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Firm Policies and Critical Data Sources

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Abstract

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In the dynamic fluctuating economic landscape, firm policies are the guiding principles that steer market conditions and firms' behaviour. In the past, these policies were formulated based on limited data and a heavy reliance on expert opinions. However, a new era is dawning, characterised by vast amounts of data processing using advanced statistical and computer science methodologies. Data-driven decision-making uses these methodologies to consolidate and process data into actionable information, leading to firm policies. The critical data sources are the data sources on which the policies are based. The data-driven decision-making allows the data to speak for itself, relying less on expert opinions for policymaking. However, it also necessitates a higher requirement of validation. This thesis investigates five different cases of firm policy and critical data sources. Each one of them will present one aspect of this broad topic. The first paper investigates selecting auxiliary variables to estimate firm characteristics, aiming to reduce bias and improve accuracy. Simple variables outperform complex ones, and complete data enhances accuracy. The second paper introduces a methodology for quantitative inductive research on ordinal survey data by new- and traditional- penalising methods. The new methods outperformed the old and could find a significant variable, while the older models could not. The third paper examines how macro-factors impacted various Small and Medium Enterprises (SME) sectors in the European Union's member states from 2005 to 2019. The research offers valuable insights for policymakers and business leaders, aiding in tailored policy interventions and support mechanisms to address regional disparities and economic conditions. The fourth and fifth papers investigated Short-Time Work (STW), a primary policy tool during the COVID-19 pandemic. These studies used Swedish firm-level data to assess the STW policy. In the fourth paper, STW was associated with a reduction in employee numbers and a slightly increased productivity level compared to non-STW firms. In the fifth paper, STW did not increase the survival of SMEs. In conclusion, the ever-evolving economic landscape necessitates data-driven decision-making for informed actions and policymaking. This thesis is by no means a complete investigation, and further research is needed on this topic.

Keywords: Firm policies, Critical data, Large data, Data-driven decision-making, Quantitative inductive methods

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To my family

Preface

Since I started my PhD, it has been a long journey, and I have encountered many people who have greatly impacted me. I cannot adequately express my gratitude to every one of you personally. Therefore, I write this letter this way so no one is mentioned or forgotten. Thanks to you, this journey has been such a bliss.

I am deeply grateful to all my supervisors and co-authors for your invaluable comments and unwavering support throughout this long journey. You have answered my questions and sometimes just acted as moral support. Your guidance has been instrumental in my growth.

To my colleagues in the Economics and Business subjects, I have loved working next to you and enjoying interesting discussions during lunches and fikas. You have helped me grow and get new perspectives.

Thank you to everyone in the Microdata Analysis research group. Your courses, lectures, and seminars have greatly impacted me and helped me become more confident.

Thank you to all the fellow PhD students with whom I have shared this journey. It has been a pleasure attending this journey together.

To all my friends, you mean so much to me and have been such great support. You have cheered and made me laugh, which has been so much needed.

To my family, you have helped so much and have been such moral support. I would never have finished this journey without you.

April 24th, 2024
Åsa Grek

List of Papers

This thesis is based on the following papers, which are referred to in the text by their Roman numerals.

I. Grek, Å., Hartwig, F., Dougherty, M., (2024). Improved Accuracy in Firm Modelling and Prediction – A Variable Suggestion. *Submitted.*

II. Grek, Å., Hartwig, F., Dougherty, M., (2024). An Inductive Approach to Quantitative Methodology? – Application of Novel Penalising Models in a Case Study of Target Debt Level in Swedish Listed Companies. *Journal of Risk and Financial Management 17*(5).

III. Grek Å., Nordström, C., Cialani, C., (2024). Unravelling the Dynamics – Which Macro-Factors are Shaping the SME Sector Landscape Within the European Union? *Submitted.*

IV. Grek, Å., Mortazavi, R., Nordström, C., (2024). Short-Time Work as a Response to the COVID-19 Crisis – A Study on SME Firm-Level Data in Sweden. *Submitted.*

V. Grek, Å., (2024). The Effect of Short-Time Work on SME Firm Survival during the COVID-19 Pandemic. *Submitted.*

My contribution to each of the papers:

Paper I: Literature review, data management, formal analysis, writing original draft and editing.

Paper II: Conceptualisation, literature review, data management, formal analysis, writing original draft and editing.

Paper III: Conceptualisation, literature review, data management, formal analysis, writing original draft and editing.

Paper IV: Conceptualisation, literature review, data management, formal analysis, writing original draft and editing.

Paper IV: Conceptualisation, literature review, data management, formal analysis, writing original draft and editing.

Paper V: Conceptualisation, literature review, data management, formal analysis, writing and editing.

Contents

Part I: Introduction

This section introduces the thesis. After the introduction, the papers follow. Then, there is the discussion and conclusions section. In the end, the reference list can be found for the introduction, discussion, and conclusions.

