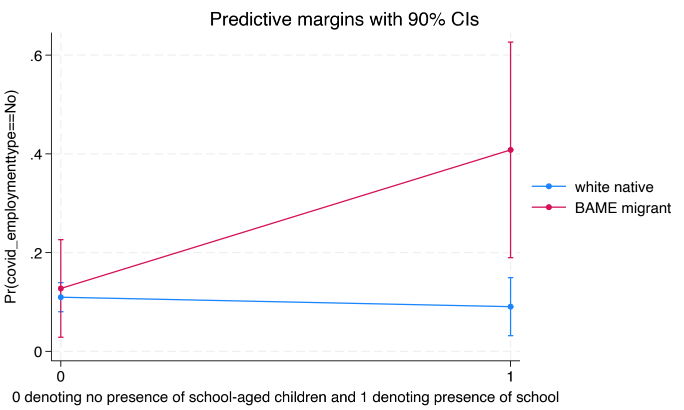
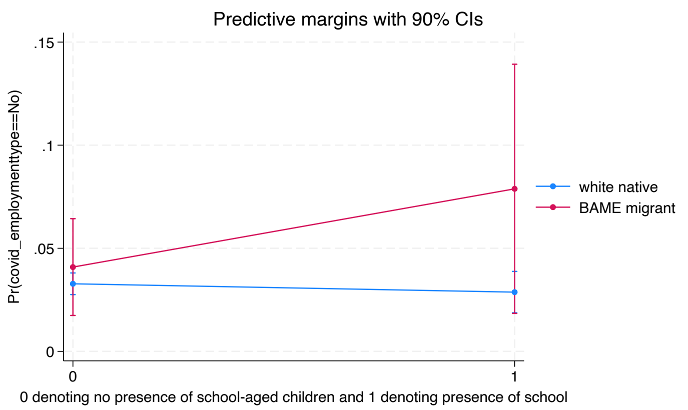


Figure 5C: The relationship between having school-aged children and probability of transitioning to unemployment conditional on ethnic migrant status among white-collar females



The stark differences in the joint influence of childcare responsibility and ethnic migrant status on employment outcomes between blue-collar and white-collar mothers can be explained by several factors. First, compared to white-collar females, blue-collar BAME females, particularly those in lower-income brackets, are more likely to have limited access to social support networks (Gilchrist and Kyprianou, 2011), hindering their ability to find new job opportunities. Additionally, longstanding labour market discrimination facing BAME immigrant females, especially in lower-skilled blue-collar jobs (Blackaby *et al*, 2002), further hinders securing new employment amidst pandemic job losses relative to white native counterparts. These prejudicial barriers perpetuate disparities in hiring and occupational opportunities for BAME women. Research by Heath and Di Stasio (2019) demonstrates significantly lower call-back rates for ethnic minority applicants across European countries, even when they possess identical qualifications. These exclusions become particularly pronounced during economic downturns when competition escalates for available positions. Furthermore, the closure of schools and childcare facilities during lockdowns increased unpaid work burdens, disproportionately impacting BAME mothers struggling to balance employment and heightened domestic duties (Sevilla and Smith, 2020). Analysis of UK labour data reveals that mothers spent 15% less time in paid work owing to increased childcare demands, with effects being 30% larger for ethnic minority women (Gustafsson and McCurdy, 2020). With limited flexibility in their low-income roles, BAME migrant females were left with limited ability to absorb these obligations alongside work requirements, forcing them to exit the labour market.

4.3.1.3 The Interplay of the Presence of School-Aged Children and Ethnic Migrant Status across the Male Sample

Comparing with the results obtained from similar regression models among the female cohort, the coefficient associated with the interaction between the presence of school-aged children and ethnic migrant status, although positive, is not statistically significant on the likelihood of transitioning from paid employment to unemployment among males, as reported in Column (1) of Table 9. This result highlights potential differences in how these factors influence labour market outcomes between genders. As shown in Figure 6A, the overlapping confidence intervals indicate that the differences in the impact of ethnic migrant status on the probability of employment transition are not statistically significant for males with and without school-aged children.

Table 9: Estimation results predicting changes in employment status with interaction between the presence of school-aged children and furlough status across the male sample

	(1)	(2)	(3)
	All males	Blue-collar males	White-collar males
VARIABLES	No vs paid employment	No vs paid employment	No vs paid employment

Children (ref.=no)	-0.397*	1.454***	-0.669
	(0.214)	(0.301)	(0.413)
Ethnic_migrant (ref.=white native)	-1.229	1.455	0.760**
	(1.355)	(1.261)	(0.384)
Children#Ethnic_migrant	0.455	2.115***	0.752
	(0.525)	(0.593)	(0.647)
Controls	Yes	Yes	Yes
Observations	6,627	2,687	3,940

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

Using a similar estimation strategy as the female sample, the interacting effects between the presence of school-aged children and ethnic migrant status are estimated among the blue-collar and white-collar groups, as reported in Column (2) and (3) of Table 8, respectively. Although the coefficient enters positively and significantly among blue-collar males, no statistically significant difference emerges in the likelihood of employment displacement between the white native group and the BAME migrant group, regardless of the presence of school-aged children. This is evidenced by the 90% overlapping confidence intervals in Figures 6B. Among white-collar males, there is no statistically significant differences in the probability of becoming unemployed between the white native group and the BAME migrant group, as shown in Figure 6C.

While the presence of school-aged children coupled with ethnic migrant status exerts significant impacts on females' labour market transitions, this effect does not manifest similarly among males, regardless of occupational skill levels. The divergence highlights the gender-specific barriers, intertwined with childcare responsibility and ethnic migrant status, faced by females in the labour market.

Figure 6A: The relationship between having school-aged children and probability of transitioning to unemployment conditional on ethnic migrant status across the male sample

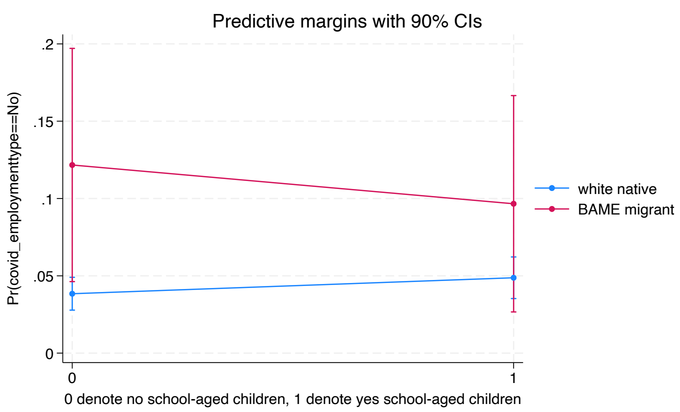


Figure 6B: The relationship between having school-aged children and probability of transitioning to unemployment conditional on ethnic migrant status among blue-collar males

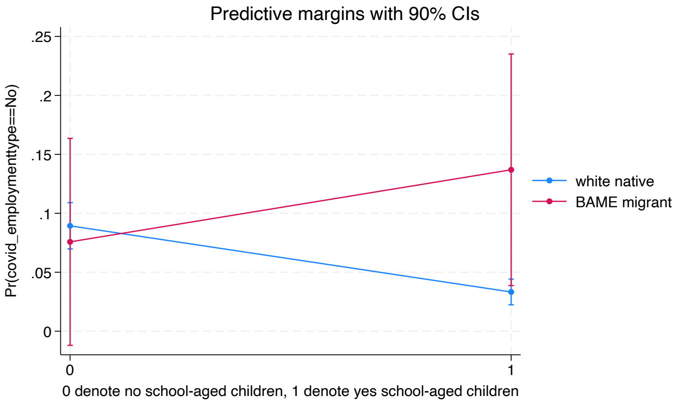
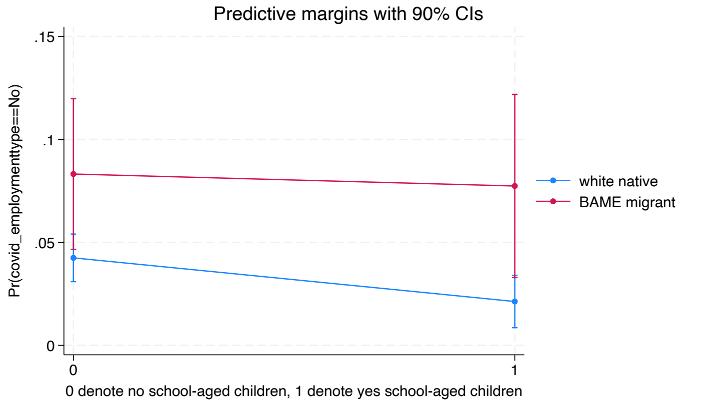


Figure 6C: The relationship between having school-aged children and probability of transitioning to unemployment conditional on ethnic migrant status among white-collar males



4.3.2 Investigating Intersectional Penalties across Gender Sub-Samples

This section examined disparities in the likelihood of displacement into unemployment during the pandemic, conditional on[24] health conditions and family support in childcare.

4.3.2.1 The Interplay between School-Aged Children, Ethnic Migrant Status, and Health Conditions within the Female Sample

A three-way interaction analysis between the presence of school-aged children, ethnic migrant status, and health conditions is adopted to investigate how health conditions moderate the impacts of ethnic migrant status and having school-age children on females' employment outcomes. As reported in Column (1) of Table 10A, the coefficient of the three-way interaction term is positive at a significance level of 10%. The presence of school-aged children, ethnic migrant status, and health conditions have a three-way interaction effect on a women's probability of transitioning from paid employment to unemployment, suggesting that the effect of having school-aged children on the likelihood of job displacement as a function of ethnic migrant status is significantly influenced by one's health conditions.

Table 10B reports the AME results illustrating how the presence of children affects unemployment probability among female samples with school-aged children,

[24] The interplay between the presence of school-aged children, ethnic migrant status, and contact intensity of employment industry has been investigated among the female sample as well. Due to the intuitive nature of the results, I am not presenting the results here. In general, working in non-contact-intensive industries mitigates the likelihood of job displacement by around 5 percentage points among BAME migrant mothers of school-aged children. For blue-collar BAME migrant mothers, working in non-contact-intensive industries decreases the probabilities of becoming unemployed by approximately 6 and 3.4 percentage points among blue-collar and white-collar BAME mothers, respectively.

moderated by ethnic migrant status and health status. For females with either BAME or migrant background and being clinically more vulnerable to the Coronavirus in the entire sample, having children is associated with a substantial 28.14% increase in unemployment probability. This effect is similarly pronounced in the blue-collar sample, where BAME migrant female who are more vulnerable to the Coronavirus experience a 29.49% increase in unemployment probability when they have children. However, for white native females and females in good health conditions across both blue- and white-collar samples, having children does not significantly affect unemployment probability. These findings reveal the compounded vulnerability faced by BAME migrant women with health conditions and caregiving responsibilities.

Table 10A: Estimation results predicting changes in employment status with three-way interaction between the presence of school-aged children, ethnic migrant status, and health conditions across the female sample[25]

	(1) All females	(2) Blue-collar females	(3) White-collar females
VARIABLES	No vs paid employment	No vs paid employment	No vs paid employment
Children (ref.=no)	-0.0682	-0.0999	-0.455
	(0.259)	(0.288)	(0.454)
Ethnic_migrant (ref.=white native)	0.546	0.548	-0.889
	(0.371)	(0.426)	(1.083)
Children#Ethnic_migrant	0.459	-0.615	1.888
	(0.704)	(1.143)	(1.589)
Health (ref.=good)	0.115	-0.138	0.112
	(0.205)	(0.244)	(0.354)
Children#Health	-0.291	0.0533	-1.391
	(0.511)	(0.568)	(1.791)
Ethnic_migrant#Health	-1.624	-1.189	-1.406
	(1.104)	(1.136)	(1.774)
Children#Ethnic_migrant#Health	3.041**	3.820**	1.273
	(1.443)	(1.747)	(1.081)
Controls	Yes	Yes	Yes
Observations	9,573	4,304	5,269

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

[25] The full table of regression results can be found in Appendix 4.2.6 and 4.2.7.

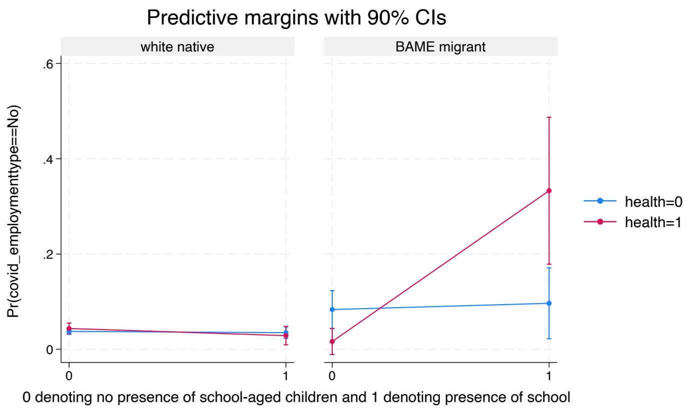
Table 10B: Average marginal effects (AMEs) of ethnic migrant status, the presence of school-aged children, and health conditions across the female sample with school-aged children

Variable	Conditions	AME (%)	p-value	95% Confidence Interval
Entire Female Sample				
Children (with school-aged children)	White native, With good health condition	-0.27	0.749	-1.90, 1.37
Children (with school-aged children)	White native, Without good health condition	-1.52	0.260	-4.15, 1.12
Children (with school-aged children)	BAME migrant, With good health condition	+1.29	0.767	-7.28, 9.86
Children (with school-aged children)	BAME migrant, Without good health condition	+28.14	0.001	+11.34, 44.93
Blue-Collar Female Sample				
Children (with school-aged children)	White native, With good health condition	-0.39	0.630	-1.98, 1.20
Children (with school-aged children)	White native, Without good health condition	-0.37	0.782	-2.97, 2.23
Children (with school-aged children)	BAME migrant, With good health condition	-2.83	0.374	-9.22, 3.84
Children (with school-aged children)	BAME migrant, Without good health condition	+29.49	0.004	+9.49, 49.48
White-Collar Female Sample				
Children (with school-aged children)	White native, With good health condition	-0.82	0.542	-3.44, 1.81
Children (with school-aged children)	White native, Without good health condition	-1.10	0.140	-2.56, 0.36
Children (with school-aged children)	BAME migrant, With good health condition	-1.80	0.316	-5.33, 1.75

Children (with school-aged children)	BAME migrant, Without good health condition	+0.20	0.947	-5.95, 6.38

The three-way interaction effect on the probability of transitioning to unemployment is plotted in Figure 7A. For white native females, regardless of the presence of school-aged children, health conditions do not significantly influence the probability of switching to unemployment from paid employment during the initial stage of the pandemic, as indicated by the overlapping 90% confidence intervals. By contrast, having health deficits (being clinically vulnerable to Coronavirus) will significantly increases BAME migrant mothers' probability of transitioning to unemployment by approximately 25%.

