Technische Universität München
TUM School of Management

# A Flexibility Perspective on Supply Chain Finance

**Begimai Marlenova**

Complete reprint of the dissertation approved by the TUM School of Management of the Technical University of Munich for the award of the Doktorin der Wirtschafts- und Sozialwissenschaften (Dr.rer.pol.).

**Chair:** Prof. Dr. Martin Meißner

**Examiners:**

1. Prof. Dr. David Wuttke
2. Prof. Dr. Stefan Minner

The dissertation was submitted to the Technical University of Munich on 7 November 2023 and accepted by the TUM School of Management on 1 February 2024.

# Abstract

In this dissertation, we consider the flexibility perspective on supply chain finance. Specifically, we look at the specific aspect of it–reverse factoring. We study the flexibility view on supply chain finance during disruptive and non-disruptive times. We analyze how supply chain finance helps small firms to operate better during disruptive times such as COVID-19 and what other motives might drive them to use supply chain finance during non-disruptive times. First, we study how supply chain finance and supply chain resilience are interlinked through a literature review. We find that supply chain finance and supply chain resilience together give more rigorous supply chain resilience practices.

Further, we study the impact of supply chain finance on supply chain resilience empirically. We use firm-level data and analyze it with econometrics. We compare firms' revenues using supply chain finance with the same size firms with general revenues. We find that firms using supply chain finance return to their normal operations faster than those not under the supply chain finance program. We also find that extending payment terms during disruptive times negatively affects firms that have not adopted supply chain finance. Therefore, we conclude that firms using supply chain finance are more resilient during disruptive times than firms with general revenues.

Lastly, we study the motives of the suppliers that use dynamic discounting through reverse factoring. We analyze data from one of the leading supply chain finance providers with econometrics. Specifically, we study suppliers that discount their invoices not immediately. We find that suppliers are more likely to discount their invoices close to the reporting period–end of the quarter. We also find that larger suppliers are more likely to discount their invoices close to the end of the quarter. As well as, larger-value invoices are more likely to be discounted close to the end of the quarter.

# Acknowledgements

First, I would like to thank my supervisor, Professor David Wuttke. His ongoing support, feedback, and guidance were beneficial during the doctorate process. I am grateful for the opportunity to explore the topic of supply chain finance with econometrics. His knowledge of this method and his ideas were helpful to me in shaping my research topic and expanding my knowledge and skills. I broadened my understanding of supply chain management, operations, and econometrics to solve research and managerial problems.

I thank Professor Eve Rosenzweig for the collaboration. It was a pleasure to work with her and shape my theoretical knowledge. I also want to thank Professor Hans S. Heese for his input in my research development. I want to thank Professor Stefan Minner for being my second examiner and Professor Martin Meißner for being a chair.

In addition, I want to thank my colleagues at the Center of Digital Transformation at the Technical University of Munich. Specifically, I want to thank Sai for his support throughout my doctorate. Discussing our topics and sharing knowledge and ideas was a pleasure. I want to thank Mrunal and Daun, with whom it was fun and fruitful to work. I also want to thank Ung, Charlotte, Batu, Michaela, Johannes, Alida, and Jasper.

Lastly, I want to thank my family and friends for supporting me during challenging times and my educational process.

# Contents

# List of Figures

# List of Tables

# CHAPTER 1

# Introduction

Disruptive events such as the 9/11 terror attack, the 2011 Japan earthquake, the 2007/2008 financial crisis, the COVID-19 pandemic, and the 2022 Russian invasion of Ukraine increased the importance of supply chain resilience, which is the ability to recover quickly from supply chain disruption (Chopra and Sodhi 2004, Sodhi et al. 2012, Cohen and Kouvelis 2021, Choi et al. 2020). Sheffi and Rice (2005) state two ways to achieve supply chain resilience: redundancy and flexibility. Authors define redundancy as keeping extra resources in reserve in case of disruptive events, while flexibility is about building capabilities to respond to disruptions quickly. However, even if firms invested in redundancy and flexibility of supply chains, major crises still affect them (Cohen and Kouvelis 2021). Specifically, the COVID-19 pandemic showed weaknesses in most global supply chains—despite almost 20 years of research on supply chain resilience. These weaknesses call for novel solutions to enhance supply chain resilience facing contemporary dynamics and structures (Cohen and Kouvelis 2021, Cohen et al. 2022*a*).

The COVID-19 pandemic resulted in a shortage of essential life-saving products such as face masks, face shields, and disinfectants (Müller et al. 2023). Many companies responded to this by adopting ad hoc supply chains in a very short time. Müller et al. (2023) find that these companies embraced agile methods when building ad hoc supply chains and leveraged their dynamic capabilities quickly. Jiang et al. (2023), based on the analysis of 23,440 Chinese listed firms and their performance during the COVID-19 pandemic, find that supplier concentration positively affects the firms' resilience during the disruptive event. In addition, Shen and Sun (2023) find while studying the firm JD.com's performance during the COVID-19 pandemic that the firm used operational flexibility by modifying their delivery processes and intelligent platforms to deal with such a substantial disruptive event as the COVID-19 pandemic. These findings show that firms leveraged operational flexibility during the COVID-19 pandemic to ensure supply chain resilience.

Supply chain resilience depends on both downstream and upstream firms in supply chains; it is not enough for focal firms to independently engage in pro-active and reactive action. Without the commitment of supply chain partners, supply chain resilience remains fairly limited. Not all firms in supply chains have good financial positions as many lack access to appropriate financial markets due to small size and insufficient credit ratings (Campello et al. 2010, Kouvelis and Zhao 2016). Upstream suppliers and downstream customers might face bankruptcy risks (Yang et al. 2015, Gernert et al. 2023), and some companies recently filed for bankruptcy after lacking liquidity following enormous supply chain disruptions. Managing financial flows along supply chains then becomes crucial in establishing resilience.

Badakhshan and Ball (2022) find that supply chain disruptions lead to issues with cash management for small firms, which further result in payment delays. Payment delays cause a ripple effect and affect the upstream suppliers. Such effects from the disruptive events create fragile supply chains, meaning suppliers are more prone to suffer due to the lack of financial resources to keep up with their everyday operations (Gernert et al. 2023, Yang et al. 2015). This fragility requires more comprehensive financial supply chain solutions to improve the resilience of supply chain participants (Cohen et al. 2022*b*,*a*).

The financial supply chain management research field considers the financial aspects of supply chains. Financial supply chain management considers optimizing planning, managing, and controlling supply chain cash flows to facilitate the efficient flow of materials in supply chains (Wuttke, Blome and Henke 2013, Hofmann 2005). Efficient cash flow optimization highly depends on the financing terms between the buyers and suppliers. The financing terms usually are divided into pre-shipment and post-shipment financing methods. Pre-shipment financing is when the payment for goods and services is made before the goods are shipped (Wu 2021), while post-shipment financing is when the payment for goods is made after the goods were shipped (Wuttke, Blome and Henke 2013).

However, global trade has not yet reached efficient financing between buyers and suppliers as almost 80% of the world supply chain assets do not benefit from efficient financing of firms working capital (Botta et al. 2020). The significant value of assets in the global financial supply chain is still underused, and to reach optimal financing terms, there is a need for a higher degree of working capital optimization (Botta et al. 2020). Besides reaching the optimal financing terms in supply chains, since the COVID-19 pandemic, researchers started promoting financing mechanisms that tackle small suppliers' financial needs and the improvement of the overall supply chain resilience (Cohen et al. 2020).

One of the financial solutions that has been promoted recently is supply chain finance (Cohen et al. 2022*b*). Supply chain finance is a platform a bank or supply chain finance provider offers buyers and suppliers based on reverse factoring. In this thesis, we look at the specificity of supply chain finance, such as reverse factoring, while we use supply chain finance in cases where we define the broader term. Reverse factoring is one of the financing methods in post-shipment financing. It is a buyer-led initiative, enabling better financing terms for suppliers and buyers. Reverse factoring works like a credit arbitrage that relies on the stronger credit rating of the buyers (Wuttke, Blome and Henke 2013, Grüter and Wuttke 2017). Under reverse factoring, suppliers immediately get their money with a discount from the reverse factoring provider, and a buyer pays the money to the reverse factoring provider later, based on their contract terms. This financing mechanism is a practical way to meet suppliers' liquidity needs immediately (Hurtrez and Salvadori 2010).

One of the industry examples that successfully implemented reverse factoring is Siemens, which fully benefits from the triple win situation (Siemens n.d.). As Siemens acts as a buyer here, it gets longer payment terms from the reverse factoring providers as the provider first pays the invoice amount to Siemens' suppliers. As a result, Siemens can repay the reverse factoring provider based on the payment term agreements. Also, Siemens' suppliers improve their liquidity by immediately receiving money with a discount from the reverse factoring provider after delivering goods to buyers. The platform provider gets an interest rate from the transaction as it acts as an intermediary between Siemens and its suppliers (Lekkakos and Serrano 2016, Van der Vliet et al. 2015, Tanrisever et al.

2015).

During the COVID-19 pandemic, companies started signing up their suppliers to the reverse factoring programs. One of the examples is the food company Danone. Danone started several reverse factoring programs facilitating liquidity to their suppliers in response to the COVID-19 pandemic (Salecka 2021). The company aimed to ensure that their suppliers worldwide have enough liquidity for their operations and would not go out of business during the pandemic (Salecka 2021). This would have resulted in a huge disruption of Danone's supply chains if they did. Similarly to Danone, luxury fashion company Gucci partnered with Intesa Snapaolo ISP bank, Italy's biggest retail bank, to ease financing for small suppliers. Intesa enabled Gucci's suppliers to have better financing conditions to access their cash faster. Even small suppliers in this program can borrow on attractive terms, which banks used to provide to larger, better-rated firms only (Friedman 2021). With reverse factoring, these companies ensured the resiliency of their supply chains.