1. Data-driven decision-making

In the dawn of the complex digital world, there is an emerging need for sophisticated decision-making. The transformative impact of technological advancements on data collection and the exponential growth in digitised data has changed the decision-making processes (Shahid & Sheikh, 2021). Given the enormous volume of available data, governments, policymakers, and researchers must implement robust data processing and management strategies to utilise this large data for proper decision-making (McAfee et al., 2012). The data-driven decision-making process emerged from the need to simplify large data into straightforward and actionable information. This is also what microdata analysis is about, going from data collection to data storage, data processing and storage, and analysis, which should lead to decision-making and action.

The transition from traditional to data-driven decision-making signifies a paradigm shift in how data are processed and analysed for information (Provost & Fawcett, 2013). Governments and other institutions have previously relied heavily upon experts, intuition, and historical performance (Howlet, 2018); while these factors remain highly relevant, data-driven decision-making is an additional process that empowers the government and other institutions. The data-driven decision-making leads to a more proactive and adaptive approach to policymaking and management (Troisi et al., 2020). By using advanced analytics, statistics and machine learning algorithms, governments and institutions can identify patterns, correlations, and trends that may have otherwise gone unnoticed. Furthermore, it has broader implications for firm-level financial and societal consequences. Consequently, governments, policymakers and researchers can apply data-driven decision-making to enhance performance and drive innovation effectively (Manyika et al., 2011). The decision-making process in a government setting offers the potential to form better policies that could benefit the business market (Mikalef, 2019). As a result, governments, policymakers and researchers can utilise data-driven methods to respond swiftly to emerging opportunities and challenges, enacting effective firm policies and enabling firms to gain a competitive edge in the dynamic market landscape (Troisi et al., 2020).

Significant hurdles exist in applying data-driven decision-making: ensuring data quality, integrity, and security is critical. Additionally, data storage and fragmentation can hinder the seamless flow of information across departments. The lack of a centralised database can lead to inefficient data sharing and utilisation, limiting the view necessary for informed policy formulation. Furthermore, data privacy regulations and ethical considerations are pivotal in determining how data is collected, stored, and utilised. However, this raises challenges in extracting actionable insights and ensuring data accuracy while withholding security and privacy (Sivarajah et al., 2017; Quach et al., 2022; Sarathy & Robertson, 2003). The further evolution of technology allows organisations to collect and analyse data at an unprecedented scale, which is relevant for studying micro- and macro-perspectives.

Data-driven decision-making can be applied on both micro- and macroeconomic levels. The number of data points needed for micro- and macro-level decision-making can vary widely depending on the decision's specific context, industry, and complexity (Chernega et al., 2021). Notably, a data source relevant to micro- or macro-level decision-making might differ substantially. Micro-level decisions may require a more targeted and specific set of data relevant to the context in which the decision is being made (Frick, 2009). Therefore, micro-level data points may be substantial but are typically more specific to the context. The precision and accuracy of data may be more critical at the level where decisions can have immediate and direct impacts on specific areas. On the other hand, decision-making on the macro-level involves large-scale considerations impacting entire industries or economies. These decisions often deal with complex and interconnected systems, requiring a comprehensive understanding of various factors. Macro-level decisions typically involve a larger scale of data and a broader analysis of multiple factors. The data at the macro level is often more extensive, but the data are often more aggregated. Therefore, the decision-makers must analyse trends, market dynamics, and economic indicators. Macro-level decisions have far-reaching consequences and can influence the overall direction of an industry or economy. Macro-level decisions typically involve a larger scale of data and a broader analysis of various factors, given their broader scope and potential impact. Independently of the micro- or macro-level perspective, no fixed amount or standard number of data points exists for either level, depending on case-specific contexts, for example, factors such as the level of the decision, the variables involved, and the desired level of accuracy.

Optimisation procedures have been developed for rational decision-making processes to solve the issue of better practices. Notably, the multicriteria decision analysis is based on microdata, which provides a method for evaluating alternatives when multiple criteria must be considered simultaneously. Therefore, the decision-making processes can be improved, and the robustness of decisions can be increased. Better practices may also involve considering factors such as the scope of the decision, the variables involved, and the desired level of accuracy (McGregor, 2001). Establishing better practices for data utilisation ensures the efficient use of available information and promotes consistency and reliability in decision-making. Moreover, sharing better practices within and across industries can facilitate knowledge-sharing and foster innovation in data-driven decision-making approaches. By analysing case-specific contexts and industry standards, firms can develop guidelines or frameworks that outline optimal data utilisation practices for different decision-making scenarios. Furthermore, in adopting data-driven decision-making, the challenge of balancing data quality must be faced (Brynjolfsson et al., 2011).

In applying data-driven decision-making, there is a need for sufficient, accurate, and appropriate data analysis methods. One strong argument for using an inductive approach to data analysis is to let data speak for itself. However, a sufficient volume of data is needed to know that it is saturated, and a lack of quality can undermine its utility. Incomplete, biased, or inaccurate datasets can lead to flawed analyses and misguided decisions. Biases, whether inherent in the data collection process or introduced during analysis, can perpetuate inequality, reinforce stereotypes, and distort perceptions of reality. Therefore, appropriate data analysis methods are needed to interpret the data accurately.