Figure 7A: The relationship between having school-aged children and probability of transitioning to unemployment conditional on health conditions by ethnic migrant status across the female sample



The stronger moderating impact of health conditions among BAME migrant mothers compared to their white native counterparts can be attributed to several factors. First, at-risk underlying health conditions may partially explain the differences in health impacts on employment status between the white native and BAME migrant groups. According to Platt and Warwick (2020b), some ethnic minorities are more likely to have long-term health conditions that increase vulnerability to infection-induced mortality, which may influence decisions about work continuation during the pandemic. Research by Nazroo (2020) also highlights that BAME migrant communities in the UK often have higher rates of chronic diseases, potentially intensifying susceptibility to severe COVID-19 outcomes. These health disparities intersect with occupational risks, as BAME individuals are overrepresented in frontline sectors with greater virus exposure risk (Otu *et al*., 2020). As a result, BAME individuals with underlying conditions may have heightened concerns about work environment risks, potentially contributing to higher rates of employment exit compared to white natives. Furthermore, longstanding workplace discrimination and biases towards the BAME group have been exacerbated during the pandemic (Haynes, 2020). These workplace discrimination and biases could have limited their access to job protection, flexible working arrangements, financial support, or adequate healthcare benefits during the pandemic, contributing to their transition to unemployment, particularly if they faced health challenges (Blundell *et al.*, 2022).

4.3.2.2 The Interplay of School-Aged Children, Ethnic Migrant Status, and Health Conditions across Different Levels of Occupational Skills within the Female Sample

To investigate the differences in the moderating effect of health conditions between different occupational skill groups, the three-way interaction effect is estimated within the blue-collar female and the white-collar female sample, respectively. As reported in Column (2) and (3) of Table 9, the moderating effect of health conditions on the relationship between having school-aged children and the probability of transitioning to unemployment is only statistically significant among blue-collar females with school-aged children while not statistically significant among white-collar females.

Figure 7B and 7C demonstrate the three-way interaction effect among blue-collar and white-collar females, respectively. The moderating effect of health conditions on the relationship between having school-aged children and the probability of transitioning to unemployment was found to be statistically significant among blue-collar BAME migrant females with school-aged children. Relative to BAME migrant mothers in blue-collar positions who are clinically vulnerable to COVID-19, maintaining good health reduces the likelihood of job displacement by approximately 30 percentage points. In contrast, no significant moderating effect of health conditions is observed on the relationship between having school-aged children and the probability of employment exit among white-collar females, regardless of health conditions.

Figure 7B: The relationship between having school-aged children and probability of transitioning to unemployment conditional on health conditions by ethnic migrant status among blue-collar females

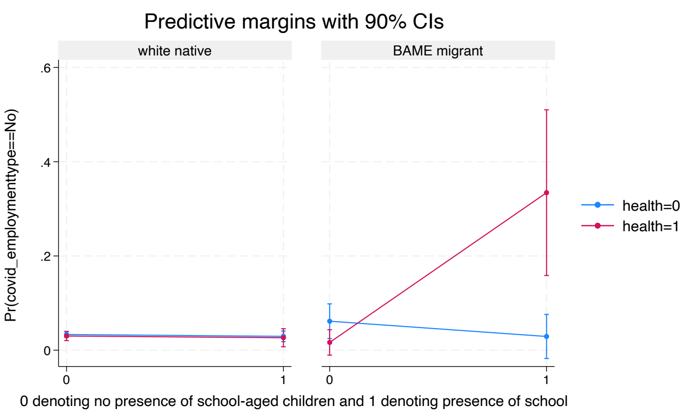
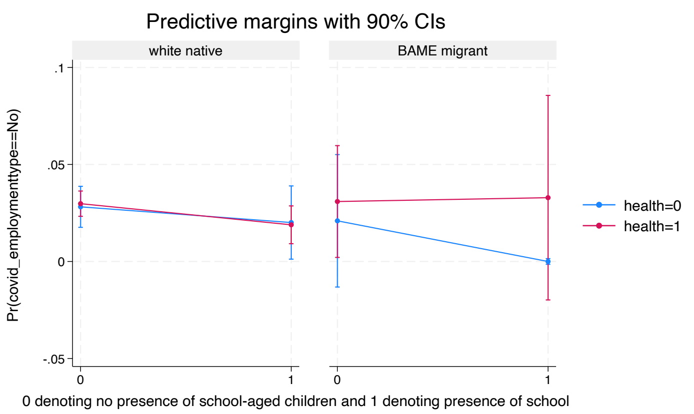


Figure 7C: The relationship between having school-aged children and probability of transitioning to unemployment conditional on health conditions by ethnic migrant status among white-collar females



The more pronounced effect of health conditions on blue-collar BAME migrant mothers' employment status, compared with their white-collar counterparts can be attributed to limited access to affordable healthcare and discrimination. Compared with blue-collar workers, white-collar workers tend to have larger and more diverse social networks and resources, such as employer-sponsored health insurance and medical assistance, which provide them with a safety net to cope with health issues without risking immediate unemployment during the pandemic (Steptoe *et al*., 2013). By contrast, some blue-collar BAME migrant females may find it difficult to pay for baseline National Health Service (NHS) charges, especially for those low-income EU immigrants struggling to pay for NHS surcharges after the Brexit[26]. According to articles published in The Guardian, certain migrants, especially those earning slightly above the minimum wage, have expressed challenges in meeting the costs of NHS surcharges (Gentleman, 2020; Grant & Gentleman, 2020; Malik, 2020). Additionally, heightened discrimination and stereotyping experienced by BAME migrant females in blue-collar roles exacerbate challenges in attaining employment while navigating health issues, contributing to unemployment amidst the pandemic (Navarro-Román and Román, 2022).

4.3.2.3 The Interplay of School-Aged Children, Ethnic Migrant Status, and Health Conditions across the Male Sample

Conducting parallel regressions on the entire male sample, the blue-collar male sample, and the white-collar male sample, no significant coefficients of the interactions between the presence of school-aged children, ethnic migrant status, and health conditions results have been found, as reported in Column (1), (2), and (3) in Table 11, respectively.

Table 11: Estimation results predicting changes in employment status with three-way interaction between the presence of school-aged children, ethnic migrant status, and health conditions across the male sample

	(1)	(2)	(3)
	All males	Blue-collar males	White-collar males
VARIABLES	No vs paid employment	No vs paid employment	No vs paid employment
Children (ref.=no)	0.123	0.661	0.123
	(0.589)	(0.600)	(0.589)
Ethnic_migrant (ref.=white native)	-0.831	-1.701**	-0.203
	(0.658)	(0.864)	(1.092)
Children#Ethnic_migrant	1.034	1.239	1.034
	(1.265)	(1.107)	(1.265)
Health (ref.=good)	0.170	0.0252	0.129
	(0.407)	(0.721)	(0.623)
Children#Health	-0.299	-0.156	-0.299
	(0.743)	(0.777)	(0.743)

[26] Detailed information about NHS surcharges can be accessed at: https://www.gov.uk/guidance/healthcare-for-eu-and-efta-nationals-living-in-the-uk#surcharge.

Ethnic_migrant#Health	0.184	0.528	0.0508
	(0.858)	(1.143)	(1.261)
Children#Ethnic_migrant#Health	1.343	1.419	1.346
	(1.540)	(1.412)	(1.540)
Controls	Yes	Yes	Yes
Observations	6120	2858	3262

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

Visualising the three-way interaction effects among the entire male sample, blue-collar male sample, and white-collar samples, as in Figures 8A-C, reveals no statistically significant difference in the probability of transitioning from paid employment to unemployment based on health conditions between white native males and BAME migrant males, given the overlapping confidence intervals. These results suggest that health conditions do not significantly influence unemployment risk during the early stage of the pandemic for different groups of males. Additionally, the observed disparities in the three-way interaction effect between the presence of school-aged children, ethnic migrant status, and health conditions highlight a distinct disparity between females and males.

Figure 8A: The relationship between having school-aged children and probability of transitioning to unemployment conditional on health conditions by ethnic migrant status across the male sample

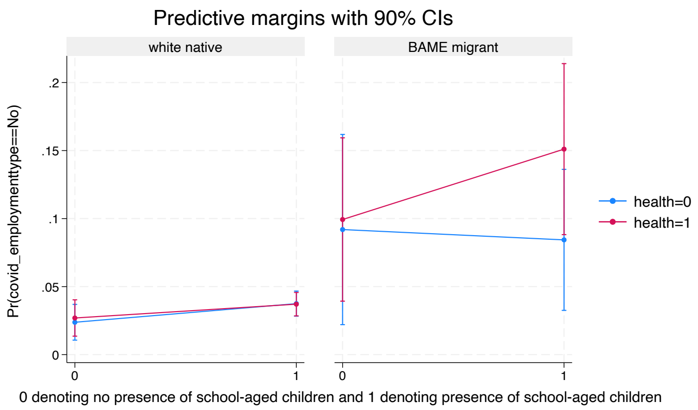


Figure 8B: The relationship between having school-aged children and probability of transitioning to unemployment conditional on health conditions by ethnic migrant status among blue-collar males

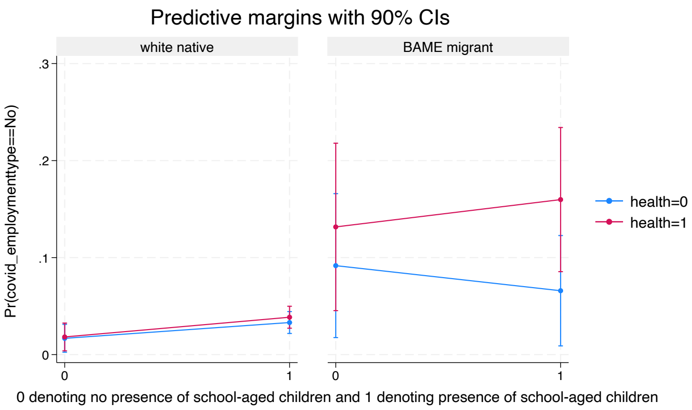
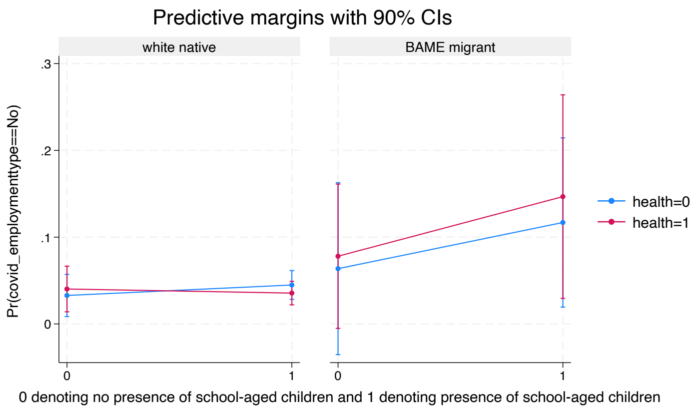


Figure 8C: The relationship between having school-aged children and probability of transitioning to unemployment conditional on health conditions by ethnic migrant status among white-collar males



4.3.3 The Interplay of School-Aged Children, Ethnic Migrant Status, and Family Support in Childcare

4.3.3.1 The Interplay of School-Aged Children, Ethnic Migrant Status, and Family Support in Childcare across the Female Sample

The three-way interaction effect between the presence of school-aged children, ethnic migrant status, and family support in childcare on employment outcomes across the female subsample is reported in Table 12A. As shown in Column (1), this three-way interaction term enters negatively and positively on the probability of switching to unemployment. This result suggests that the effect of having school-aged children on the likelihood of job displacement as a function of ethnic migrant status is significantly influenced by whether there is family support in childcare for females.

The AME results in Table 12B reveal significant interactions between ethnic migrant status, family support in childcare, and job type on the probability of unemployment among female samples. In the blue-collar female sample, being a BAME migrant without family support in childcare is associated with a notable increase in unemployment probability. A similar effect is observed among white-collar females in comparable situations. Conversely, for white native females, the presence of children does not significantly impact unemployment likelihood across job types. These findings highlight the complex intersection of ethnic migrant status, job type, and family support in childcare on employment vulnerability.