Reverse factoring has not been extensively researched as a facilitator of supply chain resilience. Liebl et al. (2016) find that firms adopt reverse factoring to improve cash flows and reduce risks. Interestingly, the risk aspects have not been central to other studies since then. Most of the literature on reverse factoring considers inventory flexibility and financial incentives of small suppliers (Kouvelis and Zhao 2016, Kouvelis and Xu 2021*a*, Yang et al. 2019, Wuttke et al. 2019). These works emphasize the core driver of reverse factoring: suppliers get their money more quickly at attractive financing rates, reducing costs. Since the COVID-19 pandemic, Cohen et al. (2020) picked the risk aspects mentioned by Liebl et al. (2016) of reverse factoring again, and they proposed an idea: that reverse factoring can help increase supply chain resilience. They consider reverse factoring as an operational flexibility enabler for resilience because it allows the suppliers to get their money immediately and continue their operations even during disruptive events. With reverse factoring, suppliers do not need to consider long payment terms, which might not be the case for firms that do not use reverse factoring. However, it needs extensive exploration as it is challenging to examine the effect of reverse factoring due to the little public knowledge of suppliers that use reverse factoring (Wuttke et al. 2019, Xu et al. 2018).

Besides promoting supply chain resiliency with reverse factoring and its working capital optimization goal, the financial flexibility that reverse factoring brings during disruptive times might also be applicable during non-disruptive times. Central to financial flexibility, liquidity is indispensable for firms in the upstream supply chain to maintain optimal inventory levels (Kouvelis and Xu 2021*a*) and invest in process improvements (Boyabatlı et al. 2016). And still, most buyers pay their suppliers after long payment terms instead of paying upon delivery. As of January 2023, for instance, Walmart paid its suppliers after about 42 days.[1] Paying late benefits buyers, as it corresponds to a free loan—in the Walmart case this loan amounts to $ 53.7 bn. But receiving their revenue late, suppliers suffer. Walmart noticed this problem and identified reverse factoring as a supply chain solution, making every player better off (Walmart 2021). Upon delivery, Walmart approves invoices so their reverse factoring provider can lend money to suppliers based on Walmart's interest rate. This way, Walmart still pays late (after 42 days), whereas suppliers may collect their receivables immediately at often attractive interest rates. Numerous other large firms have adopted reverse factoring, rendering this financial arrangement a preeminent practice within supply chain finance (Wuttke et al. 2019, Herath 2015).

In many reverse factoring programs, suppliers can decide whether to get paid immediately after invoice approval and pay their buyer's interest or wait to reduce the interest charge. This charge—or invoice discount—decreases every day they wait, and so managers refer to waiting as dynamic discounting in reverse factoring. Wuttke et al. (2019) report that about one out of six firms uses dynamic discounting in their sample. Those firms tend to have good credit ratings, good access to financing, and sophisticated liquidity man-

[1] days payables outstanding = accounts payable ($ 53,742 mn) / costs of sales ($ 463,721 mn) × 365 days, `https://s201.q4cdn.com/262069030/files/doc_financials/2023/ar/Walmart-10K-Reports-Optimized.pdf`

agement approaches. Those are exactly the features of healthy suppliers that strengthen a buyer's supply chain. Such suppliers are crucial. However, given their strong access to financing, they do not strictly benefit from reduced financing costs—if they did, they would also discount all their invoices immediately.

Extant literature mainly focuses on suppliers seeking immediate payment under reverse factoring for cheaper access to financing (Wuttke, Blome and Henke 2013, Lekkakos and Serrano 2016, Van der Vliet et al. 2015, Tanrisever et al. 2015, Kouvelis and Xu 2021*a*). These studies explicitly assume the supplier's status quo interest rate exceeds the reverse factoring interest rate, which explains immediate discounting but not dynamic discounting in reverse factoring. We identified one analytical study that relaxes this assumption and allows potentially higher reverse factoring interest rates. Grüter and Wuttke (2017) derive a game-theoretic model and show that even for suppliers with relatively low financing costs, RF can be attractive by providing flexibility: those suppliers can use it when needed but do not have to. We complement former work with empirical evidence to close the gap between analytical models and industry practice.

To close the gap in the idea that supply chain finance enhances the financial flexibility of suppliers, we perform several studies demonstrating it with empirical evidence. We use econometric analysis as the primary method. Chapter 3 empirically examines the impact of reverse factoring on supply chain resilience and attempts to close a gap on how supply chain finance can bring financial flexibility during disruptive times. In Chapter 4, we look at the perspective of financial flexibility on supply chain finance during non-disruptive times, thus enhancing suppliers' financial performance.

## 1.1 Contribution and methodology

In research, reverse factoring has been primarily examined analytically. For example, Wuttke et al. (2016), Kouvelis and Xu (2021*a*), Tanrisever et al. (2015) research reverse factoring analytically, but there are many more studies. Besides analytical studies, there are some studies based on empirical research methods. For example, Wuttke, Blome and Henke (2013) and Liebl et al. (2016), through case study research method, find that post-shipment financing reduces the need for liquidity in the supply chain as well as reduces the suppliers' default risk. Wuttke, Blome, Foerstl and Henke (2013) explore the adoption of reverse factoring by multiple case study method. Other studies explore reverse factoring with rigorous econometric analysis. Other than in corporate finance, reverse factoring data are not publicly disclosed, so there are no publicly available datasets on reverse factoring. Researchers only report on secondary data on reverse factoring and related practices in a few cases–for example, Wuttke et al. (2019) research supply chain finance adoption with quantitative firm-level data. Similar to Wuttke et al. (2019), we aim to study flexibility perspective on supply chain finance with an econometric analysis.

Even if authors such as Cohen et al. (2022*b*) promote the idea of flexibility that reverse factoring brings for supply chain resilience, and Grüter and Wuttke (2017) show how reverse factoring can bring flexibility to suppliers, these authors do not provide empirical evidence on their findings. This thesis aims to generate new insights into the flexibility perspective on supply chain finance: how supply chain finance impacts supply chain resilience and enhances firms' cash flow flexibility with dynamic discounting. This constitutes the overall research question:

*How can supply chain finance enhance the flexibility of firms during disruptive and non-disruptive times?*

We aspire to tackle this problem by analyzing literature and secondary data on reverse factoring with econometric analysis. First, we start with an extensive literature review on supply chain finance and supply chain resilience in Chapter 2. This chapter is co-authored with David Wuttke. There, we show the interconnection between two concepts and how combining both leads to more rigorous supply chain resilience practices. In Chapter 3, we assess the impact of supply chain finance on supply chain resilience with econometric analysis. This chapter is co-authored with David Wuttke and Eve Rosenzweig from Emory

University. We use data from one of the leading banks in Europe, with around 180 billion in total assets, to assess the impact of supply chain finance on supply chain resilience. We employ causal inference and duration models, such as difference-in-difference and Cox proportional hazard rate, respectively.

Lastly, in Chapter 4, we used data from one of the leading supply chain finance providing platforms to assess how dynamic discounting through reverse factoring enhances supply chain flexibility. Chapter 4 is co-authored with David Wuttke and Hans S. Heese from NC State University. Similarly to Chapter 3 methodology, we used the Cox proportional hazard rate model to analyze our data. Due to the limited number of research on supply chain finance with econometric analysis, our studies substantially contribute to the literature on supply chain finance and show how supply chain finance can add value to the supply chain flexibility, which we demonstrate with empirical evidence.

In addition, the only AI tool used to write this dissertation is Grammarly.

## 1.2 Research questions and outline

We assess the impact of supply chain finance on supply chain resilience in Chapter 3. However, before that, we review relevant literature on supply chain finance and supply chain resilience in Chapter 2. Our review shows that combining supply chain resilience with supply chain finance leads to more rigorous supply chain resilience practices by optimizing small firms' liquidity and helping them operate normally during disruptive times. We define resilience as the process of returning to normal operations as before the disruptive event. Usually, operations are measured with the revenues, whether the revenue decreased after the disruptive event and when they returned to operations as before the disruptive event. To understand it, we compare reverse factoring firms' revenues with comparative size firms retrieved from Bloomberg and assess which revenues returned to normal operations faster. Hence, our research questions for Chapter 3 arise:

**Research Questions for Chapter 3**:

1. *Do suppliers under the supply chain finance program suffer less in the first year after a significant shock than the comparable suppliers?*

2. *Are they back to their operations faster than before the disruption?*

3. *Are firms that use reverse factoring more resilient than comparable firms?*

In Chapter 3, we answer these questions and provide empirical evidence on the impact of supply chain finance on supply chain resilience. We create a theoretical framework for the supply chain resilience and supply chain finance and analyze how firms using reverse factoring performed during the COVID-19 pandemic compared to the same-size firms. We find that reverse factoring positively impacts supply chain resilience, and firms that use reverse factoring return to their normal operations faster than firms in the comparison group. This financial flexibility helps small firms to be more resilient during disruptive times and continue their operations as before the disruption.