Due to the vastness of data-driven decision-making, this thesis cannot encompass this topic. Therefore, the investigation needs to be delimited to fit within the boundaries of the thesis. Consequently, this thesis investigates five cases in the emerging field of data-driven decision-making in enacting firm policies. Furthermore, it aspires to discuss the implications of data-driven decision-making and the recurring "good-enough" data dilemma.

2. Critical Data

In recent years, technological advancements have transformed data collection and analysis. The business landscape has become more interconnected and complex, with companies, researchers, and governments accessing a considerably large volume and variety of data. These data are often referred to as large data and are characterised by their volume. However, they differ from big data because they do not cover the three V's: volume, velocity, and variety[1] (Kitchin & McArdle, 2016). Big data encompasses datasets which are too large and complex to be processed by traditional means. Hence, advanced statistical- and computer science-mixed methodologies are needed for meaningful analysis (Jianqing et al., 2014). Traditional data processing can manage large data, but they may still require specialised tools and approaches for efficient handling (Sakr et al., 2011). Large data is available on many platforms, such as the Internet, social media, e-commerce, and other digital platforms. Large data differs from big data as there are no requirements for real-time accessibility (Quach et al., 2022; Oussous et al., 2018; Günther, 2017). The accumulative volume of big and large data can come from various sources, such as monitoring customer interactions, online transactions, and social media interactions. In utilising traditional statistical methodologies, large data can provide great accuracy in interpreting the data. After processing, large data may provide better information for decision-making than smaller datasets due to the large information they encompass (Ekbia et al., 2015). However, utilising large data presents the formidable task of correctly harnessing the data to drive informed decision-making (Krafft et al., 2021).

Integrating data from various sources and formats of databases requires robust knowledge and expertise to ensure consistency and reliability (Rodríguez-Espíndola et al., 2022b). By leveraging advanced analysis techniques, the data can be used to uncover hidden patterns and correlations. However, these hidden patterns may suggest associations rather than causal relationships, and the new information can possess predictive and confirmatory values. Predictive information can forecast future outcomes, while confirmatory information provides feedback on previous predictions. By accessing

[1] Large data can encompass the three V's; however, they do not always do it. The primary difference between big data and large data is the volume and the velocity, i.e., the high speed at which the data is collected.

both types of information, more accurate predictions and better-informed decision-making can be performed (Rodríguez-Espíndola et al., 2022a).

The "good-enough" data dilemma arises from a trade-off between having accurate and complete data and the need for timely decision-making. In some instances, gathering the highest quality data may not be feasible or necessary, given the precision required for a particular decision (Neely & Cook, 2011). The primary challenge of data-driven decision-making applications on big data lies in the volume of the data (Gandomi & Haider, 2015). If policymakers and researchers can utilise the available data, their efficiency in decision-making can be improved. However, if the organisation cannot utilise the data, it risks missed opportunities due to this misinformed data utilisation (Quach et al., 2022). Hence, policymakers must find the optimal balance between processing vast datasets and the practicality of data utilisation in their decision-making process. However, the "good-enough" data dilemma highlights the tension between ensuring the accuracy and completeness of data versus the need for timely decision-making. Balancing these two factors is crucial for meaningful insights from the data. The data-driven decision-making process becomes a beacon, offering a novel solution to transform vast datasets into streamlined, actionable results. This approach empowers the government by providing actionable quantitative data, fostering a more proactive and adaptive approach to policymaking and management (Mikalef, 2019). Uncertainty can necessitate decision-makers to process large amounts of information, which is essential for facilitating preplanning, efficiency enhancements, resource management, and management changes. This holds particularly true for knowledge-intensive activities, where a comprehensive understanding of information processing aids in optimising activities across diverse locations (Chen & Lin, 2016).

Selecting the most relevant and reliable data sources becomes crucial, especially considering the perspective of data application. Hence, optimally utilising the data-driven decision-making process aspires to enact effective policies. The policies are guiding principles that further promote decision-making, resource allocation, and overall strategic directions (Rodríguez-Espíndola et al., 2022b). Critical data sources refer to sufficient volume data, are unbiased, and can correctly portray the studied outcome. The critical data sources can concern various topics and actions. Therefore, these data sources can consist of market data, industry-specific data, and economic indicators, to name a few. Moreover, the analysis of a critical data source can result in a direct alteration of a pre-existing firm policy, which in turn could affect the behaviour of many firms (Mikalef et al., 2019). Furthermore, by understanding the data generation process, crucial analysis and interpretation of the outcome becomes more efficient. Therefore, it is important to understand how the data is collected and generated for correct interpretation. Furthermore, new technologies can strengthen the use of critical data sources, increasing the understanding of market conditions and outcomes (Grashof & Kopka, 2023). The comprehensive use of new technologies in conjunction with data sources, especially critical data sources, has dawned the era of data-driven decision-making (Mikalef, 2019; Mikalef, 2020; Sarker, 2021). Papers III, IV, and V in this thesis contain critical data discussions on different aspects.