Table 12A: Estimation results predicting changes in employment status with three-way interaction between the presence of school-aged children, ethnic migrant status, and family support in childcare across the female sample[27]

	(1) All females	(2) Blue-collar females	(3) White-collar females
VARIABLES	No vs paid employment	No vs paid employment	No vs paid employment
Children (ref.=no)	-0.635	0.0739	0.187
	(0.534)	(0.454)	(0.549)
Ethnic_migrant (ref.=white native)	-1.514***	-0.738	-0.755
	(0.543)	(0.842)	(0.642)
Children#Ethnic_migrant	4.235***	2.728***	3.001***
	(1.235)	(0.956)	(0.892)
Family_support (ref.=no)	0.0784	-0.915***	0.460**
	(0.302)	(0.301)	(0.231)
Children#Family_support	0.0398	-0.380	-0.586
	(0.562)	(0.567)	(0.610)
Ethnic_migrant#Family_support	2.012*	1.727	2.064**
	(1.061)	(1.191)	(0.919)
Children#Ethnic_migrant#Family_support	-4.773**	-4.179***	-3.212***
	(1.946)	(1.469)	(1.194)
Controls	Yes	Yes	Yes
Observations	8,803	3,697	5,106

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

Table 12B: Average marginal effects (AMEs) of ethnic migrant status, the presence of school-aged children, and family support in childcare across the female sample with school-aged children

Variable	Conditions	AME (%)	p-value	95% Confidence Interval
Entire Female Sample				
Children (with school-aged children)	White native, Without family support in children	-1.19	0.405	-4.08, 1.62
Children (with school-aged children)	White native, With family support in children	-1.79	0.108	-3.77, 0.20

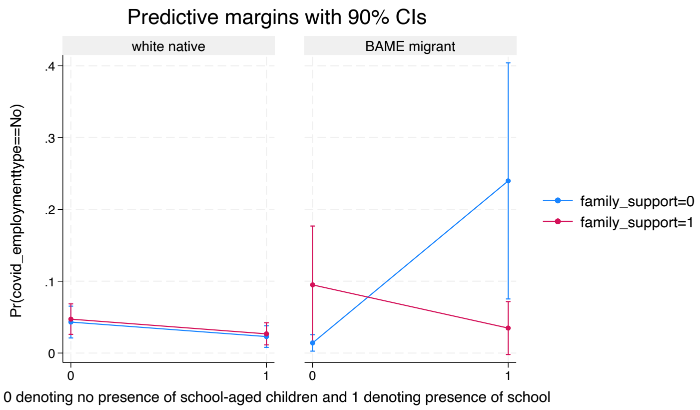
[27] The full table of regression results can be found in Appendix 4.2.8 and 4.2.9.

Children (with school-aged children)	BAME migrant, Without family support in children	+17.70	0.093	-0.88, 34.52
Children (with school-aged children)	BAME migrant, With family support in children	-11.57	0.114	-25.79, 2.77
Blue-Collar Female Sample				
Children (with school-aged children)	White native, Without family support in children	+0.42	0.851	-4.37, 5.29
Children (with school-aged children)	White native, With family support in children	-0.66	0.425	-2.27, 0.95
Children (with school-aged children)	BAME migrant, Without family support in children	+27.34	0.001	+13.44, 41.28
Children (with school-aged children)	BAME migrant, With family support in children	-4.96	0.233	-13.11, 3.20
White-Collar Female Sample				
Children (with school-aged children)	White native, Without family support in children	+0.18	0.910	-2.97, 3.26
Children (with school-aged children)	White native, With family support in children	-1.40	0.188	-3.54, 0.69
Children (with school-aged children)	BAME migrant, Without family support in children	+18.45	0.001	+8.04, 28.86
Children (with school-aged children)	BAME migrant, With family support in children	-5.53	0.399	-18.29, 7.28

Figure 9A demonstrates the three-way interacting effect between the presence of school-aged children, ethnic migrant status, and family support in childcare on the probability of transitioning to unemployment. For white native females, family support in childcare does not exert a statistically significant impact on one's likelihood of job loss during the pandemic, given the overlapping confidence intervals. For BAME migrant females with school-aged children[28], having family support in childcare significantly lowers the probability of switching from paid employment to unemployment by approximately 20 percentage points.

[28] The wide confidence interval of the female group with school-aged children, BAME migrant background, and no family support in childcare may indicates a small size of this group.

Figure 9A: The relationship between having school-aged children and probability of transitioning to unemployment conditional on family support in childcare by ethnic migrant status with the female sample



Several key factors provide explanations of the moderating effect of family support in childcare on females' employment outcomes. As highlighted in Gromada *et al*. (2020), family support networks, including extended family members including grandparents and siblings, provided a safety net by assisting in childcare duties especially during the pandemic. With the work of childcare predominantly done by women (Gromada *et al*., 2020), this assistance from family allowed mothers to manage their work responsibilities without compromising their childcare duties, thus reducing the likelihood of leaving employment due to caregiving demands. For BAME migrant mothers, who frequently encounter obstacles in accessing professional childcare services due to financial constraints or geographical disparities (Carlson and Kail, 2018), reliance on family support became essential to reconcile childcare needs and maintain employment. In addition, cultural norms prevalent within many BAME migrant communities emphasize the significance of family involvement in childcare (Taylor *et al*., 2022; Uttal, 1999). As a result, BAME migrant mothers may rely more heavily on extended family networks due to cultural expectations, amplifying the impact of familial support structures on their ability to balance work and childcare responsibilities during the early stage of the pandemic.

4.3.3.2 The Interplay of School-Aged Children, Ethnic Migrant Status, and Family Support in Childcare across Different Levels of Occupational Skills within the Female Sample

Grouping the female sample based on levels of occupational skills, the three-way interaction between the presence of school-aged children, ethnic migrant status, and family support in childcare on the probability of transitioning to unemployment remain negative and significant among both blue-collar and white-collar females, as reported in Column (2) and (3) of Table 11, respectively.

Figure 9B graphs the moderating effect of family support in childcare on the relationship between having school-aged children and the probability of transitioning to unemployment among blue-collar females. The results demonstrate a statistically significant difference in the likelihood of switching to unemployment between BAME migrant females who have family support and those without such support. Blue-collar BAME mothers with family support experienced a decreased probability of job displacement by approximately 30 percentage points compared to those without family support in childcare. Although the coefficient of the three-way interaction term is significant, Figure 9C illustrates that no statistically significant difference is exerted by family support in childcare among white-collar BAME migrant mothers on the likelihood of job displacement.

Figure 9B: The relationship between having school-aged children and probability of transitioning to unemployment conditional on family support in childcare by ethnic migrant status among blue-collar females

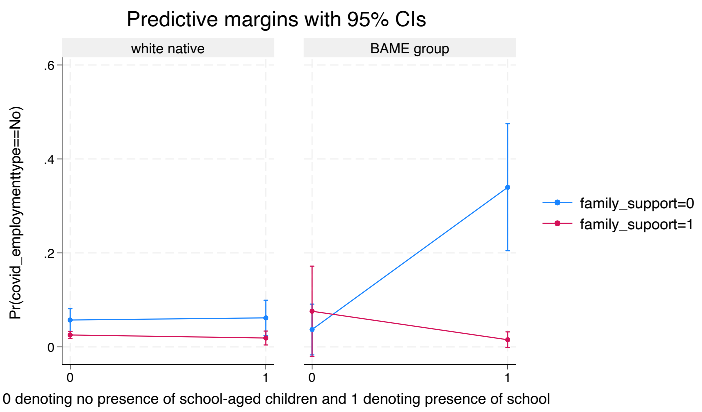
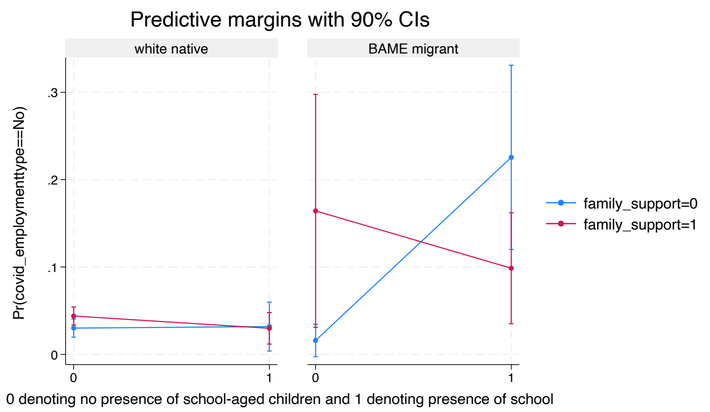


Figure 9C: The relationship between having school-aged children and probability of transitioning to unemployment conditional on family support in childcare by ethnic migrant status among white-collar females



Several factors can explain the stronger impact of family childcare support in mitigating negative employment outcomes for blue-collar mothers than for their white-collar counterparts. First, compared with white-collar females, blue-collar females have limited access to affordable professional childcare services due to their lower incomes (Cooke and Gash, 2010). For these mothers, having family share childcare becomes the most viable option to balance work and family. In the absence of such support during lockdowns, these mothers were more likely to transition to unemployment. Additionally, flexible remote working arrangements that are more common among white-collar jobs allows for a balance between the professional and the caregiving role, without depending solely on family. With limited income and flexibility, family members sharing care become indispensable for blue-collar BAME mothers to balance work and childcare during lockdowns.

4.3.3.3 The Interplay of School-Aged Children, Ethnic Migrant Status, and Family Support in Childcare across the Male Sample

Parallel regression with the three-way interaction between the presence of school-aged children, ethnic migrant status, and family support in childcare was conducted with the male sample. The results, as presented in Table 13, reveal a significant coefficient for the three-way interaction among blue-collar males in Column (2). However, no significant estimation results are obtained for the entire male sample or the white-collar male sample, as in Column (1) and (3), respectively.

Table 13: Estimation results predicting changes in employment status with three-way interaction between the presence of school-aged children, ethnic migrant status, and family support in childcare across the male sample

	(1) All males	(2) Blue-collar males	(3) White-collar males
VARIABLES	No vs paid employment	No vs paid employment	No vs paid employment
Children (ref.=no)	-1.009*	-0.954*	-0.785
	(0.565)	(0.573)	(0.621)
Ethnic_migrant (ref.=white native)	0.781	0.873	1.222**
	(0.544)	(0.568)	(0.619)
Children#Ethnic_migrant	1.644*	1.500	1.242
	(0.913)	(0.928)	(1.006)
Family_support (ref.=no)	-0.245	-0.328	-0.0485
	(0.253)	(0.261)	(0.303)
Children#Family_support	0.813	0.821	0.116
	(0.625)	(0.637)	(0.798)
Ethnic_migrant#Family_support	0.297	0.180	-0.491
	(0.635)	(0.668)	(0.796)
Children#Ethnic_migrant#Family_support	-1.690	-2.027*	-0.756
	(1.136)	(1.195)	(1.425)
Controls	Yes	Yes	Yes
Observations	6,104	2,885	3,219

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

Figure 10A-C demonstrates the interacting effects across the entire male sample, blue-collar males, and white-collar males, respectively. The results reveal no significant moderating effect of having family support in childcare on the probability of transitioning from paid employment to unemployment. This pattern is consistent across all male subgroups, despite the significant coefficient of the three-way interaction among blue-collar males. These findings contrast with the significant moderating effects observed in the female samples, highlighting distinct gender disparities in the impact of these factors on labour market outcomes.

Figure 10A: The relationship between having school-aged children and probability of transitioning to unemployment conditional on family support by ethnic migrant status across the male sample

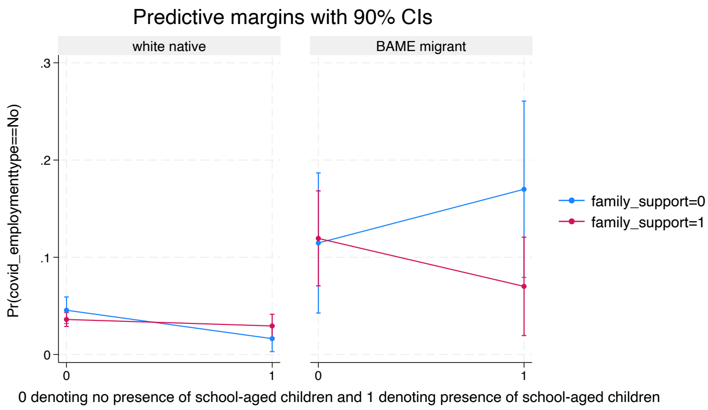


Figure 10B: The relationship between having school-aged children and probability of transitioning to unemployment conditional on family support by ethnic migrant status among blue-collar males

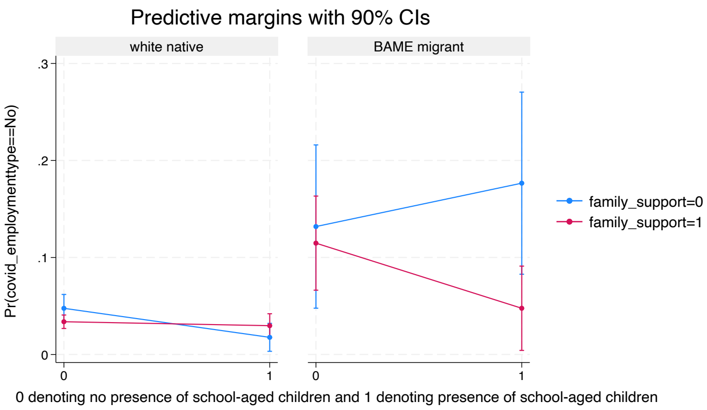
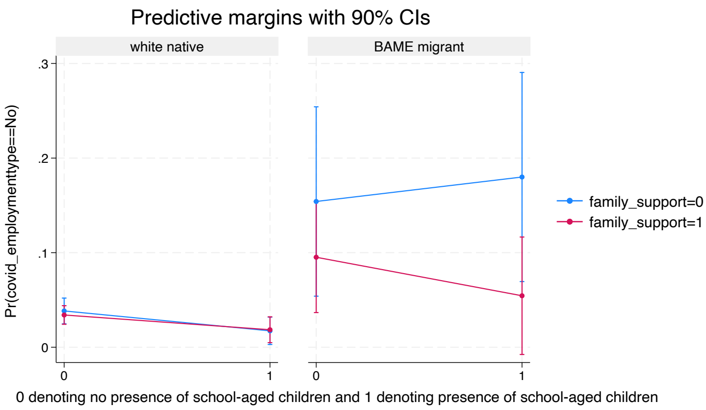


Figure 10C: The relationship between having school-aged children and probability of transitioning to unemployment conditional on family support by ethnic migrant status among white-collar males



4.4 Summary

First, the comparative analysis between male and female subsamples reveals significant gender disparities in the impact of ethnic migrant status on the likelihood of job loss during the initial stage of the pandemic. BAME migrant females faced a higher probability of becoming unemployed compared to their white native counterparts, whereas this pattern was not observed among the male sample.

Secondly, analysing job loss penalties through the lens of ethnic migrant status shows a clear pattern of increased vulnerability among BAME migrant females, compared to their white native counterparts within the same occupational skill levels. However, this disproportionality cannot be solely attributed to ethnic-migrant-based disparities; rather, it intertwines with various intersecting sociodemographic factors. Table 14 summarizes the factors moderating the probability of employment transitions during the initial stage of the pandemic. Bad health conditions and the lack of family support in childcare amplify the negative shocks from the pandemic borne by BAME migrant mothers with school-aged children. Among blue-collar BAME migrant mothers, being clinically vulnerable to Coronavirus and lacking family support in childcare has relatively large economic significance in influencing their employment outcomes, increasing the probability of job displacement by around 30% during the early stage of the pandemic.