As discussed before, the financial flexibility that reverse factoring brings is also present during non-disruptive times. Even if suppliers aim to get cheap financing, not all suppliers discount their invoices immediately. For example, suppliers use dynamic discounting through reverse factoring and discount their invoices when they want to. To find out the reasons that drive suppliers not to discount their invoices immediately, we raise the following research questions:

**Research Questions for Chapter 4**:

1. *Why do firms using dynamic discounting adopt reverse factoring if it is not for cheaper access to financing? What is driving them?*

We answer these questions in Chapter 4. We analyze the data on firms that use dynamic discounting through reverse factoring. We find that suppliers are more likely to discount their invoices close to the reporting period. In addition, suppliers, especially larger ones, are more likely to discount their invoices close to the reporting period. Similarly, invoices with larger values are more likely to be discounted close to the reporting period. We assume that one of the primary reasons for suppliers to discount their invoices close to the reporting period is to show better liquidity and balance sheet positions.

Lastly, Chapter 5 concludes the thesis with the main findings of our research. In addition, we discuss general remarks and provide future research opportunities. The overview of my dissertation can be seen in Figure 1.1.

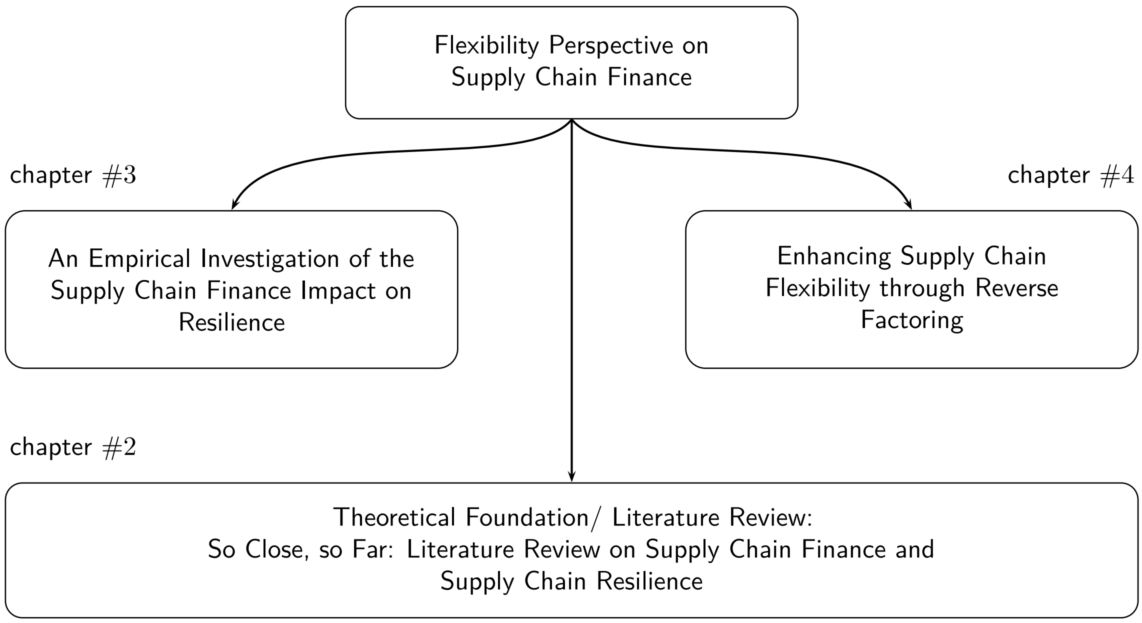



Figure 1.1: Chapters

CHAPTER 2

# So Close, so Far: Literature Review on Supply Chain Finance and Supply Chain Resilience

This chapter posits that supply chain resilience and supply chain finance are closely connected. Supply chain resilience requires a solid understanding of financial flows as those contribute substantially to the survival of other supply chain firms and their financial ability to invest in proactive resilience measures. Therefore, firms that seek to improve their supply chain resilience should consider supply chain finance . At the same time, when engaging in some supply chain finance arrangements, firms might expose themselves to elevated risks, such as when they financially support distressed suppliers (Gernert et al. 2023), which in turn requires a solid understanding of supply chain resilience and whether firms that focal firm finance will continue to exist in the future. Taken together, supply chain resilience requires a solid understanding of supply chain finance, and supply chain finance requires a solid understanding of supply chain resilience.

Whereas there is considerable literature covering supply chain resilience (e.g., Cohen and Kouvelis 2021, Cohen et al. 2022*a*, Sheffi and Rice 2005, Sodhi et al. 2012) and significant work the explores supply chain finance (e.g., Kouvelis and Zhao 2016, Kouvelis and Xu 2021*a*, Yang et al. 2019, Wuttke et al. 2019), only a few papers cover the interface between both areas. We note that some recent literature reviews epitomize this phenomenon as they provide insight into research either on supply chain resilience or supply chain finance, but not both. For example, Han et al. (2020) explore supply chain resilience performance metrics and their capabilities in their literature review paper. Those authors develop resilience dimensions such as response, recovery, and readiness, which help to assess supply chain resilience. That study also considers trade-offs between different capabilities and supply chain resilience performance metrics. Tukamuhabwa et al. (2015) propose complex adaptive systems theory to study supply chain resilience. In their attempt to classify former research, those authors observe that supply chain resilience is similar to many characteristics of complex adaptive systems such as adaptation and co-evolution (Tukamuhabwa et al. 2015). Kochan and Nowicki (2018) and Hohenstein et al. (2015) define the phenomenon and compare definitions of supply chain resilience based on former studies.

There are also literature review papers on supply chain finance. For example, Gelsomino et al. (2016) defines supply chain finance based on finance and supply chain perspectives. Xu et al. (2018) provide a bibliometric analysis and identified four research clusters for supply chain finance such as inventory decisions with trade credit policy, trade credit policy, the interaction between replenishment decisions and delay payment strategies in the supply chain, and roles of financing service in the supply chain. In addition, Chakuu et al. (2019) explore mechanisms of supply chain finance and the relationship between supply chain finance actors, instruments, and contextual factors, whereas Jia et al. (2020) explore supply chain finance from an information processing perspective. However, there is no literature review so far that examines the interface between supply chain finance and supply chain resilience.

Through this chapter, we seek to provide a transparent overview of recent contributions combining aspects of supply chain resilience with supply chain finance; we identify research opportunities arising from combining supply chain finance and supply chain resilience. We provide recommendations for researchers that predominantly focus on supply chain resilience; for instance, they could strongly focus on subtle differences in financial arrangements and emphasize the flow of liquidity and cash. We recommend researchers on supply chain finance to also consider further vital supply chain resilience implications of their work. The key to supply chain resilience is not to maximize profits (often seen as the objective in supply chain finance-related studies) but to strengthen the ability to resume normal operations quickly. Supply chain finance scholars could thus emphasize this concept more to derive and analyze novel, timely, and relevant approaches. Overall, we contribute ten ideas for future research building on our identified research gaps.

## 2.1 Method

This paper aims to analyze the connection between supply chain finance and supply chain resilience in recent research studies. To contribute to the current research on supply chain finance and supply chain resilience, we use the systematic literature review approach proposed by Tranfield et al. (2003) together with a principal component analysis-based clustering where we leverage author-provided keywords.

### 2.1.1 Literature review

We leverage author-provided keywords in a search string to systematically identify all relevant studies on supply chain finance and supply chain resilience. To build this search string, we first require a connection to the operations and supply chain domain by including terms such as "supply chain" or "value chain". We then combined a list of supply chain resilience and finance-related keywords. For supply chain resilience, we used keywords mainly used in the resilience perspective on supply chains. For example, Tukamuhabwa et al. (2015), in their literature review paper on supply chain resilience, used word combinations such as "supply chain resilience", "supply chain resiliency", and "supply resilience". Besides these synonyms for the research areas, many studies on supply chain resilience revolve around concepts such as "disruption", "risk management", and "default risk", which we also added. The keywords related to supply chain finance build on former reviews like Xu et al. (2018) and include terms such as "supply chain finance" and "trade credit".

Not all authors that study supply chain resilience and elements of supply chain finance also provide keywords on both domains and vice-versa; not all studies on supply chain finance that relate to supply chain resilience feature author-provided keywords on supply chain resilience. Since our study is on the content of papers and not the use of keywords, we decided to be more inclusive and concatenate the search results using "OR". To be included in our initial search, studies must include either a supply chain resilience-related or a supply chain finance-related keyword (in subsequent steps, based on reading the article, we eventually decided whether the article covers both areas). At this stage, this resulted in our search string of "(((supply chain) OR (value chain) OR (inventory) OR (purchasing) OR (operational) OR (Newsvendor)) AND ((resiliency) OR (resilient) OR (resilience) OR (supplier default risk) OR (liquidity risk) OR (disruption))

OR ((finance) OR (financing) OR (bank credit) OR (trade credit) OR (factoring) OR (payment extension) OR (finance and operations interface)))."

We chose one of the most common databases in management and finance, Clarivate's Web of Science, as it features all relevant journals, and we used the advanced search function (Web of Science 2023). In addition, we used the Journal Citation Report database from Clarivate (Journal Citation Report 2023) to select a list of journals where the papers were published. We used only journals with the impact factor in quartile 1, which fall into Management, Business, Business Finance, Economics, Social Sciences, Interdisciplinary, Operations Research, and Management Science. We chose only quartile 1 as we believe that the journals with the highest qualities belong to this quartile, thus allowing us to have more quality papers and avoid most predatory journals or non-peer-reviewed outlets. We retrieved 225 journals that we also included in our search string in Web of Science.