Four papers in the thesis used accounting data and utilised their qualitative characteristics to ensure the usefulness of applied data-driven decision-making. However, it is important to consider the cost constraint on financial reporting. Its benefits must justify the costs associated with reporting information. The International Accounting Standards Board (IASB) assesses costs and benefits to determine reporting requirements (Donnelly, 2007). According to IASB, the financial information must fulfil six qualitative criteria for achieving high quality. The criteria require the information to be relevant, accurately represented, comparable, verifiable, timeliness, and understandable (Agienohuwa & Ilaboya, 2018). Furthermore, there must be a balance between producing financial information and its utility. These criteria are fundamental in assessing the quality of financial information. Relevance and accurate representation are crucial qualitative characteristics of useful financial information. Relevant financial information can influence decision-makers and possess predictive and confirmatory values (Morais & Curto, 2009). Accurate representation involves accurately representing the substance of economic phenomena, ensuring completeness, neutrality, and freedom from error (Whittington, 2008). The other qualitative characteristics, such as comparability, verifiability, timeliness, and understandability, further enhance the usefulness of the information obtained from the data. Comparability enables users to identify similarities and differences among the data points. At the same time, verifiability assures that the data truthfully represent the economic phenomena investigated. Timeliness ensures that information is available for decision-makers promptly. Understandability ensures that information obtained after processing data is presented clearly and concisely (Kaminski & Carpenter, 2011). High-quality critical data can be employed in both inductive and deductive approaches.

Inductive reasoning involves predicting new situations based on previous knowledge and experience (Hayes et al., 2010). These predictions are primarily based on probabilities, as they are not proven or specific. Inductive reasoning involves the shared knowledge and logic most people use daily. Hence, inductive reasoning differs significantly from deductive reasoning. The deductive reasoning is based on a pre-existing hypothesis with corresponding conclusions that can be proven true or false, given that certain premises are known to be true (Hayes et al., 2010). Deductive reasoning is connected to quantitative research, while inductive reasoning is more strongly linked to qualitative research. This is because qualitative research primarily investigates areas where the phenomena cannot easily be measured quantitatively. Sometimes, the phenomena investigated qualitatively may be impossible to prove true quantitatively. If the phenomena can be proven true, qualitative and inductive-based research can generate hypotheses that can be rejected through a deductive approach. However, inductive reasoning is broad and can encompass even quantitative research if it generates hypotheses (Williams et al., 2002; Hayes et al., 2010). The concept of applying a quantitative inductive method is relatively new. However, it is a growing field, where Papers I and II of this thesis will outline two additional approaches to applying quantitative inductive research.

3. Firm Policies

Firm policies are principles for managing a firm's activities, laws and regulations affecting the firm. Along with emerging technological advancements, the data-driven decision-making process provides new insight into policymaking. Critical data may be processed into actionable information, allowing policymakers to shape policies to give the firm a competitive edge in the dynamic market. Effective policies are therefore crucial for firms to remain and adapt to the changing market conditions in today's competitive landscape. Notably, data-driven decision-making has increasingly become necessary for policy formulation and implementation in various sectors, including macroeconomic policies targeting firms. Therefore, potential gains are present for the government and firms affected by the policy (Verhoef et al., 2021). The ability to process this complex and large data has changed policymaking. Policymakers can gain valuable insights from data-driven decision-making to bolster the economic landscape, identify trends, and make informed decisions that have the potential to drive growth, enhance competitiveness, and foster financial stability (Loukis et al., 2020; van Ooijenm et al., 2019).

Considering the volume and variety of data available, it becomes essential to determine the optimal amount of data required at different levels of decision-making (Vercellis, 2011). In the era of big and large data, the traditional approach of selecting data based solely on its statistical significance may need to be revisited. Instead, one must consider the context and relevance of additional data to the specific decision, balancing these principles to ensure that the selected data effectively informs decision-making processes (Ghasemaghaei & Calic, 2019). Even though the potential benefits of data-driven policies are apparent, it is essential to acknowledge the possible pitfalls and ethical considerations, such as data privacy concerns, which highlight the need for transparency in data collection and usage (van Hoboken & Fathaigh, 2021). The papers III, IV and V address firm policies and are presented and discussed below.

4. Path of Investigation

This compilation thesis comprises five subjects: critical data and firm policies. Each paper addresses specific facets of the intersection between data-driven decision-making, critical data sources and firm policies. The thesis also presents research on data-driven decision-making from both the macroeconomic- and microeconomic perspectives. Several statistical methods are applied to contribute to decision-making and firm policies properly. Paper I outlines the case of auxiliary variable selection and presents a method for selecting the most suitable auxiliary variables. Paper II investigates new penalising methods, such as Element-Linked Multinomial-Ordinal (ELMO) and Cumulative Generalised Monotone Incremental Forward Stagewise (GMIFS), when the variable of interest follows an ordinal distribution. Paper III examines the effect of several macro factors on micro-, small-, and medium-sized firms (MSME) sectors. Paper IV examines the effect of Short-Time Work (STW) on keeping employees' and firms' productivity levels during the COVID-19 pandemic. The final paper, Paper V, investigates STW's effect on MSME survival during the COVID-19 pandemic. As the importance of data-driven decision-making grows, I hope this thesis's findings can be valuable to governments, policymakers and researchers.