Table 14: Summary of the moderating effects on employment transitions among the female sample during in initial stage of the pandemic

Factors moderating the probability of employment transitions	Sub-sample	Probability in percentage points (%)
Transitions from paid employment to unemployment		
Health	Blue-collar BAME migrant mothers	30
Family support in childcare	Blue-collar BAME migrant mothers	30
Health	BAME migrant mothers	25
Family support in childcare	BAME migrant mothers	20

In contrast to the significant intersectional impacts on mothers' employment displacement, the estimation results for males reveal no equivalent moderating effects across key disadvantage markers among fathers of school-aged children. These disparities emphasize the distinct experiences of men and women in the labour market during the pandemic, highlighting the importance of examining employment outcomes through an intersectional lens.

5. Discussions

5.1 Motherhood Penalty and Cohabitation during the Initial Stage of the Pandemic

The short-term mitigating effect of cohabitation on mothers' likelihood of job loss lends empirical backing to the intra-household insurance hypothesis as advanced by Mazzocco (2007). This welfare microeconomic theory posits that households can act as risk-sharing units by redistributing resources to buffer income or consumption shocks facing individual members. This can be accomplished through reallocating finance, modifying savings or investments, leisure reallocations, and the transfer of time from one partner to others through expanded domestic and caregiving tasks. The potential for fathers to expand contributions, when mothers faced external crisis shocks to balance competing demands, provides strong evidence of such intra-household insurance against sudden unemployment risks via shared domestic duties.

While this reallocation of childcare time within the household, to some extent, supports egalitarian norms, the findings also align with feminist perspectives arguing that gendered care responsibilities remain entrenched, as evidenced by the consistently higher unemployment risks for mothers in the UK. In summary, while intra-household adjustments have offered some relief for cohabiting mothers in navigating crisis shocks, more comprehensive transformations are needed to address structural constraints.

5.2 Intersectional Disadvantages Faced by BAME Migrant Mothers

The disproportionate impact of the pandemic on BAME migrant mothers' employment outcomes, especially those among the blue-collar group, lends empirical support to intersectionality theory's premise that disadvantage intertwines across multiple identities such as gender, ethnic migrant background, and social class (Crenshaw, 1989). Our findings reveal how mothers of minority and migrant backgrounds face compounding vulnerabilities arising from structural discrimination and gendered imbalances. The significance of health conditions and family support in childcare underscores the multidimensional nature of marginalisation of this group.

5.3 Addressing Intersectional Inequalities in Policy Response

The UK government has implemented the Coronavirus Job Retention Scheme, the Job Support Scheme, and the Business Grants and Loans Scheme to aid the labour market during the pandemic. While offering generalised support, these schemes failed to sufficiently account for the specific needs arising from intersecting vulnerabilities. Based on the gendered impacts revealed, a more targeted policy approach is necessary to mitigate compounded disadvantages. Although the disparities in employment displacement are not huge between genders, the intersectional gendered impacts suggest a more targeted policy approach, mitigating the compounded disadvantages experienced by the most vulnerable groups, is necessary.

First, adaptable work structures and emergency caregiving provisions could be implemented, particularly targeting at single mothers, to alleviate the exacerbated challenges endured during crisis periods. Although certain family structures offer some reliefs, labour market responses underscore the necessity for broader measures aimed at addressing the vulnerabilities specifically encountered by unpartnered individuals and those lacking family support in childcare, ensuring an equitable distribution of support mechanisms during unforeseen emergencies.

Secondly, hybrid policies that reduce barriers to participation for primary caregivers, often mothers, should be implemented as they present an optimistic prospect for narrowing the probability gap between mothers engaged in contact-intensive versus non-contact-intensive sectors. The enhancement of workplace agility, tailored to accommodate the needs of mothers even beyond the pandemic's scope, could potentially mitigate intersectional childcare penalties. However, as Goldin (2021) suggests, the critical imperative lies in ensuring that such flexibility extends uniformly across different skill tiers, fostering an inclusive environment that addresses the needs of all mothers, especially those in blue-collar occupations, offering them greater support in balancing work and childcare responsibilities.

Thirdly, targeted measures to improve health conditions are crucial as well, as the research findings indicate that staying in good health conditions significantly mitigates displacement among the most vulnerable group—BAME migrant mothers in blue-collar roles. Policymakers could prioritise initiatives that improve access to healthcare services and resources for marginalised communities, such as BAME migrant females and low-income workers. This could include ensuring equitable access to preventative care, mental health services, and treatments for chronic conditions that may disproportionately affect specific demographic groups.

Lastly, policies could aim to dispel persistent gender stereotypes and make care work more equitable. Public messaging, government campaigns, and promotion of involved fatherhood and co-parenting could be developed to normalise men's domestic roles.

6. Conclusions

The COVID-19 pandemic has exacerbated existing inequalities along various dimensions such as gender, ethnic migrant status, and occupational skill level within the labour market. Based on the data from the USoc COVID-19 Study, this research reveals that mothers of school-aged children faced higher risks of job loss compared to females without dependent children, highlighting a persistent motherhood penalty in the UK. In contrast to males, cohabitation, contact intensity of employment industries, and ethnic migrant status are factors that mitigate unemployment risk for mothers with school-aged children. In light of the motherhood penalty, cohabiting with a partner lowers the probability of becoming unemployment during the early stage of the pandemic for mothers with school-aged children in the UK. Echoing this result, Blaskó *et al*. (2020) concluded that single mothers in European countries are exposed to higher employment rates due to increased care duties during the pandemic.

With an intersectional approach, this research also reveals that BAME migrant mothers, especially in blue-collar roles, experienced disproportionate unemployment risks, which reflects compounding disadvantages in the labour market. Being clinically vulnerable to Coronavirus and the lack of family support in childcare further amplified job loss probabilities for this group. Similarly, among the European labour market, women of minority groups are disproportionately suffered from displacement due to gender discrimination and precarious working conditions (Kambouri, 2020). These intersectional penalties align with broader evidence that COVID-19 exacerbated existing gender inequities in UK and European labour markets.

The distinct disparities in the probability of job displacement between groups, such as the BAME migrant female group and the white native female group, highlight the UK government's inadequate policy response to the intersectional impacts of the pandemic and the underlying structural barriers encountered by BAME migrant females in blue-collar roles. Future research could adopt a comparative approach to investigate pandemic employment outcomes between countries with differing childcare provisions, workplace regulations, and minority protections within the Europe. Undertaking coordinated intersectional studies across international contexts could help to identify effective policy mechanisms for fostering gendered resilience to crises. Building a robust evidence base around multidimensional pandemic impacts and policy responses remains critical for promoting gender and social equity during recoveries from the pandemic and beyond.

Chapter 5 *Conclusions*

1. Summary of Key Findings

The COVID-19 pandemic has catalysed enormous shifts in global economic and social landscapes, resulting in unprecedented challenges and disruptions across the world. Through a comprehensive examination of the economic impacts of pandemic-induced interventions, this thesis contributes to the understanding of the economic impacts of the pandemic and pandemic-enforced NPIs, adopting a multi-level approach for the analysis. The findings presented in this thesis underscore the interplay between public health measures, economic systems, and societal dynamics.

Beginning with a macro-level examination of stock market reactions to pandemic-induced lockdowns, the analysis of stock market reactions has revealed the intricate dynamics of stock markets to lockdown announcements and lockdown measures in both developed markets and emerging markets. By investigating the adaptive learning process of stock markets, Chapter 2 highlights the role of rational decision-making in shaping market reactions during the initial stage of the pandemic.

Followed by a meso-level analysis, the investigation into industry resilience in Chapter 3 highlights the pivotal role of digitalisation, in both tangible and intangible terms, in mitigating the adverse impacts of pandemic-induced disruptions. Through empirical analysis, this research has underscored the imperative for policymakers and industry leaders to prioritise investments in digital infrastructure development as a means of enhancing resilience in an increasingly uncertain world.

Concluding with a micro-level exploration of labour market outcomes, the intersectional approach of Chapter 4 confirms the differential impacts of the pandemic on various demographic groups, such as males and females as well as white native females and BAME migrant females. By uncovering the compounding disadvantages faced by BAME migrant mothers, especially those in blue-collar roles, this research has underscored the importance of targeted policy interventions aimed at addressing structural barriers and promoting inclusive economic recovery.

2. Research Contributions to Relevant Fields

The contributions of these three empirical chapters to their respective fields are multifaceted. Chapter 2 makes the following contributions to several relevant fields. By examining how stock markets dynamically adapt and adjust their expectations in response to non-economic events like the pandemic, this chapter offers valuable insights into the learning behaviors of global financial markets. It highlights that market responses are not entirely driven by sentiment but also influenced by rational decision-making processes. This deepens our understanding of how markets integrate and respond to extraordinary circumstances, providing crucial insights for investors, policymakers, and financial analysts. In addition, this chapter enriches the literature on behavioral finance by emphasizing the adaptive learning process of global stock markets amidst the pandemic, thus shedding light on the complex interplay between new information, market expectations, and investor behaviors.

Chapter 3 contributes significantly to the existing literature on digitalisation and industry resilience during pandemics in several ways. First, while previous studies have primarily focused on firm-level and cross-country evidence, this research offers valuable insights at the industry level by examining the role of pre-pandemic digitalisation levels on industry resilience. Additionally, this chapter contributes to the literature by employing the real value of investments in digital technologies as proxies for digitalisation, capturing both tangible and intangible aspects, rather than relying on categorical variables. This nuanced approach provides a more valid understanding of digitalisation's impact.

Chapter 4 makes several contributions to multiple fields within labour economics and gender studies. First, this chapter addresses a gap in existing literature by exploring the intersectional penalties faced by individuals, particularly focusing on mothers with school-aged children, during the COVID-19 pandemic. While prior studies have highlighted gender disparities in employment outcomes based on binary categorisation of occupations, this chapter offers a more nuanced understanding of how various factors intersect to shape employment outcomes jointly. In addition, by adopting an intersectional approach, this chapter emphasizes the interconnected nature of various factors contributing to employment disparities, particularly among marginalised groups such as BAME migrant mothers. This highlights the need for targeted policy interventions to address systemic inequalities in the labour market. Furthermore, this chapter reveals the disparities in employment outcomes between females and males, offering evidence-based recommendations for gender-sensitive policy development in the UK labour market. Together, these empirical chapters advance scholarly understanding and inform evidence-based policymaking in response to the multifaceted challenges posed by the COVID-19 pandemic across financial, industrial, and social domains.

3. Policy Implications

Collectively, the findings of this chapter point out the need for targeted and adaptive policy responses to promote economic resilience and social equity. At the macroeconomic level, the insights gained from the examination of stock market reactions have significant policymaking implications First, policymakers should consider the adaptive learning process of stock markets when implementing interventions in the context of managing public health crises and their economic consequences. As markets respond to new information and changing circumstances, policies should be flexible and responsive to evolving conditions. Secondly, policymakers are recommended to provide transparent and well-reasoned explanations for policy decisions to help investors make informed decisions, supporting rational decision-making by providing accurate information about the economic landscape. Thirdly, regular monitoring and assessment of market dynamics should be conducted to provide policymakers with timely information on how investors are processing and reacting to new information, informing more effective policy interventions and helping maintain market stability.

Moving to the meso-level analysis of industry resilience, the research emphasizes the critical role of digitalisation in enhancing resilience to pandemic-induced disruptions. Policymakers and industry leaders are recommended to prioritise investments in digital development to strengthen the adaptive capacity of industries and promote economic resilience in the face of future crises. The empirical evidence also shows the importance of adopting a nuanced approach that considers both tangible and intangible aspects of digitalisation. In addition, policymakers are recommended to support the digital transformation of industries across diverse industries, especially for the contact-intensive industries.

At the micro-level, the intersectional analysis of labour market outcomes sheds light on the differential impacts of the pandemic on various demographic groups, particularly among marginalised individuals such as BAME migrant mothers with school-aged children. This highlights the imperative for targeted policy interventions aimed at addressing structural barriers and promoting inclusive economic recovery. Policymakers should prioritize measures to address systemic inequalities in the labour market, including targeted support for marginalised groups and initiatives to promote gender-sensitive policies and practices. By addressing these disparities and promoting inclusive economic recovery, policymakers can foster a more resilient and equitable post-pandemic economy.

4. Recommendations for Future Studies

In synthesizing these multiple strands of analyses, this thesis has not only advanced our theoretical and empirical understanding of the economic impacts of the COVID-19 pandemic but also offered actionable insights for policymakers, practitioners, and society at large. Building on the findings of this thesis, future studies could further investigate the mechanisms underlying the observed phenomena, particularly regarding the transmission channels through which public health measures affect economic outcomes. In addition, further research could explore the long-term implications of the pandemic on socioeconomic structures and examine the effectiveness of policy responses in fostering resilience and recovery. By building upon the foundations laid by this collection of research, future studies can continue to contribute to our understanding of the evolving dynamics of crises and inform evidence-based strategies for building a more resilient and equitable society in the post-pandemic era.