Our study features articles published in the last 16 years, between 2007 and March 2023, the end of our data collection. We filtered our search based on the Web of Science Citation Topics 'Meso' with topics on economics, management, supply chain and logistics, risk assessment, and operations research & management. This citation method helps us focus only on relevant papers, omitting papers that are out of the scope of our research, such as those focusing on healthcare, medicine, etc. In total, we identified 5,969 papers. We followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach, a series of standard evaluation stages to filter papers and identify the critical publications of relevance. Figure 2.1 depicts the process stages and outcomes.

We read titles and abstracts in the first evaluation stage and identified 149 relevant papers. We evaluated papers in the second evaluation stage by reading the full text. When assessing whether the papers address supply chain resilience (disruption, risk management) or supply chain finance (trade credit, bank credit, factoring, payment terms

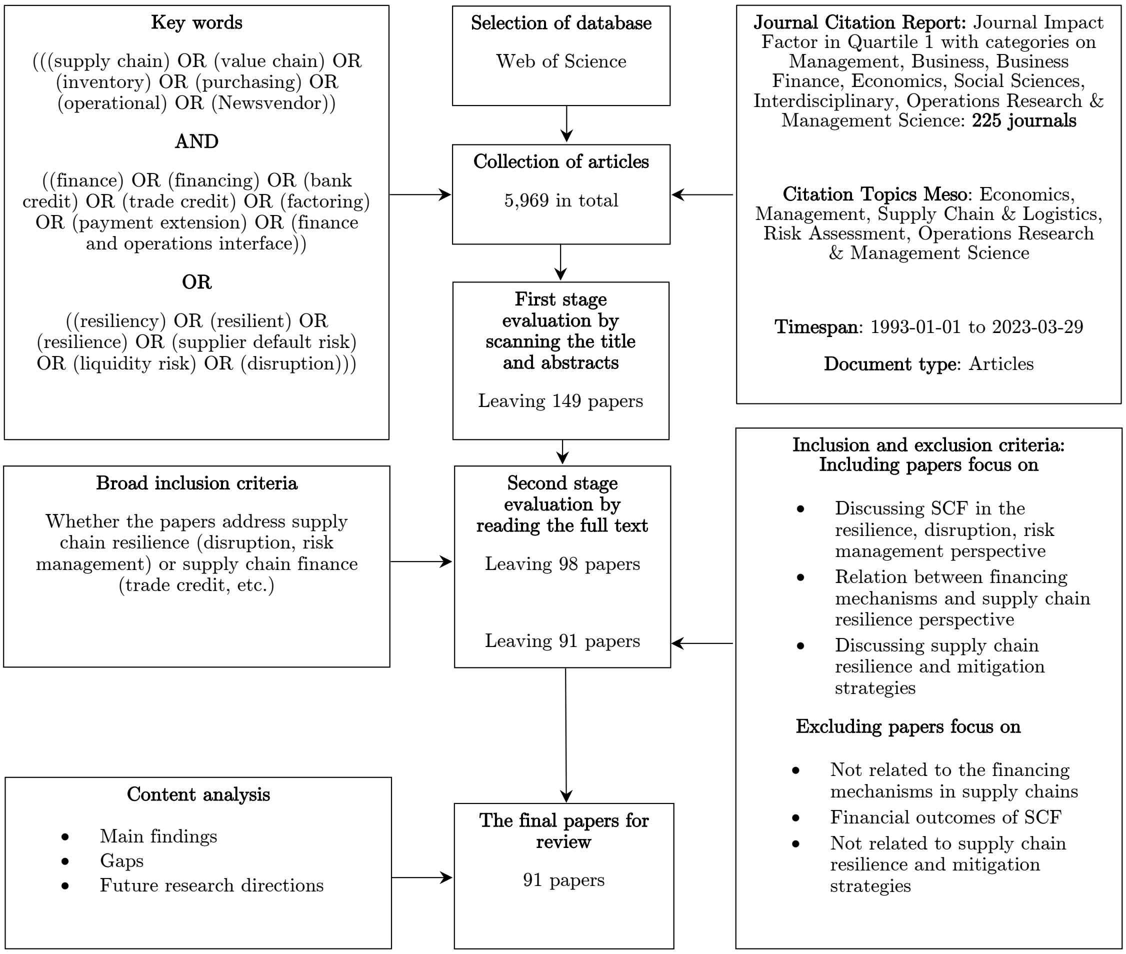



Figure 2.1: Paper inclusion and exclusion process

extension), we found 98 papers. Next, we used stricter inclusion and exclusion criteria. We only used papers that discuss supply chain finance in the resilience, disruption, and risk management context. We also left papers that discuss the relationship between financing mechanisms, supply chain resilience perspective, and supply chain resilience and mitigation strategies. We excluded papers unrelated to the financing mechanisms in supply chains, financial outcomes of supply chain finance, or not related to supply chain resilience and mitigation strategies. As a result, we included 91 relevant papers in our content analysis. This relatively large fraction (91 out of 98) reflects that we also included papers covering both domains briefly. For instance, a supply chain resilience paper mentions cash flows between supply chain parties, or a supply chain finance paper talks about upstream supply chain risks. The extent of the overlap of both areas was more relevant in the next step of the analysis.

Turning to the analysis of the specific content of each paper and the relationships among those papers, we again began our analysis by examining the author-provided keywords. As there is no standard terminology, authors use various synonyms. For instance, "resilience" and "resiliency". As an aggregation step and to find patterns, we aggregated highly related terms into keywords used in our analysis. Table 2.1 summarizes all synonyms used by authors and our keywords. As a reading example, when we refer to the keyword "supply chain capabilities," this relates to studies where authors used keywords such as "dynamic capabilities" or "production capabilities". Whereas we do not contend that those concepts overlap precisely and it is reasonable to use different keywords, in the scope of our analysis, they are closely related enough to aggregate them. Since we focus on supply chain resilience and finance and less on technology or methodology, we removed sparse keywords such as those containing specific technology names like "digital twins", "analytics", or "blockchain", and keywords related to theory and methodology. Table 2.2 features an overview of all studies used in our analysis and their related keywords. The first column assigns a number to each paper, which results from the Web of Science search algorithm. We did not use this ranking for our analysis.

Finally, to identify commonalities across all 91 papers systematically, we leverage principal component analysis, presented in Figure 2.4 based on the keywords of selected papers. The principal component analysis is often used in exploratory data analyses as it helps to reduce higher-dimensional data. In our context, each keyword is a dimension. So, we used the principal component analysis to reduce 22 dimensions to two key dimensions. Using this quantitative technique in combination with our qualitative approach based on an in-depth understanding of the papers helps to derive paper clusters more systematically and transparently. It further helps to replicate the study later since the principal component analysis only requires a very limited degree of subjective judgment (e.g., which keywords to aggregate) but does not leave further room for human judgment. The benefits of principal component analysis notwithstanding, we also read each paper carefully and decided which cluster each paper belongs to based on the actual content, consistent with the principal component analysis outcome.

| Keywords in our analysis | Synonyms in papers |
|---|---|
| Account receivables financing | account receivables |
| Advance payment | early payment |
| Bankruptcy risk | buyers bankruptcy risk, bankruptcy |
| Cash management | cash holding, cash-constrained supply chain |
| Contingency planning | contingency theory |
| Covid-19 | COVID-19 pandemic, pandemic, coronavirus, COVID-19 |
| Credit risk | credit risk |
| Delayed payments | delayed payments, deferred payments |
| OM-Finance interface | operations-finance interface, operations management and finance interface |
| Payment terms extension | payment extension, payment terms |
| Purchase order finance | purchase order finance |
| Reverse factoring | reverse factoring, factoring |
| Supplier selection | supplier selection |
| Supply chain capabilities | dynamic capabilities, production capabilities, dynamic capability, analytics capabilities |
| Supply chain collaboration | collaboration, collaborative factors |
| Supply chain coordination | multi-product supply chain coordination |
| Supply chain disruption | supply chain disruption orientation, disruption impacts, disruption management, supply disruption, disruptions |
| Supply chain finance | supply chain finance practices, supply chain financing |
| Supply chain integration | supply-chain integration |
| Supply chain resilience | supply chain resilience, resilience, resiliency |
| Supply chain risk management | supply risk, supply chain risk, risk management |
| Trade credit | trade credit, trade finance |

Table 2.1: Keywords in our analysis mapped to synonyms of former research.

| # | Paper | Relevant keywords |
|---|---|---|
| 1 | Qiao and Zhao (2023) | Supply chain risk management; Supply chain finance; Supply chain integration |
| 2 | Li et al. (2023) | Supply chain finance; Supply chain collaboration |