The basis of the thesis was not pre-constructed. Instead, the basis and main aim were constructed after the included papers were formed. Therefore, this thesis consists of papers with broad research questions and approaches. The path of investigation serves as the map of the creation of this thesis. Outlining the initial starting ground and the process towards the later formation of the papers should make the process transparent and replicable.

The initial research ideas addressed the inadequacy of variable selection methods for analysing firms. The inadequacy of methods has implications for the decision-making process, which leads to a discussion regarding the need for more data to implement firm policies. An additional discussion emerged regarding the dilemma between the accuracy of complete data sets and the swiftness of reduced data sets. The "good enough" data dilemma has been presented previously. Later, my research touched on the need to re-evaluate the STW policy. A policy of this magnitude needs evaluation to ensure it fulfils its intended purpose. Due to the papers' complex nature, they are presented in the order they were started.

4.1 Path of Investigation for Paper I

Daunfeldt and Hartwig (2014) inspired the first research idea, "*What Determines the Use of Capital Budgeting Methods? Evidence from Swedish Listed Companies*". In that paper, the authors investigate the determinants of Swedish companies' budgeting methods on the Stockholm Stock Exchange. However, several possible methodological improvements emerged. Firstly, some potential independent variables excluded from the abovementioned paper must be observed[2]. Secondly, a more complete dataset could be constructed and analysed using statistical imputation methods based on the observables. The authors had already performed a non-response analysis. However, their inference could only be drawn from within the sample. Therefore, an alternative would be to weigh the parameter estimates from the estimations based on the limited sample with auxiliary data from all listed companies. This would result in parameter estimates based on observables representative of the population under study. During the outlining of the study, a significant research question came to mind: Are there any guidelines for selecting auxiliary variables? A literature search was performed, and no definitive answer could be found. Some argue for selecting auxiliary variables based on their theoretical connection to the variable of interest, while others argue that measurement should form the basis for selection. Ultimately, it was decided to utilise an inductive research method, i.e., letting the data speak for itself. This inductive selection was performed by testing various potential auxiliary variables with the q^2*-value* suggested by Särndal and Lundström (2005, 2008). The study results showed that suitable auxiliary variables are easily obtained and do not have many missing values. Our study found that firm age and Standard Industry Classification (SIC)-code effectively estimated the different study variables. This became Paper I.

4.2 Path of Investigation for Paper II

Paper II was derived from the same dataset as Paper I. The idea for a second study emerged because of the exclusion of potential independent variables in the original study by Daunfeldt and Hartwig (2014), which was the area of research regarding the target debt level of companies. It was revealed that no theory existed explaining what determines a company’s target debt level. To verify a hypothesis deductively, a hypothesis was needed to begin with. Hence, an inductive approach was needed to create a hypothesis. The first thing that came to mind was penalising models to exclude potential explanatory variables regarding the target debt level. However, the traditional penalising models did not function appropriately on ordinal data. Therefore, a literature search began to investigate if there existed penalising models that could

[2] This would later lead to Paper II in the thesis.

be used on ordinal data. The novel models, Element Linked Multinominal Ordinal (ELMO) and Generalised Monotone Incremental Forward Stagewise (GMIFS) were discovered from the search. These models have been developed for biostatistical application in cancer research to select different potential genes in different types of cancers. Later, these novel models were applied to the dataset regarding the target debt level, and we discovered the ability to utilise the novel models inductively to generate a hypothesis based on quantitative data. Hence, after this discovery, the ability to utilise quantitative ordinal data inductively was determined as the primary aim of this paper. Therefore, the main aim of Paper II was changed to a methodological paper presenting the method of utilising these novel penalising models on ordinal survey- and register data to generate hypotheses. The hypothesis generated from these novel penalising models was later tested if the selected variables were statistically significant in the same paper.