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Appendixes

Chapter 2

Appendix 2.1 Information about sample countries, leading stock indices, and dates of lockdown announcement by one's government

Country	Leading stock index	Date of lockdown announcement
Australia	S&P_ASX 200	03/23/2020
Belgium	BEL 20	03/17/2020
Canada	S&P_TSX Composite	03/16/2020
China	Shanghai Composite	01/23/2020
France	CAC 40	03/12/2020
Germany	DAX	03/17/2020
India	BSE Sensex 30	03/24/2020
Indonesia	Jakarta SEC	03/14/2020
Israel	TA 35	03/19/2020
Italy	FTSE MIB	03/13/2020
Japan	Nikkei 225	03/13/2020
Mexico	S&P_BMV IPC	03/14/2020
Netherlands	AEX	03/12/2020
New Zealand	NZX 50	03/23/2020
Pakistan	Karachi 100	03/13/2020
Philippines	PSEi Composite	03/09/2020
Poland	WIG 30	03/11/2020
Russia	MOEX	03/16/2020
Saudi Arabia	Tadawul All Share	03/25/2020
Singapore	FTSE Straits Times	03/24/2020
South Africa	TOP 40	03/23/2020
South Korea	KOSPI	02/24/2020
Spain	IBEX 35	03/13/2020
Sweden	OMX Stockholm 30	03/11/2020
Thailand	SET Index	03/21/2020
Turkey	BIST 100	03/12/2020
United Arab Emirates	ADX General	03/25/2020
United Kingdom	FTSE 100	03/16/2020
United States	S & P 100	03/23/2020

Appendix 2.2 Detailed information about the variables

Variables	Description	Data source
Stock index return	The variable measures country-level returns as the log returns of the leading stock index of one country.	Author's calculation from data of Refinitiv DataStream database
Stringency index (used in the difference form in regressions)	The variable is measured by Stringency index, recording the strictness of 'lockdown style' policies that primarily restrict people's behaviour of one's country. It is calculated using all ordinal containment and closure policy indicators, plus an indicator recording public information campaigns. Individual measures include school closures, workplace closures, public events cancellations, gathering restrictions, public transport closures, stay-at-home requirements, internal movement restrictions, international travel controls, and public information campaigns.	Compiled from Oxford COVID-19 Government Response Tracker
World stringency (used in the difference form in regressions)	The variable is computed as the daily average stringency of lockdown measures of other countries	Author's calculation from data of Oxford COVID-19 Government Response Tracker
Sentiment index (used in the difference form in regressions)	The index measures the level of sentiment about COVID-19 related information within a country, with the most positive value (100) standing for the most positive sentiment, the most negative value (-100) representing the most negative sentiment, and 0 representing neutral sentiment.	Compiled from RavenPack via the Wharton Research Data Services
Period prior/post the lockdown announcement (dummy variable)	The indicator is used to characterise the period that is one-, two-, and three-week prior/post the lockdown announcement of one country.	Constructed from data of Oxford COVID-19 Government Response Tracker and official government websites
Fiscal package (used in the difference form in regressions)	The variable measures the size of fiscal package announced by one's government as a percentage of the country's GDP (at constant prices).	Compiled from the Database of International Monetary Fund COVID-19 Policy Tracker
Interest rate cut (used in the difference form in regressions)	The variable measures the cut in key policy rate from December 31, 2019.	Compiled from the Database of International Monetary Fund COVID-19 Policy Tracker
Macroeconomic package (used in the difference form in regressions)	The variable measures the size of the macro-financial packages in each country as a percentage of one's GDP (at constant prices).	Compiled from the Database of International Monetary Fund COVID-19 Policy Tracker
Other monetary policies	A dummy variable with 1 denoting there is other	Compiled from the

(dummy variable)	monetary policy announced by one's government, and 0 denoting no other monetary policy announced by one's government.	Database of International Monetary Fund COVID-19 Policy Tracker

Appendix 2.3 Control variable addition to baseline specification

The baseline regression shows that some of the coefficients, such as for the fiscal package and other monetary policies are not statistically significant. This may be due to multicollinearity, as these economic measures were introduced simultaneously during the pandemic, potentially obscuring their individual effects on stock market returns. To address this, I conducted a stepwise regression analysis, gradually adding control variables to the baseline model. This approach isolates the impact of each variable by reducing potential multicollinearity. The results indicate that the significance of the coefficients remains stable, suggesting that the control variables are not highly correlated, and each contributes uniquely to the model's explanatory power. Detailed results are provided below.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES							Baseline
Lockdown stringency	0.021*	-0.028***	-0.026**	-0.030**	-0.028**	-0.032**	-0.03161**
	(0.011)	(0.010)	(0.013)	(0.015)	(0.012)	(0.016)	(0.0159)
Fiscal package		-0.140*	-0.098*	-0.090	-0.102	-0.096	-0.0838
		(0.081)	(0.056)	(0.062)	(0.065)	(0.059)	(0.0656)
Interest rate cut			-0.077*	-0.114*	-0.138*	-0.097*	-0.1150*
			(0.046)	(0.146)	(0.076)	(0.057)	(0.0669)
Macro-financial package				0.190*	0.088*	0.055*	0.0598**
				(0.100)	(0.046)	(0.031)	(0.0265)
Other monetary policies					0.349	0.627	0.553
					(0.742)	(0.594)	(0.360)
World stringency						-0.239**	-0.752*
						(0.120)	(0.454)
Sentiment index							-0.00558*
							(0.00336)
Lagged return	-0.108***	-0.117***	-0.135***	-0.412***	-0.447***	-0.462***	-0.214***
	(0.036)	(0.063)	(0.094)	(0.095)	(0.103)	(0.0967)	(0.0674)
Constant	1.548**	0.550**	0.395*	0.643*	0.249**	-0.529**	0.537**
	(0.778)	(0.276)	(0.224)	(0.384)	(0.123)	(0.261)	(0.261)
Observations	2,427	2,427	2,427	2,427	2,427	2,427	2,427
R-squared	0.101	0.183	0.260	0.355	0.429	0.557	0.606
Number of countries	29	29	29	29	29	29	29
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: (1) Robust standard errors in parentheses; (2) *** p<0.01, ** p<0.05, * p<0.1.

Appendix 2.4 First-stage regression results of the IV-2SLS regression

VARIABLES	First-stage regression results
IV	0.751***
	(0.122)
Fiscal package	-0.0429
	(0.0268)
Interest rate cut	-0.329*
	(0.181)
Macro-financial package	0.0089*
	(0.0053)
Other monetary policies	0.0005
	(0.0241)
World stringency	0.135*
	(0.076)
Sentiment index	-0.0824*
	(0.0434)
Lagged return	-0.0763**
	(0.0387)
Constant	-0.603**
	(0.255)
Observations	2,392
R-squared	0.551
First-stage F statistic	85.10

Notes: (1) Robust standard errors in parentheses; (2) *** p<0.01, ** p<0.05, * p<0.1; (3) Lockdown stringency is the endogenous variable; the quotient of the daily log growth rate of COVID-19 confirmed cases and the number of hospital beds per thousand people is used to instrument lockdown stringency; (4) A high F statistic, typically greater than 10, indicates that the instrument is strong and provides reliable estimates in the two-stage least squares (2SLS) procedure, reducing the risk of weak instrument bias.

The first-stage regression results show a significant relationship between the instrument and the lockdown stringency, with the F-statistic (>10) confirming that the instrument is strong, as a rule of thumb. The results support the validity of the IV-2SLS approach, allowing for the second stage, where the predicted values of the stringency measure are used to estimate their effect on the stock market return, as reported in Table 5 in Chapter 2.

Chapter 3

Appendix 3.1 Definitions and sources of main variables used in regression analyses of Chapter 3

Variable	Definition and construction	Source
Resilience (%)	Quarterly changes in gross value added (as	National Statistical Institutes of

	a percentage of gross domestic product) by industry in 2020, compared with the corresponding period in 2019, which are seasonally and working day adjusted	sample countries
Lockdown stringency	Quarterly average of each sample country's stringency index	Oxford COVID-19 Government Response Tracker
Computing equipment	The share of computing equipment in capital stock net	EUKLEMS and INTANProd 2021
Communication equipment	The share of communication equipment in capital stock net	EUKLEMS and INTANProd 2021
Computer software and databases	The share of computer software and databases in capital stock net	EUKLEMS and INTANProd 2021
Capitals	Gross capital formation or total assets by industry in natural logarithms	EUKLEMS and INTANProd 2021
Research and development	The share of research and development in capital stock net by industry	EUKLEMS and INTANProd 2021
Training	The share of training for employees in capital stock net by industry	EUKLEMS and INTANProd 2021
Education	The share of education in capital stock net by industry	EUKLEMS and INTANProd 2021
GDP per capita	Quarterly Gross Domestic Product (GDP) per capita at constant prices (in natural logarithms)	Original data for GDP per capita is collected from the World Bank Group; Results of the natural logarithms are from the author's computation
Inflation	Inflation rate (annually average %), measured by the consumer price index reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services.	The World Bank Group
Debt	Central government debt, including domestic and foreign liabilities, as a share of total gross domestic product (measured in units of currency and as the last day of the fiscal year)	The World Bank Group
VA 2019	The lagged form of quarterly value added by industry of a country (in natural logarithms)	Original data for gross value added by industry of a country is collected from the National Statistical Institutes of sample countries; Results of the natural logarithms of the data are from the author's computation

Appendix 3.2 List of industries covered in this study (Classification by ISIC Rev. 4/ NACE Rev. 2 sections)

ISIC Rev. 4/ NACE Rev. 2 sections	Industry name	Contact intensity
A	Agriculture, forestry, and fishing	Low
B	Mining and quarrying	Low
C	Manufacturing	Low
D	Electricity, gas, steam, and air conditioning supply	Low
E	Water supply; sewage, waste management and remediation activities	Low
F	Construction	Low
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	High
H	Transportation and storage	High
I	Accommodation and food service activities	High
J	Information and communication	Low
K	Financial and insurance activities	Low
L	Real estate activities	Low
M	Professional, scientific and technical activities	Low
N	Administrative and support service activities	Low
O	Public administration and defence; compulsory social security	Low
P	Education	Low
Q	Human health and social work activities	Low
R	Arts, entertainment and recreation	High
S	Other service activities	High
T	Activities of households as employers; undifferentiated goods-and services-producing activities of households for own use	High
U	Activities of extraterritorial organisations and bodies	High

Appendix 3.3 Top 10% rank of most digital sectors by digitalisation measures

The statistics in the following tables describe the industries whose digitalisation investments are among the top 10% of our sample. Rather than concentrating in industries of the Western European countries, industries with the top 10% in digitalisation investments mainly distributed in information and communication, financial and insurance activities, and professional, scientific, and technical activities.

Appendix 3.3a: Industries that are among the top 10% in net investments in computing equipment

Code	Country_Industry	Share of computing equipment in net capital stock
FI_J	Finland_Information and communication	0.1666
FI_K	Finland_Financial and insurance activities	0.1435
BE_J	Belgium_Information and communication	0.1305
DE_K	Germany_Financial and insurance activities	0.1265
FR_K	France_Financial and insurance activities	0.1092
UK_Q	United Kingdom_Human health and social work activities	0.1062
SI_K	Slovenia_Financial and insurance activities	0.1016

CZ_C	Czech_Manufacturing	0.0986
UK_J	United Kingdom_Financial and insurance activities	0.0871
SK_K	Slovekia_Financial and insurance activities	0.0867
UK_M	United Kingdom_Professional, scientific and technical activities	0.0860
BE_K	Belgium_Financial and insurance activities	0.0823

Appendix 3.3b: Industries that are among the top 10% in net investments in communication equipment

Code	Country_Industry	Share of communication equipment in net capital stock
SI_J	Slovenia_Financial and insurance activities	0.2589
AT_J	Austria_Financial and insurance activities	0.1990
SK_J	Slovekia_Financial and insurance activities	0.1655
UK_J	United Kingdom_Financial and insurance activities	0.1440
DE_J	Germany_Financial and insurance activities	0.1309
BE_J	Belgium_Financial and insurance activities	0.1176
FI_K	Finland_Financial and insurance activities	0.1127
DE_K	Germany_Financial and insurance activities	0.1086
FI_J	Finland_Financial and insurance activities	0.1059

Appendix 3.3c: Industries that are among the top 10% in net investments in computer software and databases

Code	Country_Industry	Share of computer software and databases in net capital stock
CZ_K	Czech_Financial and insurance activities	0.6753
CZ_J	Czech_Information and communication	0.6224
HU_K	Hungary_Financial and insurance activities	0.5821
FI_K	Finland_Financial and insurance activities	0.5668
FR_J	France_Financial and insurance activities	0.5357
SI_K	Slovenia_Financial and insurance activities	0.4585
UK_M	United Kingdom_Professional, scientific and technical activities	0.4319
AT_K	Austria_Financial and insurance activities	0.4318
UK_K	United Kingdom_Financial and insurance activities	0.4285
AT_J	Austria_Financial and insurance activities	0.3441
SI_J	Slovenia_Financial and insurance activities	0.3426
SK_J	Slovekia_Financial and insurance activities	0.3324

Appendix 3.4 Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Resilience	1.000												
(2) Lockdown	-0.148	1.000											
(3) IT	0.100	0.011	1.000										
(4) CT	0.172	-0.006	0.505	1.000									
(5) DB	0.066	0.007	0.475	0.452	1.000								
(6) Capitals	0.026	0.025	-0.094	-0.046	0.094	1.000							
(7) RD	0.169	0.017	-0.077	0.105	0.134	0.373	1.000						
(8) Training	-0.040	-0.015	-0.046	-0.126	-0.040	0.127	-0.056	1.000					
(9) Education	0.053	0.010	0.021	0.229	0.254	0.346	-0.131	0.032	1.000				
(10) GDP	-0.337	-0.032	0.046	0.211	0.208	0.538	0.226	0.221	0.129	1.000			
(11) Inflation	-0.005	-0.025	-0.001	0.033	-0.302	-0.808	-0.210	-0.077	-0.258	-0.617	1.000		
(12) Debt	-0.256	0.048	0.196	0.168	0.235	0.679	0.415	0.033	0.192	0.534	-0.719	1.000	
(13) VA_2019	-0.049	0.021	-0.076	-0.026	0.135	0.927	0.408	0.329	0.318	0.544	-0.820	0.713	1.000

Source: author's computation

Appendix 3.5 Results of stationarity tests

Variable	Statistic	Z	p-value
Resilience	-0.5696	-18.2142	0.0000
Lockdown	-0.0779	-8.9771	0.0000
Value added in 2019 (in natural logarithms)	-0.0609	-7.3921	0.0000
GDP per capita (in natural logarithms)	-0.0393	-7.0446	0.0000

Notes: (1) Among tests with the highest power, we prefer the HT test as it is suitable for a panel with a relatively large N and small T; (2) Considering the similarities among industries of European countries, we removed the cross-sectional averages from the data to help control for cross-sectional correlation by using the *demean* option to *xtunitroot*.