(*table continues*)

| # | Paper | Relevant keywords |
|---|---|---|
| 3 | Juan and Li (2023) | Supply chain resilience; Supply chain capabilities; Supply chain disruption; Covid-19 |
| 4 | Liu and Wei (2022) | Supply chain disruption; Supply chain risk management; Supply chain capabilities; Supply chain resilience |
| 5 | Vega et al. (2023) | Supply chain resilience; Covid-19 |
| 6 | Wissuwa et al. (2022) | Supply chain disruption; Supply chain risk management; Supplier selection |
| 7 | Alexander et al. (2022) | Supply chain resilience |
| 8 | Phraknoi et al. (2022) | Supply chain finance; Reverse factoring |
| 9 | Badakhshan and Ball (2022) | Supply chain disruption; Cash management |
| 10 | Zhao et al. (2022) | Supply chain finance; Supply chain disruption |
| 11 | Dong et al. (2022) | Supply chain finance; Supply chain disruption; Advance payment |
| 12 | Cohen et al. (2022*b*) | Supply chain integration; Supply chain resilience |
| 13 | Piprani et al. (2022) | Supply chain disruption; Supply chain resilience; Supply chain risk management |
| 14 | Huang et al. (2022) | Payment terms extension; Supply chain finance; Reverse factoring; Supply chain risk management |
| 15 | Lee et al. (2022) | Trade credit; Supply chain finance |
| 16 | Wu et al. (2022) | Supply chain finance; Advance Payment |
| 17 | Choi et al. (2020) | Supply chain finance; Supply chain disruption |
| 18 | Chen et al. (2023) | Supply chain coordination; Supply chain integration; Supply chain finance |
| 19 | Raj et al. (2022) | Covid-19; Supply chain resilience; Supply chain risk management |
| 20 | Münch and Hartmann (2023) | Supply chain capabilities; Supply chain disruption; Supply chain resilience |
| 21 | Ozdemir et al. (2022) | Supply chain resilience; Covid-19; Supply chain disruption |
| 22 | Wu (2022) | OM-Finance interface; Purchase order financing |
| 23 | Queiroz et al. (2022) | Supply chain resilience; Supply chain disruption; Covid-19 |
| 24 | Aral et al. (2022) | Bankruptcy risk; Trade credit |
| 25 | Kähkönen et al. (2023) | Supply chain resilience; Supply chain disruption; Supply chain capabilities |
| 26 | Shen and Sun (2021) | Covid-19; Supply chain resilience |
| 27 | Liu and Wei (2022) | Supply chain finance; Reverse factoring |

(*table continues*)

| # | Paper | Relevant keywords |
|---|---|---|
| 28 | Kouvelis and Xu (2021*a*) | Supply chain finance; Reverse factoring; Credit risk; Payment terms extension |
| 29 | Moretto and Caniato (2021) | Supply chain finance; Covid-19, Contingency planning |
| 30 | Ronchini et al. (2021) | Supply chain finance; Contingency planning |
| 31 | Yan et al. (2021) | Supply chain finance; Account receivables financing; Reverse factoring; Trade credit |
| 32 | Nigro et al. (2021) | Supply chain finance; Trade credit; Covid-19 |
| 33 | Salama and McGarvey (2023) | Supply chain resilience; Covid-19 |
| 34 | Banerjee et al. (2021*a*) | Supply chain finance; Reverse factoring |
| 35 | Shou et al. (2021) | Supply chain finance; Reverse factoring; Supply chain capabilities |
| 36 | El Baz and Ruel (2021) | Supply chain disruption; Supply chain risk management; Supply chain resilience; Covid-19 |
| 37 | Yang and Birge (2018) | Supply chain risk management; Supply chain resilience, Supply chain disruption |
| 38 | Ding and Wan (2020) | OM-Finance interface; Advance payment; Supply chain coordination |
| 39 | Ma et al. (2020) | Supply chain finance; Supply chain collaboration |
| 40 | Centobelli et al. (2020) | Supply chain disruption; Supply chain resilience |
| 41 | Wu et al. (2019) | Supply chain finance; Advance payment; Delayed payment; Reverse factoring |
| 42 | Mackay et al. (2020) | Supply chain resilience; Supply chain risk management; Supply chain disruption |
| 43 | Wetzel and Hofmann (2019) | Supply chain finance |
| 44 | Yang et al. (2019) | Supply chain finance |
| 45 | Chakraborty et al. (2020) | Supply chain disruption |
| 46 | Hosseini et al. (2019) | Supplier selection; Supply chain resilience; Supply chain risk management |
| 47 | Wuttke et al. (2019) | OM-Finance interface; supply chain finance |
| 48 | Gelsomino et al. (2019) | Supply chain finance; Reverse factoring |
| 49 | Li et al. (2023) | Supply chain finance; Credit risk; |
| 50 | Martin and Hofmann (2019) | Supply chain finance; Reverse factoring; Account receivables financing |
| 51 | Moretto et al. (2019) | Supply chain finance; Credit risk |
| 52 | Pellegrino et al. (2019) | Supply chain finance; Supply chain risk management |

(*table continues*)

| # | Paper | Relevant keywords |
|---|---|---|
| 53 | Pettit et al. (2019) | Supply chain resilience; Supply chain risk management |
| 54 | Tang et al. (2018) | OM-Finance interface; Supply chain risk management; Supply chain finance; Purchase order finance |
| 55 | Yang and Birge (2018) | Trade credit; OM-Finance interface |
| 56 | Sáenz et al. (2018) | Supply chain risk management; Supply chain disruption; Supply chain resilience |
| 57 | Macdonald et al. (2018) | Supply chain risk management; Supply chain disruption; Supply chain resilience |
| 58 | Namdar et al. (2018) | Supply chain risk management; Supply chain disruption; supply chain resilience, supply chain collaboration |
| 59 | Scheibe and Blackhurst (2018) | Supply chain risk management; Supply chain disruption |
| 60 | Chowdhury and Quaddus (2017) | Supply chain resilience; Supply chain capabilities |
| 61 | Peura et al. (2017) | Trade credit; OM-Finance interface |
| 62 | Brusset and Teller (2017) | Supply chain resilience; Supply chain capabilities |
| 63 | Birkie et al. (2017) | Supply chain resilience; Supply chain capabilities; Supply chain disruption |
| 64 | Grüter and Wuttke (2017) | Supply chain finance; Reverse factoring |
| 65 | Jain et al. (2017) | Supply chain resilience; Supply chain risk management |
| 66 | Revilla and Saenz (2017) | Supply chain collaboration; Supply chain disruption |
| 67 | Hosseini and Barker (2016) | Supply chain resilience; Supplier selection |
| 68 | Wuttke et al. (2016) | Supply chain finance; Reverse factoring; OM-Finance interface |
| 69 | Kamalahmadi and Mellat-Parast (2016) | Supply chain disruption; Supply chain resilience; Supplier selection |
| 70 | Chowdhury and Quaddus (2016) | Supply chain resilience; Supply chain disruption; Supply chain risk management |
| 71 | Lekkakos and Serrano (2016) | Supply chain finance; Reverse factoring |
| 72 | Liebl et al. (2016) | Supply chain finance; Reverse factoring |
| 73 | Yang et al. (2015) | OM-Finance interface; Bankruptcy risk |
| 74 | Van der Vliet et al. (2015) | Supply chain finance; Reverse factoring; Delayed payments |
| 75 | Ambulkar et al. (2015) | Supply chain resilience; Supply chain risk management |

(*table continues*)

| # | Paper | Relevant keywords |
|---|---|---|
| 76 | Dello Iacono et al. (2015) | Reverse factoring; Supply chain finance |
| 77 | Scholten and Schilder (2015) | Supply chain disruption; Supply chain collaboration; Supply chain resilience |
| 78 | Brandon-Jones et al. (2014) | Supply chain risk management; Supply chain resilience |
| 79 | Bandaly et al. (2014) | Supply chain risk management; Credit risk |
| 80 | Kling et al. (2014) | Cash management; Trade credit |
| 81 | Scholten et al. (2014) | Supply chain collaboration; Supply chain risk management; Supply chain resilience |
| 82 | Macdonald and Corsi (2013) | Supply chain disruption; Supply chain risk management |
| 83 | Pettit et al. (2013) | Supply chain resilience; Supply chain disruption; Supply chain risk management |
| 84 | Babich and Tang (2012) | OM-Finance interface; Supply chain risk management; Trade credit |
| 85 | Blackhurst et al. (2011) | Supply chain resilience; Supply chain risk management; Supply chain disruption |
| 86 | Raghavan and Mishra (2011) | Supply chain finance; Supply chain risk management; Cash management |
| 87 | Jüttner and Maklan (2011) | Supply chain resilience; Supply chain risk management; Supply chain disruptions |
| 88 | Babich (2010) | Supply chain risk management; OM-Finance interface; Bankruptcy risk |
| 89 | Pettit et al. (2010) | Supply chain disruption; Supply chain resilience; Supply chain risk management |
| 90 | Knemeyer et al. (2009) | Supply chain disruption; Supply chain risk management |
| 91 | Babich et al. (2007) | Supply chain resilience; Supply chain risk management; Supply chain disruption |

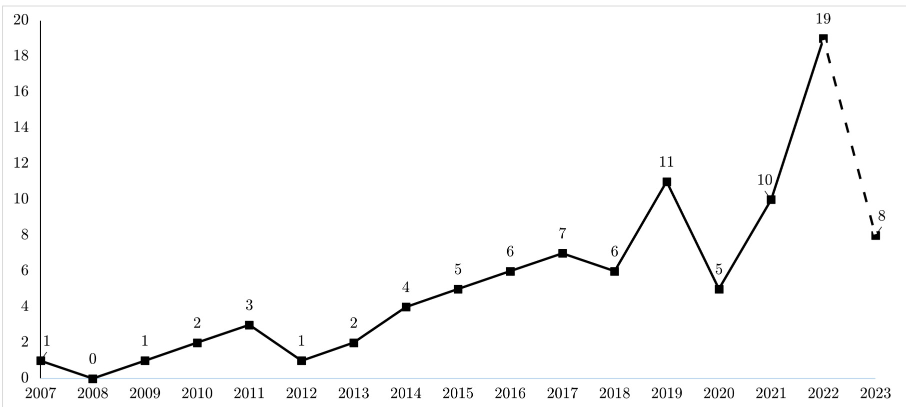
Table 2.2: Included papers and keywords

## 2.2 Results

There are some noteworthy descriptive observations. Table 2.3 shows the most contributing journals, displaying their number of contributions included in our analysis. The International Journal of Production Economics is thus the journal with the largest number of publications (17) included in this review; put differently, about 19% of the studies on supply chain resilience and supply chain finance are published in that journal. Figure 2.2 shows the number of publications each year, emphasizing an apparent uptake (in 2023, our sampling stopped in March; extrapolating the number of papers suggests ongoing growth). Although our sampling period started in 1993, we did not identify any papers before 2007 that met all inclusion criteria. This partially reflects that supply chain finance became relevant about a decade later than supply chain resilience.