4.3 Path of Investigation for Paper III

Paper III emerged due to a conference call for a conference in Italy in 2018. The conference themes were entrepreneurship, small business economics and innovation. From the conference's themes, a literature search examined any knowledge gaps. The literature search revealed a need for studies in macro-factors affecting different MSME sectors. A paper by Thai and Turkina (2014) was discovered during the literature search. Their study examined how different macro-factors influenced formal and informal entrepreneurship. In further investigation, other studies used the same or nearly identical macro-factors. In addition, a variable West is used to differentiate between countries with a history belonging to the Western Bloc or Eastern Bloc of Europe. In designing the study, it was hypothesised that there would be apparent differences in the various sectors of MSMEs. Nevertheless, the study results did not confirm this hypothesis. Generally, the same variables had broad and all-encompassing effects on the MSMEs. There were no detectable patterns that a specific sector would benefit from a select macro-factor variable alone. The study found that factors such as the Social Security and Human Development Index were positively correlated with a rise in the number of MSMEs. However, the variables GDP per capita and Innovation had a negative effect on almost all MSME sectors. Furthermore, it is important to mention that innovation was measured as the number of patent applications per capita. Hence, if Innovation was estimated differently, it could produce a different result. Moreover, the study found that the number of MSMEs steadily increased within the EU from 2005 to 2019. However, during the Great Recession of 2009 and its subsequent economic downturn, a decline in the number of MSMEs was produced. The evident decline in the number of MSMEs during the Great Recession and the same recurring risk of firm exits during the COVID-19 Pandemic led to the research area of job retention and firm survival during the COVID-19 pandemic. This, in turn, led to the production of Paper IV and Paper V.

4.4 Path of Investigation for Paper IV

Further examination of the relevant data and strategies following the Great Recession became a focus in pre-planning these two studies. What was done during the Great Recession to prevent unnecessary firm exits? During the Great Recession, many OECD countries imposed a firm policy: the STW initiative. Additionally, the STW policy was reinstated during the COVID-19 pandemic. In further examination of the available research, it became evident that there were few previous studies on the efficacy of the STW policy with access to firm-level data. Hence, two research questions unfolded: Firstly, was the STW support effective in keeping employment high during the COVID-19 pandemic? Secondly, did the STW support prevent firm exits and encourage survival during the COVID-19 pandemic? The first research question led to Paper IV of this thesis, and the second research question led to Paper V.

When the Swedish government reinstated the STW policy, there were two objectives. The first was to keep people employed so the economy would have a more straightforward restart after the economic winter of COVID-19. The second was to help firms survive the economic winter. From the first objective, the fourth study of this thesis was initiated. In evaluating the STW policy, suitable data was needed. Fortunately, firm-level data was found from the Swedish Agency for Economic and Regional Growth (Tillväxtverket). This data matched firm-level accounting data from the Swedish Companies Registration Office (Bolagsverket). Because both databases had the organisational number and year, it was possible to merge these two databases into a large data set. The data included information from the firms' annual reports and information regarding their applications for STW support. However, not all firms applied for STW. Therefore, it was impossible to assume a straight comparison would be unbiased. Hence, a matching procedure was conducted. Propensity Score Matching (PSM), Mahalanobis Distance Matching, and PSM Difference-in-Difference (DiD) were used to estimate the effect. The results showed that the number of employees was fewer after the pandemic compared to before. Overall, independent of the means of measurement, the results showed a decrease of fewer than one employee per company for the whole year.

4.5 Path of Investigation for Paper V

The second objective of the STW support program was to prevent unnecessary firm exits due to the economic downturn of the COVID-19 pandemic, which led to the fifth study of this thesis. By reducing the employees' salaries, the STW initiative was to relieve the employment costs and counter the loss of revenue caused by the economic downturn. It was natural to assume that some form of matching technique was needed to reduce the bias in the firm survival analysis. Grouping the firms according to their three application states to the STW policy was necessary for future comparison. In other words, a firm was grouped into 1) Applying for STW and being granted the subsidy, 2) Applying for STW and not being granted the subsidy, or 3) Not applying for the STW support. A literature search was made to investigate different matching techniques to apply. It became evident that the bias of such models was too large. Therefore, a simplistic method of estimating a longitudinal logistic regression model was utilised. As mentioned, the firms were compared in the regression depending on their grouping. In the first regression, the firms in Group 1 were compared to those in Group 2. In the second regression, the firms in Group 1 were compared to those in Group 3. In the third regression, the firms in group 1 were compared to those in groups 2 and 3 combined. The study revealed that micro-sized firms did not benefit from the STW policy. Contrary to expectations, the results showed that STW support had no significant effect on firms that received STW support compared to those that did apply but did not receive STW support. The results also showed that micro-sized firms that applied for and received the STW subsidy had lower survival rates than those that did not apply for STW. In small-sized firms, the majority of the results were non-significant and inconclusive. However, a non-significant tendency was pointed towards an increased risk of failure for small-sized firms that received STW. Finally, for medium-sized firms, the STW did not have any significant effect when firms that received STW support were compared to those that applied but did not receive STW support. However, when firms that received STW support were compared to firms that did not apply for STW support, it showed that the STW subsidy was associated with an increased chance of firm survival.

5. Discussion and Conclusion

This thesis examines five cases of data-driven decision-making through the five included papers in this thesis. The methodologies can be applied in the discussion of the "good-enough" data dilemma and its implications for data-driven decision-making. This way, large volumes of data are analysed to identify patterns, trends, and insights without necessarily starting with a preconceived theory or hypothesis. By understanding different data processing, an improved data-driven decision-making process can be designed to account for cognitive limitations and biases, ultimately leading to more effective outcomes (Acciarini et al., 2021).