Appendix 3.6 Detailed information about using PCA to generate the alternative digitalisation indicator

For a proper Principal Component Analysis, I first tested whether the selected variables, including the share of computing equipment in capital stock net (IT), the share of communication equipment in capital stock net (CT), and the share of computer software and databases in capital stock net (DB), are suitable with the Bartlett test of sphericity and the value of Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) reported. The extremely small p-value (0.000) and the statistics of KMO (0.659>0.6) led to the rejection of the null hypothesis of no intercorrelation between variables.

Testing for intercorrelation

Determinant of the correlation matrix

Det = 0.570

Bartlett test of sphericity

H0: variables are not intercorrelated

Chi-square = 263.919

p-value = 0.000

Kaiser-Meyer-Olkin Measure of Sampling Adequacy

KMO = 0.659

Secondly, I conducted PCA with the variables of IT, CT, and DB, with Eigenvalue, proportion and cumulative proportion of each principal component reported in Table A6-1. Following Jolliffe and Cadima (2016)[29], I considered two issues in selecting the principal components to construct the alternative digitalisation index. First, I selected the component with the Eigenvalue greater than 1. Second, I selected all components with a cumulative proportion greater than 0.80. Therefore, Comp1 (IT) and Comp2 (CT) were selected to construct our alternative digitalisation index.

[29] Please see detailed information in Jolliffe, I. T., & Cadima, J. (2016). Principal component analysis: a review and recent developments. Philosophical transactions of the royal society A: Mathematical, Physical and Engineering Sciences, 374(2065), 20150202.

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.88874	1.2491	0.6296	0.6296
Comp2	.639645	.16803	0.2132	0.8428
Comp3	.471613	.	0.1572	1.0000

Additionally, I conducted the factor analysis to examine whether the components are proper to conduct PCA. With the values of Uniqueness smaller than 0.6, the components are appropriate to conduct PCA. See test results as the follows.

Variable	Factor	Uniqueness
IT	0.8223	0.3238
CT	0.7383	0.4548
DB	0.8170	0.3326

Chapter 4

Appendix 4.1 Detailed information about variable construction and description

	Measurement explanation (variable names in original dataset)
Dependent variable	
Employment status during the COVID-19 lockdown	Variable generated based on people's self-reported work status during the COVID-19 period (ca_sempderived and cb_sempderived). The USoc dataset recorded people's employment status in January-February and April, May 2020, respectively, using four categories: "employed," "self-employed," "both employed and self-employed," and "not employed." Based on these variables and the commonly used working-age population, a four-category measure is employed to capture changes and continuity in people's employment status before and during the COVID-19 lockdown, including "paid employment", "self-employment", "both", and "not employed".
Independent variables	
Gender	Self-reported sex including male and female (sex_dv), with male being the reference group.
The presence of school-aged children	Variable to capture whether having school-aged child(ren) (ca_child1), with 1 denoting having school-aged children and 0 denoting not having school-aged children.
Control variables and moderators	
Age	Accounting for potential age difference by using self-reported age (ca_age).
Age_squared	The quadratic term of age to account for potential non-linearity.
Baseline employment status (ref.=paid employment)	Information about baseline employment status of respondents in January-February in 2020 (ca_blwork and cb_blwork) in the COVID-19 survey. Observations with employment status "not employed" in January-February 2020 are dropped, as I intend to focus on the impacts of the pandemic on those with employment. This variable is categorized into "paid employment", "self-employment", and "both paid employment and self-employment" before the outbreak of the pandemic.
Education (ref. = bachelor's degree)	Generated from information about highest level of education achieved in Wave 9 of Understanding Society (i_nhiqual_dv & i_hiqual_dv), in terms of no qualifications; other qualifications below Level 2 (e.g., vocational certificates); Level 2 qualifications (e.g., GCSEs at grades A*-C); Level 3 qualifications (e.g., A-levels); Level 4 qualifications (e.g., Higher National Certificates, Certificates of Higher Education); Level 5 qualifications (e.g., Foundation Degrees, Higher National Diplomas); "Level 6 qualifications (e.g., Bachelor's degrees); Level 7 qualifications (e.g., Master's degrees); and Level 8

	qualifications (e.g., Doctoral degrees). Recoded into three-category variable: (1) a bachelor's degree or above (the reference group); (2) qualifications below a bachelor's degree; and (3) no qualifications.
Cohabitation (ref.=no)	De facto marital relationship (ca_couple), with 1 denoting living with a couple and otherwise 0.
Ethnic migrant status	Variable generated based on two self-reported measures: (1) whether one was born in the UK (bornuk_dv & i_ukborn); and (2) self-reported ethnicity (racel_dv & i_racel_dv). Value 0 denotes white natives (the reference group) and value 1 denotes other groups including BAME natives, BAME migrants, and white natives.
Financial stability	Variable generated by the difference between measures capturing respondents' self-reported financial situation in April, May 2020 (ca_finnow and cb_finnow) in the COVID-19 wave and previous measure and a single measure capturing respondents' self-reported financial situation in Wave 9 of Understanding Society (i_finnow). After combining the categories of "finding it quite difficult" and "finding it very difficult" into one group of "finding it difficult" due to the small proportion (<5%), a dummy variable is created to capture whether respondents find financial situations more difficult during the pandemic than before, with 1 denoting perceived financial stability and 0 denoting perceived financial instability.
Family support in childcare (ref.=no)	Variable derived from composition of household (i_hhtype_dv) from the Wave 9 of the survey, with 0 denoting no support in childcare (no siblings, grandparents, or other in-laws) and 1 denoting having family support in childcare (having siblings, grandparents, or other in-laws).
Furlough status (ref.= no)	Variable capturing whether a respondent who had been in work before the COVID-19 lockdown was furloughed during the lockdown (ca_furlough and cb_furlough).
Health conditions	Variable generated based on self-reported risk of serious illness from COVID-19 (ca_clinvuln_dv), with 1 denoting bad health conditions that are in high risk (clinically extreme vulnerable to Coronavirus) and moderate risk (clinically vulnerable) and 0 denoting good health conditions that are in no risk (not clinically vulnerable).
Household income (ref.=low)	Quintiles about low income, middle income, and high income generated from baseline household income (ca_blhhearn_amount) and income period (ca_blhhearn_period) from the COVID-19 survey.
Industry classification (ref.=contact-intensive)	Variable generated from industry classification of one's current job (i_jbiindb_dv) which uses the Cross-National Equivalent File (CNEF) for industry classification from the Wave 9 of the survey, including 34 classifications. Following the IMF's definition of industry contact intensity, these 34 classifications are categorized into contact-intensive and non-contact industries, represented by values 0 and 1, respectively. Contact-intensive industries include Restaurants (24), Health Service (28), Education/Sport (27), Communication/Entertainment (20), Retail (18), Service Industry (25), Construction (14), Wholesale (16), Food Industry (13), Transportation - Train System (19), Trash Removal (26), and Other Transportation (21). Non-contact-intensive industries include Agriculture/Forestry (1), Fisheries (2), Energy/Water (3), Mining (4), Chemicals (5), Synthetics (6), Earth/Clay/Stone (7), Iron/Steel (8), Mechanical Engineering (9), Electrical Engineering (10), Wood/Paper/Printing (11), Clothing/Textiles (12), Construction Related (15), Trading Agents (17), Financial Institutions (22), Insurance (23), Legal Services (29), Other Services (30), Voluntary/Church (31), Private Household (32), Public Administration (33), and Social Security (34).
Occupational class (ref.=managerial, administrative, and technical)	Measured using the 5-category National Statistics Socio-economic Classification from Wave 9 of the survey (i_jbnssec5_dv), including higher managerial, administrative, and professional occupations; lower managerial, administrative, and professional occupations; intermediate occupations; small employers and own account worker; and lower supervisory and technical occupations. Respondents with no NSSEC information are coded as a separate category.
Work at home (ref.=never)	Self-reported information about whether work can be done from home (ca_blwah), including never, sometimes, often, and always.
Urban residency (ref. = rural)	Based on rural-urban residence (i_ urban_dv) in Wave 9 of the survey, with 0 denoting rural and 1 denoting urban).

Appendix 4.2 Tables with full regression results in Chapter 4

Appendix 4.2.1 Estimation results predicting changes in employment status with three-way interaction between gender, the presence of school-aged children, and ethnic migrant status

VARIABLES	(1) Self employment vs paid employment	(2) Both vs paid employment	(3) No employment vs paid employment
gender (ref.=male)	-0.203	0.468	0.0244
	(0.416)	(0.400)	(0.148)
children (ref.=no)	0.439	0.794	-0.231
	(0.663)	(0.691)	(0.267)
gender#children	0.688	-1.046	-0.107
	(0.705)	(0.799)	(0.334)
Ethnic_migrant (ref.=white native)	0.882	0.964	1.024***
	(0.592)	(0.804)	(0.330)
gender#Ethnic_migrant	0.827	1.220	-0.779*
	(0.575)	(0.883)	(0.470)
children#Ethnic_migrant	-0.0293	-0.172	0.222
	(0.0845)	(0.166)	(0.565)
gender#children#Ethnic_migrant	0.000361	0.00171	1.131*
	(0.00101)	(0.00177)	(0.673)
Education (ref.=Bachelor's degree and above)			
Below Bachelor's degree	1.119	1.872	1.581***
	(0.957)	(1.032)	(0.594)
No qualification	0.0537	-0.0962	1.615**
	(0.243)	(0.387)	(0.639)
age	-0.0293	-0.172	-0.201***
	(0.0845)	(0.166)	(0.0571)
age_squared	0.000361	0.00171	0.00229***
	(0.00101)	(0.00177)	(0.000698)
urban	0.0537	-0.0962	0.164
	(0.243)	(0.387)	(0.236)
Work at home (ref.=never)			
Sometimes	-0.867	-0.916	-0.503
	(0.621)	(0.654)	(0.555)
Often	-2.173***	-0.843	-1.658***
	(0.597)	(0.617)	(0.323)
Always	-2.309***	-1.720***	-1.270***
	(0.671)	(0.437)	(0.302)
Household income (ref.=low)			
Middle	-0.404	0.154	0.0367

	(0.413)	(0.499)	(0.215)
High	-0.383	0.503	-0.682**
	(0.269)	(0.402)	(0.306)
Occupational class (ref.=managerial, administrative, and technical)			
Intermediate	-0.426	-0.343	-1.676**
	(0.447)	(0.677)	(0.795)
Small employers and own account workers	1.498***	1.111	1.300***
	(0.435)	(0.830)	(0.439)
Lower supervisory and technical occupation	0.890	-0.201	1.012***
	(0.556)	(0.502)	(0.250)
Semi-routine and routine	0.270	-0.377	0.541
	(0.303)	(0.885)	(0.353)
Not applicable (others, inactive, etc.)	1.037	0.453	1.285***
	(0.832)	(0.559)	(0.303)
Baseline employment status (ref.=paid employment)			
Self-employment	6.289***	4.670***	4.110***
	(0.434)	(0.731)	(0.327)
Both paid and self-employment	3.163***	6.959***	1.413*
	(0.740)	(0.544)	(0.722)
Constant	-3.850**	-2.060***	-0.267
	(1.785)	(0.407)	(1.195)
Observations	17,348	17,348	17,348

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

Appendix 4.2.2 Estimation results predicting changes in employment status with three-way interaction between gender, the presence of school-aged children, and de facto marriage

	(1)	(2)	(3)
VARIABLES	Self employment vs paid employment	Both vs paid employment	No employment vs paid employment
gender (ref.=male)	-0.331	0.367	0.383
	(0.407)	(0.534)	(0.512)
children (ref.=no)	-0.414	-0.639	-0.904
	(0.672)	(0.768)	(0.744)
gender#children	0.852	2.104**	1.991**
	(0.806)	(0.846)	(0.803)

Cohabitation (ref.=no)	-0.249	0.855*	0.684
	(0.449)	(0.493)	(0.480)
gender#cohabitation	0.204	-0.362	-0.330
	(0.580)	(0.596)	(0.583)
children#cohabitation	1.351	1.006	1.069
	(0.906)	(0.879)	(0.861)
gender#children#cohabitation	-1.471	-1.024	-2.719***
	(1.100)	(0.979)	(0.944)
Education (ref.=Bachelor's degree and above)			
Below Bachelor's degree	0.906	1.816*	1.188***
	(0.827)	(1.058)	(0.452)
No qualification	0.898	1.139	1.529***
	(0.818)	(1.063)	(0.479)
age	-0.242***	-0.121	-0.272***
	(0.0864)	(0.0845)	(0.0454)
age_squared	0.00296***	0.00150	0.00319***
	(0.00100)	(0.000973)	(0.000535)
ethnic_migrant (ref.=white native)	-0.326	-0.658	0.955***
	(0.953)	(0.483)	(0.251)
urban	-0.128	-0.177	-0.150
	(0.253)	(0.219)	(0.280)
Work at home (ref.=never)			
Sometimes	-0.837	-0.247	-0.791
	(0.679)	(0.409)	(0.482)
Often	-0.978	-0.232	-0.716*
	(0.676)	(0.424)	(0.405)
Always	-1.717**	-1.272***	-0.360
	(0.755)	(0.399)	(0.365)
Household income (ref.=low)			
Middle	0.172	0.0691	-0.0903
	(0.373)	(0.281)	(0.204)
High	-0.305	0.138	-0.529**
	(0.306)	(0.276)	(0.257)
Occupational class (ref.=managerial, administrative, and technical)			
Intermediate	-0.676	-0.697**	-0.552
	(0.499)	(0.277)	(0.574)
Small employers and own account workers	1.370***	1.189***	1.530***
	(0.364)	(0.448)	(0.322)
Lower supervisory and technical	0.698*	-0.300	0.653**

occupation			
	(0.375)	(0.381)	(0.276)
Semi-routine and routine	0.122	0.231	0.607***
	(0.425)	(0.281)	(0.235)
Not applicable (others, inactive, etc.)	0.225	-0.181	0.695***
	(0.536)	(0.377)	(0.243)
Baseline employment status (ref.=paid employment)			
Self-employment	9.222***	4.657***	3.749***
	(0.543)	(0.359)	(0.285)
Both paid and self-employment	4.919***	6.668***	2.114***
	(0.543)	(0.258)	(0.441)
Constant	-1.041	-4.723**	1.244
	(1.627)	(2.067)	(1.054)
Observations	16,370	16,370	16,370