| rank | journal | # studies included |
|---|---|---|
| 1 | International Journal of Production Economics | 17 |
| 2 | International Journal of Production Research | 16 |
| 3 | Supply Chain Management - An International Journal | 8 |
| 4 | Manufacturing & Service Operations Management | 7 |
| 5 | Journal of Purchasing and Supply Management | 7 |
| 6 | International Journal of Operations and Production Management | 7 |
| 7 | Journal of Operations Management | 5 |
| 8 | Journal of Business Logistics | 5 |
| 9 | International Journal of Physical Distribution and Logistics Management | 4 |
| 10 | Management Science | 4 |

Table 2.3: Number of papers in the ten most frequent journals.




The dashed line indicates that sampling lasted until March 2023. Hence, there will likely be more publications in 2023.

Figure 2.2: Publication trends on supply chain resilience and supply chain finance.

### 2.2.1 Principal component analysis

Turning to the principal component analysis, examining the variance extracted by each component is expected. In our case, the principal component analysis suggests that the first two components explain a relatively large part of the variance, 14% and 8.9%, respectively. To put these values into perspective, our coding of keywords led to 22 keywords, which means that under the assumption that all keywords contribute equally, each would only explain about 4.5% of the variance. Hence, the 22.9% in our case is substantial. Figure 2.3 displays the variance extracted by the top ten dimensions. This plot illustrates that, indeed, it is the first two dimensions that explain substantially more variance than the following ones. We further note that both key dimensions lead to a clustering of concepts (see Figure 2.4). Concepts such as "reverse factoring" and "supply chain finance" display high proximity but differ from "supply chain resilience". On a conceptual note, we observe that the outcome of the principal component analysis is plausible; it provides confidence in the subsequent clustering.

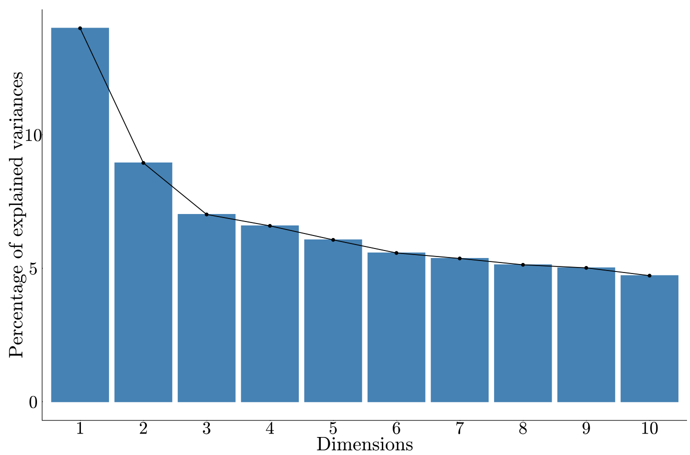



Figure 2.3: Scree plot of the ten most relevant components identified in the principal component analysis.

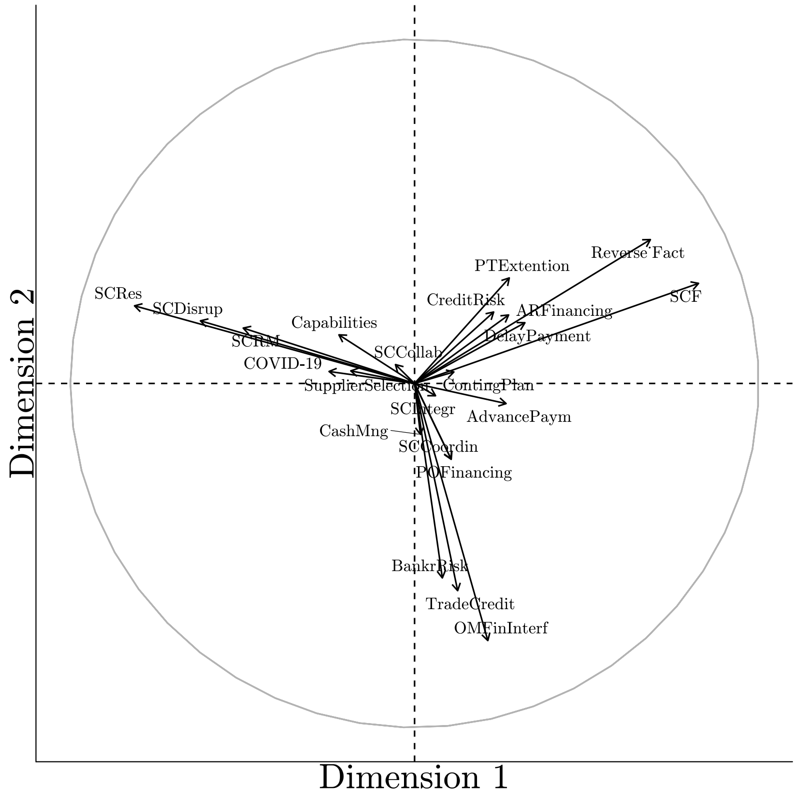
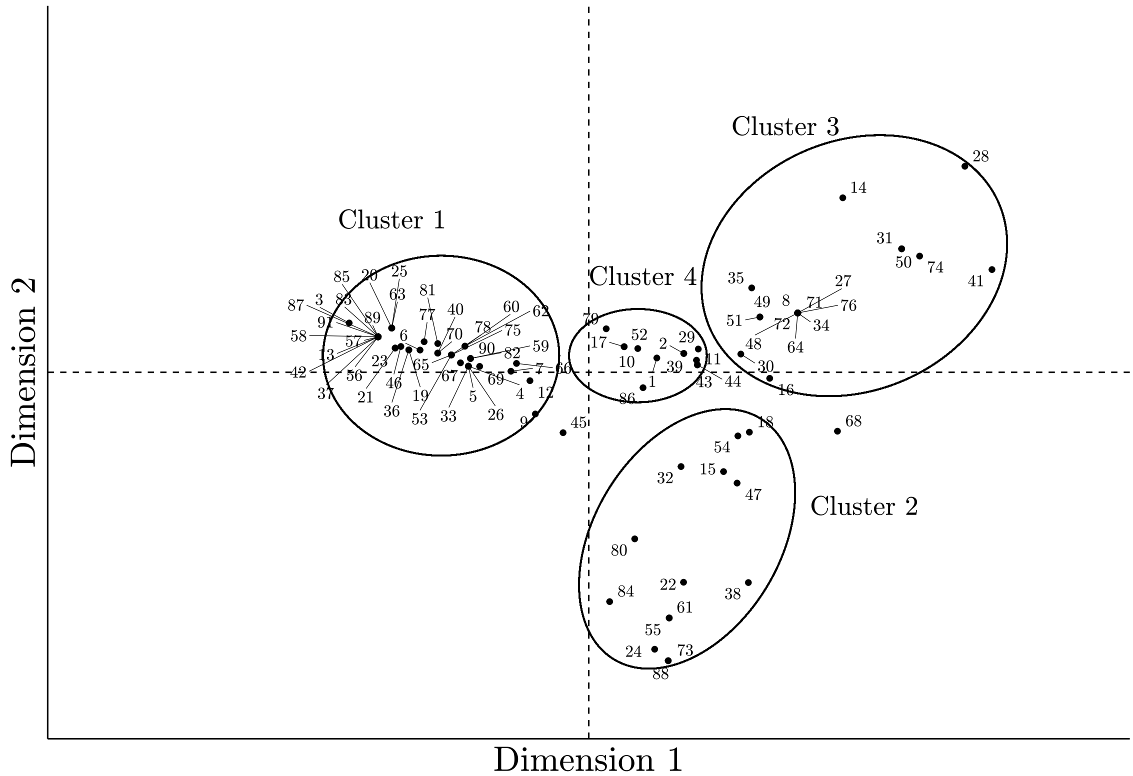



Figure 2.4: Principal Component Analysis: Illustration of keywords and their similarity based on principal component analysis displaying components 1 and 2.

Having demonstrated the plausibility of the principal component analysis, as a last step, we applied the estimates to create coordinates for each paper and plot the papers accordingly. Figure 2.5 displays the 91 papers in our final sample. For brevity and clarity, this figure abbreviates papers with numbers. Those numbers map to the first column of Table 2.2. We further identify four clusters, which we highlight using ellipses. Those clusters feature related papers. To identify the clusters, we used the graphical illustration in Figure 2.5. In addition, we read each paper carefully before including it in a specific cluster and drew the ellipses accordingly.