Paper I provided a methodology for filtering suitable auxiliary variables without preconceived notions or ideas. It tested the effectiveness of different auxiliary variables in reducing bias and improving estimation accuracy. Any selected variable can be regarded as a distinct generated hypothesis that can be tested deductively. The subsequent deductive testing is performed through bootstrapping to test and prove or disprove the hypothesis regarding the variable suitability in the auxiliary vector. These proven variables can then be implemented to enhance estimation accuracy in other settings. Ultimately, the decisions should be based on data analysis, empirical evidence and experience (Provost & Fawcett, 2013). This aligns with the central concept of critical data and data-driven decision-making, where accurate data analysis forms the basis for decision-making (Clarke, 2019). The systematic evaluation of various auxiliary variables constitutes an important factor in the data-driven decision-making process. Moreover, providing unbiased insights into which variables are most suitable provides a platform for further analysing firms. As a result, it improves the decision-making based on the firms' characteristics.

Paper II focuses on a direct methodological aspect of conducting quantitative inductive research on survey data. The methodology employs novel penalising models to analyse the survey data and identify explanatory variables correlated with the outcome of interest. An important factor regarding these novel models is their ability to be applied to ordinal data. Furthermore, the paper outlines a method of excluding non-significant explanatory variables until only the relevant variables for hypothesis formation remain. Aligning with data-driven decision-making, penalising models are used to analyse the data and identify the significant variables. The paper explores different explanatory variables correlated to the target debt level. This methodology can be further explored for data-driven decision-making by examining other potential areas of interest.

Paper III aims to identify significant factors that affect MSMEs positively or negatively. The paper used Eurostat data from the 28 states of the EU collected for 15 years (2005 to 2019), representing a substantial volume of data. The data is big data based as each country summarises the data yearly using big data principles, such as data aggregation. The study employs a data-driven approach by analysing the critical data on MSMEs in Europe to investigate the relationship between macroeconomic factors and different sectors of MSMEs. The variables were selected through a large literature review. Each variable was regarded as an individual hypothesis and was subsequently tested deductively. The results showed that broad policies would benefit or harm all MSME sectors. This result contrasted with the proposition of this study because it was hypothesised that a policy could be beneficial to one sector and non-applicable or detrimental to another. The study's findings can improve the data-driven decision-making processes, enabling policymakers to tailor interventions and support mechanisms according to the relationships uncovered in the paper. Policymakers can use the insights gained from the research to develop targeted policies that support MSMEs based on their specific sectoral needs. However, assessing how these possible policies are implemented is important.

Papers IV and V used Swedish firm-level data to evaluate the impact of STW support on various outcome variables. The study combined two data sources into a single large dataset. Analysing this extensive dataset allows for a comprehensive assessment of the effectiveness of STW policies in response to economic shocks, indicating the use of large data in the research process. Paper IV aimed to provide evidence-based insights into the effectiveness of the STW policy instrument on the number of employees, turnover per employee and productivity (working capital turnover ratio). Using STW allows firms to retain employees during periods of economic downturns, by avoiding layoffs and maintaining workforce stability. The paper employed a data-driven approach by estimating the effects of STW support. The findings suggest that firms that received STW support retained fewer employees and fewer working hours but increased their productivity, which highlights the effectiveness of the policy in preserving jobs and supporting business continuity during challenging times. The study's focus on evaluating the impact of STW support on productivity aligns with broader economic modelling principles. An important understanding is how policy interventions such as STW support can affect firm-level productivity. These findings contribute to refining economic models used to analyse the relationship between labour inputs and output levels. The paper primarily focuses on evaluating the effectiveness of STW support in mitigating the economic impact of the COVID-19 pandemic. The study also provides a broader context for potential applications in policymaking and business strategy, particularly during economic uncertainty and crisis management. The findings may guide policymakers in designating and implementing effective strategies during economic downturns. As a result, the impact of economic downturns may be mitigated.

Paper V also employed a data-driven approach and conducted a discrete survival analysis to investigate the effect of STW support on firm survival. By comparing firms that received STW support with those that did not, the research aimed to identify the impact of the support program on firm survival. In this study, firms that received STW support were compared to firms that applied and did not receive STW support. Nevertheless, the main result showed that there were no significant results. However, when firms who did receive STW support were compared to firms who did not apply, medium-sized firms benefited the most from the STW policy, while firm survival was lower in micro- and small-sized firms that received STW than those that did not receive the support. Policymakers can use the insights gained from the research to refine strategies and promote economic stability to safeguard enterprises during times of crisis. Examining the relationship between STW support and firm survival aligns with broader economic modelling principles. As the paper primarily focuses on investigating the effect of STW support on firm survival, it also implies that policymaking is a complex endeavour. The findings contribute valuable insights into the efficacy of STW policies, particularly during economic downturns or unforeseen disruptions such as the COVID-19 pandemic. It has provided insights into evaluating a costly firm policy that interests governments and policymakers. The evidence suggests that STW support programs are beneficial and disadvantageous to firm survival, depending on the context of the application. Therefore, this study highlights the importance of implementing effective policies to protect businesses facing challenges. However, it also shows that policymaking is complex. A beneficial policy in one instance might have no effect or be disadvantageous in another.