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

Appendix 4.2.3 Estimation results predicting changes in employment status with three-way interaction between gender, the presence of school-aged children, and employment industry

	(1)	(2)	(3)
VARIABLES	Self employment vs paid employment	Both vs paid employment	No employment vs paid employment
gender (ref.=male)	-0.856**	-0.365	-0.111
	(0.398)	(0.323)	(0.209)
children (ref.=no)	0.275	0.0121	-0.408
	(0.599)	(0.471)	(0.436)
gender#children	0.299	0.0370	0.347*
	(0.744)	(0.577)	(0.192)
Industry (ref.=contact-intensive)	-0.565	-0.514	0.0129
	(0.468)	(0.433)	(0.279)
gender#industry	0.584	0.222	-0.439
	(0.649)	(0.558)	(0.366)
children#industry	0.0612	0.325	0.349
	(0.861)	(0.696)	(0.593)
gender#children#industry	-0.307	0.260	-0.966*
	(1.169)	(0.904)	(0.551)
Education (ref.=Bachelor’s degree and above)			

Below Bachelor's degree	0.652	0.258	0.655
	(1.143)	(0.926)	(0.628)
No qualification	0.0142	0.320	0.841
	(1.155)	(0.931)	(0.643)
age	-0.264***	-0.0721	-0.280***
	(0.101)	(0.0857)	(0.0457)
age_squared	0.00320***	0.000925	0.00326***
	(0.00113)	(0.000958)	(0.000530)
ethnic_migrant	0.307	-0.387	0.821***
	(0.454)	(0.409)	(0.234)
urban	0.151	-0.142	0.330*
	(0.303)	(0.242)	(0.200)
Work at home (ref.=never)			
Sometimes	-0.844	-0.468	-0.306
	(0.537)	(0.475)	(0.329)
Often	-0.447	-0.412	-0.898*
	(0.466)	(0.414)	(0.489)
Always	-1.482***	-1.270***	-0.839**
	(0.425)	(0.404)	(0.376)
Household income (ref.=low)			
Middle	0.108	-0.0540	-0.542***
	(0.336)	(0.284)	(0.177)
High	-0.00439	0.121	-0.706***
	(0.341)	(0.281)	(0.195)
Occupational class (ref.=managerial, administrative, and technical)			
Intermediate	-0.660	-0.711*	-0.434*
	(0.585)	(0.380)	(0.258)
Small employers and own account workers	1.430***	1.006**	1.516***
	(0.415)	(0.411)	(0.388)
Lower supervisory and technical occupation	0.296	-0.944	-0.182
	(0.868)	(0.899)	(0.390)
Semi-routine and routine	-0.118	0.305	0.180
	(0.481)	(0.330)	(0.201)
Not applicable (others, inactive, etc.)	-0.406	-1.178	0.656*
	(0.843)	(0.902)	(0.372)
Baseline employment status (ref.=paid employment)			
Self-employment	9.483***	4.340***	3.551***
	(0.441)	(0.438)	(0.395)

Both paid and self-employment	4.872***	5.732***	1.546***
	(0.438)	(0.240)	(0.390)
Constant	-0.231	-2.442	2.036*
	(2.446)	(2.041)	(1.134)
Observations	15,567	15,567	15,567

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

Appendix 4.2.4 Estimation results predicting changes in employment status with interaction between the presence of school-aged children and ethnic migrant status with the female sample

VARIABLES	(1) Self-employment vs paid employment	(2) Both vs paid employment	(3) No vs paid employment
Children (ref.=no)	0.298	0.0565	-0.145
	(0.370)	(0.311)	(0.234)
ethnic_migrant (ref.=white native)	-0.482	-0.378	0.233
	(0.679)	(0.684)	(0.342)
children#ethnic_migrant	0.826	0.373	1.282**
	(1.105)	(1.301)	(0.556)
Education (ref.=Bachelor's degree and above)			
Below Bachelor's degree	-0.190	-0.237	1.882*
	(1.461)	(1.178)	(1.030)
No qualification	0.203	0.207	2.091**
	(1.479)	(1.190)	(1.042)
age	-0.161	-0.477	-0.300***
	(0.107)	(0.102)	(0.0469)
age_squared	0.00180	0.00564	0.00357***
	(0.00121)	(0.00416)	(0.000556)
urban	0.493	-0.330	0.426
	(0.336)	(0.288)	(0.314)
Work at home (ref.=never)			
Sometimes	-0.895	-0.316	-0.657
	(0.641)	(0.588)	(0.561)
Often	-0.471	-0.0761	-0.760
	(0.507)	(0.505)	(0.635)
Always	-1.709***	-0.963**	-0.175
	(0.450)	(0.479)	(0.373)
Household income (ref.=low)			
Middle	-0.274	-0.195	-0.420**

	(0.357)	(0.332)	(0.182)
High	-0.576	-0.178	-0.729***
	(0.392)	(0.350)	(0.213)
Occupational class (ref.=managerial, administrative, and technical)			
Intermediate	-0.687	-0.563	-0.211
	(0.643)	(0.431)	(0.267)
Small employers and own account workers	1.597***	1.121**	1.342***
	(0.508)	(0.500)	(0.477)
Lower supervisory and technical occupation	0.827	-14.29	-0.0996
	(1.050)	(521.7)	(0.453)
Semi-routine and routine	0.413	0.459	0.0664
	(0.534)	(0.407)	(0.233)
Not applicable (others, inactive, etc.)	-0.0152	0.127	0.826***
	(0.447)	(0.461)	(0.236)
Baseline employment status (ref.=paid employment)			
Self-employment	9.163***	4.694***	3.747***
	(0.491)	(0.508)	(0.427)
Both paid and self-employment	4.177***	5.977***	1.108**
	(0.533)	(0.292)	(0.549)
Constant	-1.752	-4.338*	0.621
	(2.587)	(2.385)	(1.383)
Observations	9,803	9,803	9,803

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

Appendix 4.2.5 Estimation results predicting changes in employment status with interaction between the presence of school-aged children and ethnic migrant status across blue-collar and white-collar females

	(1)	(2)	(3)	(4)	(5)	(6)
		Blue collar			White collar	
VARIABLES	Self-employment vs paid employment	Both vs paid employment	No vs paid employment	Self-employment vs paid employment	Both vs paid employment	No vs paid employment
Children (ref.=no)	-0.360	0.618	-0.274	0.436	0.0572	-0.0938
	(0.978)	(1.601)	(0.554)	(0.418)	(0.322)	(0.260)
ethnic_migrant	-2.796**	-1.099	-0.340	0.532	-0.127	0.285

(ref.=white native)						
	(1.343)	(0.792)	(0.819)	(0.866)	(0.702)	(0.393)
children#ethnic_migrant	1.211	-1.043	2.364**	0.379	0.308	0.886
	(2.219)	(0.837)	(1.172)	(1.331)	(1.317)	(0.693)
Education (ref.=Bachelor's degree and above)						
Below Bachelor's degree	2.408	0.813	1.239	-0.359	-0.297	1.366
	(1.719)	(0.564)	(1.485)	(1.499)	(1.209)	(1.042)
No qualification	0.734	-0.474	2.603*	-0.0367	0.176	1.523
	(1.720)	(1.358)	(1.586)	(1.522)	(1.224)	(1.059)
age	-0.0406	-0.0165	-0.261***	-0.205	-0.0113	-0.345***
	(0.219)	(0.353)	(0.0994)	(0.125)	(0.111)	(0.0552)
age_squared	0.000397	0.000835	0.00328***	0.00235*	0.000176	0.00405***
	(0.00258)	(0.00411)	(0.00123)	(0.00142)	(0.00126)	(0.000646)
urban	0.227	-0.467	0.593	0.559	-0.300	0.357
	(0.950)	(1.348)	(0.534)	(0.370)	(0.300)	(0.235)
Work at home (ref.=never)						
Sometimes	2.102	0.304	2.845	-1.221*	-0.356	-0.950
	(2.163)	(3.736)	(2.016)	(0.706)	(0.610)	(0.591)
Often	1.531	1.860	2.665	-0.539	-0.177	-1.128**
	(1.541)	(2.158)	(1.746)	(0.569)	(0.529)	(0.452)
Always	0.669	-2.461	-3.240*	-2.041***	-0.935*	-0.490
	(1.457)	(2.884)	(1.692)	(0.502)	(0.499)	(0.376)
Household income (ref.=low)						
Middle	0.434	1.956	-0.183	-0.374	-0.340	-0.417**
	(0.871)	(1.605)	(0.376)	(0.404)	(0.345)	(0.212)
High	-1.047	1.112	-1.584***	-0.441	-0.261	-0.538**
	(0.990)	(1.850)	(0.575)	(0.448)	(0.362)	(0.239)
Occupational class (ref.=managerial, administrative, and technical)						
Intermediate	-0.512	-0.545	0.218	-0.563	-0.574	-0.228
	(0.941)	(0.634)	(0.377)	(0.679)	(0.430)	(0.270)
Small employers and own account workers	1.607**	1.613**	1.927***	1.689***	1.154**	1.330***
	(0.743)	(0.697)	(0.638)	(0.522)	(0.503)	(0.485)
Lower supervisory and technical occupation	0.952	-1.376	0.607	1.036	-14.32	-0.110
	(1.209)	(1.406)	(0.492)	(1.079)	(550.6)	(0.456)

Semi-routine and routine	0.127	0.288	0.434	0.528	0.408	0.0181
	(0.721)	(0.550)	(0.308)	(0.571)	(0.409)	(0.243)
Not applicable (others, inactive, etc.)	-0.215	-0.135	1.205***	-0.585	0.287	-0.466
	(0.583)	(0.548)	(0.298)	(0.905)	(0.819)	(0.510)
Baseline employment status (ref.=paid employment)						
Self-employment	9.058***	4.765**	4.544***	9.439***	4.676***	3.753***
	(1.404)	(2.044)	(1.199)	(0.558)	(0.555)	(0.497)
Both paid and self-employment	3.833***	7.913***	-4.703***	4.260***	5.947***	1.299**
	(1.456)	(2.205)	(1.517)	(0.582)	(0.301)	(0.554)
Constant	-9.230	-8.793	-7.214	-0.955	-3.710	2.444
	(17.54)	(36.22)	(15.01)	(2.968)	(2.597)	(1.520)
Observations	3,235	3,235	3,235	6,568	6,568	6,568

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

Appendix 4.2.6 Estimation results predicting changes in employment status with interaction between the presence of school-aged children and health conditions with the entire female sample

	(1)	(2)	(3)
VARIABLES	Self-employment vs paid employment	Both vs paid employment	No vs paid employment
Children (ref.=no)	0.0850	0.0862	-0.0682
	(0.409)	(0.350)	(0.259)
ethnic_migrant (ref.=white native)	-1.088	-0.450	0.546
	(0.802)	(0.774)	(0.371)
children#ethnic_migrant	1.307	0.528	0.459
	(1.259)	(1.409)	(0.704)
Health (ref.=good)	-0.442	0.184	0.115
	(0.409)	(0.364)	(0.205)
children#health	0.807	-0.108	-0.291
	(0.773)	(0.625)	(0.511)
ethnic_migrant#health	2.175	0.376	-1.624
	(1.732)	(1.623)	(1.104)
children#ethnic_migrant#health	-1.484	-1.433	3.041**
	(1.767)	(2.905)	(1.443)
Education (ref.=Bachelor’s degree and above)			

Below Bachelor's degree	-0.284	-0.177	1.880*
	(1.463)	(1.206)	(1.031)
No qualification	0.152	0.274	2.088**
	(1.481)	(1.218)	(1.044)
age	-0.142	-0.00857	-0.306***
	(0.108)	(0.102)	(0.0471)
age_squared	0.00157	0.00105	0.00363***
	(0.00123)	(0.00117)	(0.000557)
urban	0.507	-0.345	0.420*
	(0.337)	(0.288)	(0.215)
Work at home (ref.=never)			
Sometimes	-0.927	-0.316	-0.685
	(0.641)	(0.588)	(0.561)
Often	-0.487	-0.0709	-0.814*
	(0.508)	(0.506)	(0.436)
Always	-1.759***	-0.956**	-0.196
	(0.452)	(0.481)	(0.373)
Household income (ref.=low)			
Middle	-0.329	-0.209	-0.421**
	(0.361)	(0.333)	(0.182)
High	-0.636	-0.196	-0.725***
	(0.394)	(0.350)	(0.214)
Occupational class (ref.=managerial, administrative, and technical)			
Intermediate	-0.693	-0.568	-0.238
	(0.645)	(0.433)	(0.267)
Small employers and own account workers	1.586***	1.117**	1.338***
	(0.508)	(0.500)	(0.477)
Lower supervisory and technical occupation	0.945	-1.485	-0.0820
	(1.048)	(1.629)	(0.452)
Semi-routine and routine	0.488	0.455	0.0458
	(0.532)	(0.406)	(0.234)
Not applicable (others, inactive, etc.)	0.0238	0.131	0.799***
	(0.452)	(0.462)	(0.238)
Baseline employment status (ref.=paid employment)			
Self-employment	9.206***	4.681***	3.747***
	(0.498)	(0.509)	(0.429)
Both paid and self-employment	4.202***	5.979***	1.115**
	(0.534)	(0.293)	(0.550)
Constant	-1.915	-4.519*	0.740
	(2.595)	(2.418)	(1.385)
Observations	9,573	9,573	9,573

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

Appendix 4.2.7 Estimation results predicting changes in employment status with interaction between the presence of school-aged children and health conditions among blue-collar females and white-collar females