Cluster 1 groups papers on supply chain resilience, supply chain disruption, and supply chain risk management and touches on supplier selection, capabilities, and supply chain collaboration. Cluster 2 groups papers on trade credit, payment terms extension, operations management, finance interface, and bankruptcy risks. Cluster 3 groups papers on supply chain finance, reverse factoring, account receivables financing, and delayed payments and touches on the risk mitigation aspects. The last one, cluster 4, groups papers on supply chain finance, supply chain disruption, and supply chain risk management and touches on supply chain collaboration and contingency planning.




Cluster 1: Supply chain resilience and supply chain risk management practices,
Cluster 2: General financing solutions for supply chain risk management,
Cluster 3: Reverse factoring as risk mitigation strategy and liquidity buffer,
Cluster 4: Supply chain finance as an approach towards supply chain resilience.

Figure 2.5: Paper clustering based on principal component analysis, numbers refer to identifiers in Table 2.2.

## 2.3 Clusters

We next summarize the research in each cluster. To enrich the content summary, we discuss, more conceptually, how papers within each cluster are related. We highlight how papers primarily focused on resilience relate to supply chain finance and, vice-versa, how papers primarily on supply chain finance relate to supply chain resilience.

### 2.3.1 Cluster 1: Supply chain resilience and supply chain risk management practices

Supply chains constantly face risks, and traditionally, supply chain risk management practices seek to mitigate those risks systematically (Alexander et al. 2022, Pettit et al. 2019, Centobelli et al. 2020). Against this background, supply chain resilience can be seen as an enhancement to supply chain risk management, but not a replacement for it (Pettit et al. 2019). Research in cluster 1 examines the literature on supply chain resilience and supply chain risk management and their interplay. This cluster differs from other clusters as it provides different practices for disruption management in supply chains, including financial risk management practices. Whereas some studies use the terms supply chain risk management and supply chain resilience interchangeably, there seems to be a tendency among supply chain resilience scholars to emphasize the quick recovery after a shock more substantially than typical studies on supply chain risk management would. Those often care equally or even more about identifying, assessing, and deflecting risks. These process steps, in turn, appear less applicable in the context of many supply chain resilience studies, as those often address unforeseen events with substantial ambiguity and uncertainty, like the Covid-19 pandemic.

According to studies in this cluster, supply chain resilience can be one of the main competitive advantages in supply chains (Blackhurst et al. 2011, Juan and Li 2023). Some of the research papers on supply chain resilience tackle the aspects of dynamic capabilities. For example, Kähkönen et al. (2023), Macdonald et al. (2018), and Birkie et al. (2017) state that big firms should invest in risk management capabilities in supply chains. However, the complexity of supply chains makes it also hard to manage due to low collaboration and low flexibility (Pettit et al. 2010). Other authors also recommend investing in proactive redundancies (Mackay et al. 2020, Sáenz et al. 2018, Chowdhury and Quaddus 2017) such as investment in insurance towards the loss aversion during disruptive events. Using backup suppliers and sourcing strategies can also be mitigation solutions during disruptive events (Namdar et al. 2018, Jüttner and Maklan 2011, Ambulkar et al. 2015).

Besides building redundancies, buyers and suppliers should also collaborate (Scholten et al. 2014, Münch and Hartmann 2023, Revilla and Saenz 2017, Brandon-Jones et al. 2014). According to studies in this cluster, one of the solutions can be information sharing across the supply chain members to enhance their performance (Chowdhury and Quaddus 2016, Scholten and Schilder 2015). This creates transparency (Münch and Hartmann 2023) and better coordination of resources (Brusset and Teller 2017). By coordinating with suppliers and sub-suppliers, supply chain participants can deal better with large-scale disruptions (Shen and Sun 2021, Jain et al. 2017), as those disruptions might create a loss for several supply chain members (Scheibe and Blackhurst 2018). Supply chain members should also exchange knowledge to identify sources of threats (El Baz and Ruel 2021).

Other studies in this cluster identify supplier selection as one of the risk management strategies in supply chain management (Babich et al. 2007, Salama and McGarvey 2023). Wissuwa et al. (2022) state that supplier selection long-term impacts the buying firm's performance, especially during disruptive times such as the Covid-19 pandemic. The internal complexity of suppliers and the complexity of collaboration with other tier-two suppliers increases the likelihood of disruptions experienced by the buyer. Thus, buyers should consider the supplier's complexity as a criterion for supplier selection (Wissuwa et al. 2022). Babich et al. (2007) state that buyers might consider diversification of suppliers if there are suppliers who might declare bankruptcy. The benefit of diversification will increase as the correlation between the different supplier defaults decreases (Babich et al. 2007, Hosseini et al. 2019). Further studies in this cluster point out that it is vital to choose resilient suppliers in key locations by computing the likelihood of disruptions within specific locations and choosing the best suppliers that satisfy certain requirements (Hosseini et al. 2019, Hosseini and Barker 2016, Kamalahmadi and Mellat-Parast 2016). In addition, it is beneficial to have backup suppliers from multiple locations (Salama and McGarvey 2023). Another risk management solution can be proactive planning for disruptive events by identifying key locations of suppliers, estimating probabilities of the disruption, and investing in redundancy in a key location to reduce its exposition to catastrophic events (Knemeyer et al. 2009), both internationally and locally (Vega et al. 2023).

Whereas papers in this cluster primarily focus on supply chain resilience, briefly treating aspects of supply chain finance, some researchers also focus on some core elements. For instance, supply chain disruptions also lead to issues in the cash management of firms and payment delays. Due to the payment delays in supply chains, a ripple effect occurs (Badakhshan and Ball 2022) with less cash for upstream suppliers and longer payment terms. Thus, there is a need for cash replenishment policies that can minimize the impact of supply chain disruption. Notably, there is often a high need for cash for the upstream suppliers. Some studies in this cluster point out that this can be managed by ensuring financing programs, such as reverse factoring (Cohen et al. 2022*b*).

Overall, in this cluster, we observe close proximity between supply chain risk management and resilience. Many risk mitigation practices increase the resilience of supply chains, such as creating redundancy and flexibility, having backup suppliers, and collaborating and coordinating in supply chains. Notably, several studies within this cluster emphasize getting back to normal quickly. However, studies in cluster 1 appear less articulated regarding financial flows. Whereas the studies cover aspects of supply chain finance, be it in the form of subsidies, default risks, or cash flows—otherwise, they would not have been included in this review—supply chain finance plays a minor role, and those authors stronger focus more on physical flows, information flows, and collaborative approaches. Thus, many studies in this cluster address supply chain finance rather briefly than substantially. Of course, this is a descriptive and not normative statement; we do not criticize those studies per se, as many reveal insights. However, we still contend that complementing this predominant perspective opens up research opportunities.

### 2.3.2 Cluster 2: General financing solutions for supply chain risk management

This cluster features studies on financing solutions facilitating financial and operations activities between buyers and suppliers. Taking a strong finance-operations interface perspective, it features a much more pronounced finance perspective than cluster 1 but is less pronounced on the resilience perspective.

Broadly, studies in this cluster suggest that financial arrangements can act as risk mitigation solutions in supply chains (Peura et al. 2017). For example, trade credit has been widely used in trade, and it is a deferred payment method (Babich and Tang 2012), where the supplier gives a loan to the buyer. For example, Babich (2010) explores the bankruptcy risks of suppliers using the trade credit solution. Peura et al. (2017) find that trade credit can benefit upstream suppliers. Also, trade credit can enhance supply chain efficiency as the buyer can partially share the demand risk with the supplier, and suppliers can offer larger early payment discounts to buyers (Yang and Birge 2018). Kling et al. (2014) find that firms experiencing liquidity shocks better use trade credit instead of bank finance. However, it has to be noted that sometimes suppliers provide trade credit even for buyers with high cash holdings (Kling et al. 2014, Nigro et al. 2021).

Besides supply chain disruption, one of the main risks in supply chains is bankruptcy risk. If there is a bankruptcy risk, it affects not only the small suppliers but all the parties involved in the supply chain (Yang et al. 2015, Chen et al. 2023). For example, Tang et al. (2018) explores purchase order financing when financial institutions lend to suppliers and buyer direct financing when the manufacturer is both a buyer and a lender. Those authors find that if suppliers are financially constrained, it is better to use buyer-direct financing as they do not need to share their sensitive information with other financial institutions (Tang et al. 2018). However, Wu (2022) finds that purchase order financing can be a better solution for small and medium-sized enterprises as buyers should focus on buying from smaller suppliers and supporting their working capital. Aral et al. (2022) find that buyers under financial distress should increase suppliers' size diversify the supplier base, and make supplier-oriented decisions. With advance payments to suppliers, buyers can support suppliers with yield uncertainty (Ding and Wan 2020, Wuttke et al. 2019). Other authors recommend other solutions, such as dynamic trade finance, which provides dynamic contract terms between buyers and suppliers via blockchain information sharing (Lee et al. 2022).

Whereas studies in this cluster consider financial aspects in supply chains, they focus on classical risk management (e.g., financial risks and operational risks), for instance, to assess and avoid risks rather than resilience as the ability to recover from shocks.

For instance, a typical study in this cluster would consider how likely a supplier was to default under a specific financial arrangement but not how this arrangement would affect the recovery time of the same supplier after a crisis. Yet, from a resilience perspective, the time-to-normal is an important dimension and is likely affected by the choice of financial arrangements. Akin studies in cluster 1 are very relevant and insightful, yet complementing them towards resilience appears promising.