Paper IV and Paper V revealed the opposite effect of most previous studies in each area. Most previous studies utilised aggregated data of smaller size and lower quality. Paper IV and Paper V analysed an extensive dataset, allowing for a more comprehensive assessment of the effectiveness of STW policies in response to the economic shock, indicating that using critical data is important in evaluating firm policies. Therefore, these studies highlight the importance of "good enough" data for reliable data-driven decisions. A better data-driven decision-making process can be designed to account for cognitive limitations and biases, ultimately leading to more effective decision-making outcomes (Acciarini et al., 2021).

As previously mentioned, critical data sources that are unbiased and of sufficient quality and volume are needed to apply data-driven decision-making correctly. Sufficient data volume may involve the usage of large and wide-spanning databases. However, these large databases might be too large to provide a swift and straightforward analysis. However, a reduced dataset could provide rapid answers with less accuracy (Sivarajah et al., 2017). The "good enough" data dilemma emerges as the underlying dilemma regarding data usage. Additionally, actionable insights and swift recommendations may improve decision-making processes and firm policies. Therefore, there is a need to balance both sides of the dilemma. The use of large data and the "good enough" data dilemma have implications for firms and society. Another interpretation of large data is the concept of data-driven decision-making. By allowing the data to lay the foundation for decision-making, real-world problems may be solved. The discussion of data-driven decision-making emphasises the importance of efficient information processing in decision-making contexts (Lorentz et al., 2020).

Inductive reasoning is characterised by moving from specific observations to broader generalisations, a valuable tool for generating new insights (Hayes et al., 2010). The inductive approach allows researchers to develop new hypotheses and theories. The hypotheses and theories serve as a starting ground to explain the observed phenomena. The inductive approach is widely unified with the qualitative methodology. This thesis presents two approaches to quantitative inductive reasoning, enabling the data to guide its examination and reveal the patterns by itself. However, there are other ways in which an inductive method can be used, which contribute to this growing literature. By doing so, unexpected connections may be found, leading to new hypotheses (Hayes et al., 2010). The inductive approach enables uncovering solutions and opportunities that may have been overlooked using deductive reasoning. The approaches adopted in Paper II extend beyond simplistic models; the paper employs a more complex methodology. This complex approach includes advanced statistical techniques and machine learning algorithms designed to capture patterns and relationships within the data. Such complexity can be necessary to address the data's multifaceted nature and improve the accuracy and robustness of the model predictions. If multiple hypothesis testing is performed, it is known that it increases the risk of Type I errors (false positives). Therefore, as data grows increasingly complex, inductive thinking can be a way to handle complex data and research questions. However, inductive reasoning has been critiqued in scientific and philosophical discourse. Our research leveraged inductive reasoning to conclude empirical data. Addressing this approach's criticisms is essential for a balanced and comprehensive perspective. The main criticism is that inductive reasoning is often criticised for its potential to lead to incorrect generalisations, particularly when based on limited or biased data. However, the scale and the data sources used in our papers can be assumed not to be limited or biased.

Data analysis can be used to explore potential improvements to existing or newly formed firm policies (Mikalef et al., 2019, 2020). The implication of a firm policy can be put into relevant actual practices, and it can encourage the replacement of old, impractical, or dysfunctional firm policies that are no longer suitable in the contemporary world. Therefore, the approach prioritises alterations that ensure the policy aligns with the intended aim. These alterations can then be feasibly implemented to enhance firm policymaking and outcomes. Selecting a firm policy should only be implemented if the underlying data and estimations are valid. The accurate estimation of firm characteristics is crucial for informed policymaking. If the data and estimations are incorrect, the policy will be based on an inaccurate real-world assumption and can be inefficient or even harmful (Saltelli & Giampietro, 2017). However, it may not solve its intended purpose. It can also be argued that the implications of large data, data-driven decision-making, and firm policymaking are part of the whole. Therefore, if one aspect is insufficient, the whole may be compromised.

In conclusion, this thesis has outlined five cases of applying data-driven decision-making and its implications for firm policies. Through the studies' comprehensive dataset, discoveries were made. Further highlighting the need for "good enough" data to evaluate firm policies. So, where do we go from here? This thesis showed five cases of data-driven decision-making. However, this research area is vast; therefore, even more research is needed. I have summarised the findings presented in the thesis on the complexity of this research area. I must emphasise the need for further research to address unanswered questions and uncertainties within the field. For instance, there is a need for further elaboration on data quality and quantity and further exploration of the decisions that conclude that a select data lacks quality and quantity. Additionally, potential- and practical- applications of addressing the firm policies and critical data sources should be considered further.

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