	(1)	(2)	(3)	(4)	(5)	(6)
		Blue collar			White collar	
VARIABLES	Self-employment vs paid employment	Both vs paid employment	No vs paid employment	Self-employment vs paid employment	Both vs paid employment	No vs paid employment
Children (ref.=no)	0.304	0.0263	-0.0999	-0.124	0.0244	-0.455
	(0.459)	(0.360)	(0.288)	(0.701)	(0.528)	(0.454)
ethnic_migrant (ref.=white native)	0.158	-0.211	0.548	0.285	-0.917	-0.889
	(1.082)	(0.800)	(0.426)	(1.438)	(1.368)	(1.083)
children#ethnic_migrant	0.635	0.492	-0.615	1.368	1.905	1.888
	(1.625)	(1.454)	(1.143)	(2.103)	(1.969)	(1.589)
health	-0.258	0.0135	-0.138	-0.324	0.427	0.112
	(0.461)	(0.388)	(0.244)	(0.709)	(0.596)	(0.354)
children#health	0.527	0.124	0.0533	1.432	-0.0739	-1.391
	(0.868)	(0.647)	(0.568)	(1.342)	(0.920)	(1.791)
ethnic_migrant#health	0.974	0.314	-1.189	0.428	1.463	-1.406
	(1.961)	(1.649)	(1.136)	(3.272)	(2.277)	(1.774)
children#ethnic_migrant#health	-1.417	-1.457	3.820**	-1.490	-1.678	1.273
	(1.941)	(3.148)	(1.747)	(1.250)	(1.402)	(1.081)
Education (ref.=Bachelor's degree and above)						
Below Bachelor's degree	-0.406	-0.263	1.375	-0.485	-0.364	1.094
	(1.505)	(1.226)	(1.043)	(0.517)	(1.967)	(1.235)
No qualification	-0.0740	0.210	1.526	-0.365	0.288	1.525
	(1.529)	(1.241)	(1.059)	(1.524)	(1.961)	(1.235)
age	-0.201	-0.0105	-0.350***	-0.151	-0.0881	-0.349***
	(0.125)	(0.111)	(0.0555)	(0.197)	(0.197)	(0.0975)
age_squared	0.00231	0.000169	0.00410***	0.00158	0.00107	0.00411***
	(0.00142)	(0.00126)	(0.000649)	(0.00220)	(0.00219)	(0.00112)
urban	0.556	-0.307	0.363	0.503	-0.313	0.459
	(0.369)	(0.299)	(0.235)	(0.595)	(0.481)	(0.396)
Work at home (ref.=never)						
Sometimes	-1.246*	-0.365	-0.987*	-0.765	-0.577	-1.039
	(0.706)	(0.610)	(0.594)	(0.967)	(0.965)	(0.863)
Often	-0.565	-0.178	-1.195***	0.130	-0.121	-1.062
	(0.570)	(0.530)	(0.455)	(0.846)	(0.888)	(0.707)

Always	-2.091***	-0.942*	-0.502	-1.645**	-0.745	-0.691
	(0.503)	(0.500)	(0.377)	(0.781)	(0.879)	(0.618)
Household income (ref.=low)						
Middle	-0.387	-0.343	-0.422**	0.213	-0.401	-0.127
	(0.405)	(0.346)	(0.212)	(0.640)	(0.535)	(0.362)
High	-0.473	-0.274	-0.545**	0.187	-0.289	-0.511
	(0.449)	(0.362)	(0.239)	(0.690)	(0.530)	(0.404)
Occupational class (ref.=managerial, administrative, and technical)						
Intermediate	-0.573	-0.583	-0.271	-1.622	-0.462	-0.700*
	(0.680)	(0.433)	(0.271)	(1.052)	(0.615)	(0.411)
Small employers and own account workers	1.688***	1.162**	1.306***	1.140	0.232	0.209
	(0.523)	(0.503)	(0.489)	(0.801)	(0.803)	(0.854)
Lower supervisory and technical occupation	1.115	-1.388	-0.867	-0.937	-13.49	-15.36
	(1.077)	(1.429)	(0.754)	(3.854)	(1,552)	(1,265)
Semi-routine and routine	0.545	0.409	-0.120	0.199	0.801	-0.622
	(0.571)	(0.408)	(0.244)	(1.086)	(0.634)	(0.464)
Not applicable (others, inactive, etc.)	-0.583	0.289	-0.582	-0.275	-1.369	0.217
	(0.905)	(0.819)	(0.512)	(1.333)	(1.705)	(0.732)
Baseline employment status (ref.=paid employment)						
Self-employment	9.435***	4.672***	3.791***	9.373***	3.405***	4.422***
	(0.560)	(0.554)	(0.499)	(0.841)	(1.216)	(0.722)
Both paid and self-employment	4.255***	5.940***	1.313**	3.967***	5.833***	1.667***
	(0.583)	(0.301)	(0.554)	(0.868)	(0.447)	(0.663)
Constant	-0.847	-3.746	2.571*	-2.065	-5.751	-11.36
	(2.956)	(2.618)	(1.523)	(4.804)	(4.735)	(1,235)
Observations	4,304	4,304	4,304	5,269	5,269	5,269

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

Appendix 4.2.8 Estimation results predicting changes in employment status with interaction between the presence of school-aged children and family support in childcare with the female sample

	(1)	(2)	(3)
VARIABLES	Self-employment vs paid employment	Both vs paid employment	No vs paid employment

Children (ref.=no)	0.278	1.088***	-0.635
	(0.458)	(0.356)	(0.534)
ethnic_migrant (ref.=white native)	-0.566	-0.132	-1.514***
	(0.649)	(0.505)	(0.543)
children#ethnic_migrant	1.237	2.405**	4.235***
	(1.162)	(0.989)	(1.235)
Family_support (ref.=no)	-0.314	0.382	0.0784
	(0.461)	(0.400)	(0.302)
children#family_support	0.0441	-1.445***	0.0398
	(0.673)	(0.483)	(0.562)
ethnic_migrant#family_support	-0.123	-1.226	2.012*
	(1.034)	(0.845)	(1.061)
children#ethnic_migrant#family_support	-0.896	3.476	-4.773**
	(1.673)	(3.689)	(1.946)
Education (ref.=Bachelor's degree and above)			
Below Bachelor's degree	0.911	2.357	1.616**
	(0.766)	(1.490)	(0.812)
No qualification	1.368	3.295**	1.629*
	(0.839)	(1.506)	(0.875)
age	-0.201*	-0.0472	-0.332***
	(0.109)	(0.103)	(0.0660)
age_squared	0.00255*	0.000890	0.00398***
	(0.00134)	(0.00120)	(0.000755)
urban	0.291	-0.310	-0.0728
	(0.370)	(0.261)	(0.198)
Work at home (ref.=never)			
Sometimes	-1.006	-0.333	-0.533
	(0.667)	(0.505)	(0.560)
Often	-0.781	0.192	-0.0520
	(0.622)	(0.476)	(0.517)
Always	-2.500***	-1.252***	0.412
	(0.627)	(0.460)	(0.420)
Household income (ref.=low)			
Middle	0.187	0.0682	-0.324
	(0.477)	(0.326)	(0.245)
High	-0.311	-0.139	-0.717***
	(0.461)	(0.391)	(0.267)
Occupational class (ref.=managerial, administrative, and technical)			
Intermediate	-0.0950	-0.276	-0.119
	(0.787)	(0.334)	(0.307)
Small employers and own account workers	2.289***	1.938***	2.065***
	(0.541)	(0.517)	(0.459)
Lower supervisory and technical occupation	1.013	-1.544	0.658

	(1.613)	(1.113)	(0.680)
Semi-routine and routine	0.272	0.913**	0.281
	(0.568)	(0.360)	(0.238)
Not applicable (others, inactive, etc.)	0.891	0.783*	0.764***
	(0.605)	(0.464)	(0.291)
Baseline employment status (ref.=paid employment)			
Self-employment	9.233***	4.818***	3.644***
	(0.653)	(0.555)	(0.533)
Both paid and self-employment	4.123***	6.691***	1.409**
	(0.628)	(0.307)	(0.630)
Constant	-2.500	-7.753***	-13.50***
	(2.135)	(2.787)	(1.548)
Observations	8,803	8,803	8,803

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

Appendix 4.2.9 Estimation results predicting changes in employment status with interaction between the presence of school-aged children and family support in childcare among blue-collar females and white-collar females

	(1)	(2)	(3)	(4)	(5)	(6)
		Blue collar			White collar	
VARIABLES	Self-employment vs paid employment	Both vs paid employment	No vs paid employment	Self-employment vs paid employment	Both vs paid employment	No vs paid employment
Children (ref.=no)	0.0392	-0.595	0.0739	0.931**	1.660***	0.187
	(0.683)	(0.554)	(0.454)	(0.473)	(0.389)	(0.549)
ethnic_migrant (ref.=white native)	-1.375**	-1.794**	-0.738	1.428***	0.329	-0.755
	(0.640)	(0.796)	(0.842)	(0.479)	(0.453)	(0.642)
children#ethnic_migrant	0.981	-1.034	2.728***	-0.182	-14.92***	3.001***
	(0.802)	(0.927)	(0.956)	(0.815)	(0.595)	(0.892)
Family_support (ref.=no)	-1.158	-1.324***	-0.915***	0.232	0.767*	0.460**
	(0.888)	(0.420)	(0.301)	(0.411)	(0.415)	(0.231)
children#family_support	-0.396	0.801	-0.380	-0.601	-1.967***	-0.586
	(1.116)	(0.596)	(0.567)	(0.653)	(0.495)	(0.610)
ethnic_migrant#family_support	1.444	1.305	1.727	-2.137**	-0.661	2.064**
	(1.073)	(0.856)	(1.191)	(0.854)	(0.589)	(0.919)

children#ethnic_migrant#family_support	-1.403	1.135	-4.179***	0.603	1.275	-3.212***
	(1.527)	(1.104)	(1.469)	(1.396)	(1.933)	(1.194)
Education (ref.=Bachelor's degree and above)						
Below Bachelor's degree	1.306	1.882	1.550	0.183	2.442	1.724
	(0.867)	(1.834)	(1.027)	(0.846)	(1.898)	(1.128)
No qualification	1.315	2.692	2.061**	0.931	3.319*	2.108*
	(0.935)	(1.857)	(1.040)	(0.895)	(1.934)	(1.137)
age	-0.0657	-0.0193	-0.333***	-0.293***	-0.142	-0.374***
	(0.151)	(0.0836)	(0.0705)	(0.104)	(0.0975)	(0.0735)
age_squared	0.000725	0.000381	0.00415***	0.00355***	0.00188*	0.00456***
	(0.00199)	(0.000956)	(0.000820)	(0.00126)	(0.00114)	(0.000850)
urban	0.461	-0.144	0.511*	0.464	-0.308	0.537**
	(0.668)	(0.262)	(0.279)	(0.383)	(0.270)	(0.272)
Work at home (ref.=never)						
Sometimes	-2.071*	-0.734	-0.495	-1.451**	-0.500	-0.936
	(1.120)	(0.501)	(0.660)	(0.659)	(0.464)	(0.581)
Often	-1.659**	-0.251	0.314	-0.974*	-0.202	-0.0175
	(0.786)	(0.388)	(0.598)	(0.554)	(0.406)	(0.489)
Always	-2.498***	-1.570***	-0.293	-2.457***	-1.376***	-0.297
	(0.735)	(0.404)	(0.517)	(0.591)	(0.412)	(0.408)
Household income (ref.=low)						
Middle	0.123	-0.307	-0.0832	0.452	-0.0501	-0.263
	(0.526)	(0.308)	(0.224)	(0.451)	(0.324)	(0.223)
High	-0.880	-0.164	-0.321	-0.245	0.0446	-0.528*
	(0.766)	(0.293)	(0.292)	(0.401)	(0.347)	(0.279)
Occupational class (ref.=managerial, administrative, and technical)						
Intermediate	0.532	-0.374	0.0650	-0.266	-0.404	0.0603
	(0.735)	(0.290)	(0.296)	(0.696)	(0.321)	(0.288)
Small employers and own account workers	2.268**	0.944**	1.394**	2.510***	1.775***	2.098***
	(1.023)	(0.435)	(0.571)	(0.480)	(0.463)	(0.427)
Lower supervisory and technical occupation	-0.0354	-1.118	0.0788	0.727	-1.420	0.162
	(1.211)	(0.929)	(0.392)	(0.619)	(1.073)	(0.393)
Semi-routine and routine	-0.175	0.304	-0.200	-0.430	0.404	0.126

	(0.891)	(0.386)	(0.296)	(0.536)	(0.340)	(0.268)
Not applicable (others, inactive, etc.)	1.772**	0.255	0.794***	0.675	0.694	0.931***
	(0.766)	(0.462)	(0.299)	(0.527)	(0.442)	(0.278)
Baseline employment status (ref.=paid employment)						
Self-employment	2.458***	5.873***	6.239***	9.211***	4.778***	3.847***
	(0.234)	(1.349)	(0.847)	(0.588)	(0.488)	(0.455)
Both paid and self-employment	4.084***	6.515***	1.345**	4.276***	6.526***	1.290**
	(0.600)	(0.281)	(0.542)	(0.627)	(0.293)	(0.604)
Constant	-18.40***	-5.334*	0.623	-0.462	-5.508*	0.641
	(3.005)	(2.932)	(1.718)	(2.020)	(3.050)	(1.776)
Observations	3,483	3,483	3,483	5,320	5,320	5,320

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

Appendix 4.2 Results of proportion tests

	White native	BAME migrant	Diff	p-value
Female sample				
Health conditions	0.2364	0.3078	-0.0714	0.0001
Family support in childcare	0.4267	0.5052	-0.0785	0.0000
Blue-collar female				
Health conditions	0.2411	0.3133	-.0722	0.0004
Family support in childcare	0.5224	0.5642	-0.0418	0.0001
White-collar female				
Health conditions	0.2187	0.2929	-0.0742	0.0007
Family support in childcare	0.3987	0.4641	-0.0645	0.0044
Male sample				
Health conditions	0.2240	0.2880	-0.0640	0.0011
Family support in childcare	0.6779	0.7013	-0.0234	0.0877
Blue-collar male				
Health conditions	0.2318	0.2903	-0.0585	0.0366
Family support in childcare	0.6896	0.7539	-0.0643	0.0462
White-collar male				
Health conditions	0.2135	0.2612	-0.0477	0.0478
Family support in childcare	0.5933	0.6619	-0.0686	0.0755