### 2.3.3 Cluster 3: Reverse factoring as risk mitigation strategy and liquidity buffer

This cluster differs from cluster 2 as it focuses on one select supply chain finance arrangement, often called reverse factoring. Because of its widespread use in industry and some people consider reverse factoring the most important approach to supply chain finance, some researchers use it interchangeably (Wuttke et al. 2019). Reverse factoring takes place after the delivery and invoice approval; it accelerates the payment to the supplier while maintaining long payment terms for the buyer. Therefore, it features relatively small risk exposure, particularly opposed to arrangements in cluster 2. However, reverse factoring relates to risks and resilience as it reduces risks and can increase resilience by injecting more liquidity into supply chains, as discussed within this cluster.

Reverse factoring has been well-researched as a cash management mechanism between buyers and their suppliers (Wu et al. 2019, Moretto et al. 2019). Kouvelis and Xu (2021*a*) systematically compares reverse factoring with factoring and finds it often but not always beneficial for supply chains. The performance of reverse factoring depends on three crucial aspects: the supplier's credit rating and liquidity risk, as well as the buyer's credit rating. In contrast, recourse factoring is adopted mainly by suppliers with high credit ratings, while low-to-medium rated suppliers should adopt non-recourse factoring (Kouvelis and Xu 2021*a*, Moretto et al. 2019). Wu et al. (2019) researched early payments, delayed payments, and reverse factoring. They find that delayed payments are better for suppliers and buyers when the suppliers have a better financial position, while early payments and reverse factoring are better for suppliers and buyers when the buyers have the financial advantage (Wu et al. 2019).

However, with reverse factoring, when there is a bank's intermediation, there is an increase in profits for both suppliers and the buyers (Wu et al. 2019). In a nutshell, reverse factoring can help suppliers collect their payments earlier, and the buyer can delay their payments to the supply chain finance provider, whether it is a bank or a firm that provides supply chain finance solution. With this mechanism, the supplier and the buyer can enhance their cash flows and improve their working capital (Wu et al. 2019, Martin and Hofmann 2019, Yan et al. 2021). Also, Wu et al. (2019) states that reverses factoring is a valuable mechanism during high demand volatility and demand uncertainty. With it, payment term decisions are made independently of inventory volatility (Van der Vliet et al. 2015).

Supply chain finance is a strategic decision for buyers, improving the competitive advantage and operating performance of firms (Shou et al. 2021, Ronchini et al. 2021) prone to supply chain risks. Upstream suppliers are the key players in supply chains but also the major risk source for buyers (Moretto et al. 2019), as small suppliers are more prone to bankruptcy risk when lacking access to financial markets (Grüter and Wuttke 2017). Due to the cash limitations of small suppliers, supply chain finance has been developed as a risk mitigation mechanism for them and overall as a mitigation strategy for supply chain risk (Moretto et al. 2019). In the supply chain context, one of the main risks for small suppliers is payment delays. Payment delays can affect the whole supply chain's working capital efficiency and even lead to bankruptcy, especially during disruptive events

(Huang et al. 2022). Small and medium enterprises are more prone to insolvency due to payment delays. However, insolvency can be mitigated with adequate knowledge and work on payment delays. Supply chain finance can be an effective solution for payment delays by helping suppliers obtain finances more easily based on the credit level of their buyer (Huang et al. 2022).

Besides efficiency gains in non-crises times, one of the main goals of supply chain finance is to reduce the supplier default risk by providing them with financial stability and liquidity (Liebl et al. 2016, Gelsomino et al. 2019). Supply chain finance can also be used as a risk management solution, especially for small and medium-sized enterprises (Phraknoi et al. 2022, Dello Iacono et al. 2015, Banerjee et al. 2021*a*). For example, Liu et al. (2021) find that supply chain finance can mitigate supplier default risk and supply chain disruption. At the same time, supply chain finance increases competitive advantage for small and medium-sized enterprises as it can increase its robustness to cash fluctuations during disruptive times (Lekkakos and Serrano 2016, Phraknoi et al. 2022).

Therefore, collectively, studies in this cluster relate supply chain finance in the form of reverse factoring to supply chain disruption risks. Several studies argue that reverse factoring facilitates suppliers with more liquidity, which mitigates cash flow risks, and so they directly relate supply chain finance with supply chain risks. However, studies within this cluster are less pronounced on the link between reverse factoring and resilience. Like studies in cluster 2, these studies do not primarily focus on enabling a faster time to normal through added liquidity.

### 2.3.4 Cluster 4: Supply chain finance as approach towards SC resilience

As per Figure 2.5, cluster 4 is located fairly central between all other clusters, which implies that it features a bit of both research areas on supply chain resilience and supply chain finance. Studies in this cluster typically depart from the observation that supply chain finance was developed as a solution for the 2007/08 financial crisis that caused the reduction of financing, particularly for small and medium-sized enterprises (Moretto and Caniato 2021). Those studies further observe how firms can use supply chain finance to accelerate the recovery.

Although supply chain finance was developed in response to the 2007/08 financial crisis, the Covid-19 pandemic indicated the necessity for new paradigms for supply chain finance to become an effective mitigation strategy. Moretto et al. (2019) find that supply chain finance should not only be considered as a financial solution for direct suppliers but should be a more substantial contributor to the whole supply chain. For example, in the case of systematic payment term extensions for financially constrained suppliers, all involved supply chain partners can be affected adversely (Wetzel and Hofmann 2019). Thus, supply chain finance can be an effective solution for supply chain resilience with a collaborative approach between all involved parties to mitigate the adverse effects of the pandemic (Moretto and Caniato 2021, Bandaly et al. 2014). For example, Choi and Shi (2022) finds that supply guarantee deposit payment, where the manufacturer guarantees the buyer on-time delivery through a deposit, and the manufacturer requests the minimum ordering quantity in return, is a better solution for supply chain coordination in the presence of disruption such as Covid-19 pandemic.

Disruptive events foster financial distress, especially for small suppliers. Suppliers with sufficiently low cash should make joint decisions on their orders with the buyer and the lender (Raghavan and Mishra 2011). For example, Ma et al. (2020) recommends a collaborative approach for disruptive event management by quality information sharing, decision synchronization, integrative supply chain processes, and management support. Li et al. (2023) find that supply chain collaboration actually has a positive relationship with supply chain finance adoption with quality information shared between the parties and the higher dependence on the buyer. Also, Zhao et al. (2022) shows that pure investment in supplier protection brings less bankruptcy risk to the buyer. In addition, for the buyer to be less likely to be subject to bankruptcy risk, a bank-supplier financing combination is a superior supplier financing method (Zhao et al. 2022).

Another way to use supply chain finance for supply chain resilience is by investing in the flexibility of supply chains and reducing redundancy to prevent inefficiency (Qiao and Zhao 2023). To that end, Qiao and Zhao (2023) propose that supply chain participants should invest more in their capabilities by strengthening communication and cooperation with suppliers and buyers and better risk management. Pellegrino et al. (2019) state that one of the typical risk management practices in mitigating volatility is by being able to switch to another supplier and by having substituting goods. Yang et al. (2019) find that new entrant manufacturers should adopt reverse factoring if it is available, especially if they are capital-constrained and might face financial risks. In addition, with the new technological enhancements, blockchain was suggested as one of the solutions for the improved financial visibility of the deep tier suppliers (Dong et al. 2022). For unreliable small and medium-sized enterprises with fixed production capacity and financial constraints, blockchain-enabled supply chain finance, with shared information visibility, can be an excellent proactive risk mitigation strategy (Dong et al. 2022).

Notably, this cluster is still in its infancy, with the preponderance in the past five years. Several studies in this cluster are conceptual, pointing towards conceivable benefits, yet lacking rigorous econometric or analytical proof. Still, this cluster demonstrates the value of relating supply chain resilience to supply chain finance. Noting its recency, we expect that expanding this work likely carries relevant and timely observations.

### 2.3.5 Other papers not included in any cluster

There are a few papers that do not entirely fit either cluster. Consider Figure 2.5. Wuttke et al. (2016) (#68) and Chakraborty et al. (2020) (#45) are not included in any clusters. Wuttke et al. (2016) examines optimal supply chain finance introduction decisions and payment terms and how the buyer can influence the adoption decision by suppliers. Chakraborty et al. (2020) talk about the pricing strategies of the suppliers during disruptive times. Both papers mention financial risks, but more indirectly than common in clusters 1 and 3; they assume that the riskiness of suppliers gives rise to asymmetric financing costs. Therefore, risks are the antecedent rather than the outcome, and neither study talks about mitigating risks or resilience explicitly.

### 2.3.6 Linkages between clusters

Although the clusters are distinct and differ in their focuses, they share some features. One of the foremost common aspects between all clusters is the role of payment terms during disruptive times (Badakhshan and Ball 2022, Wu et al. 2019). Payment terms epitomize the cash flow; how long do suppliers wait to receive their money? How much liquidity do they need? How long can buyers procrastinate the payment to avoid cash outflows when cash inflows are lacking?

Cluster 1 provides different risk management practices for supply chain resilience overall, while clusters 2 and 3 describe financial solutions in supply chains that have been used as risk management practices for supply chain disruptions. Only cluster 4 links supply chain resilience and supply chain finance more explicitly; however, the use of supply chain finance in supply chain resilience perspective is still in its infancy. From cluster 3, it can be derived that buyers increase payment terms during crises, which then affect upstream suppliers' cash limitations. Systematic extension of payment terms can negatively affect the resilience of the entire supply chain participants, not only the small suppliers (Wetzel and Hofmann 2019). As supply chain finance aims to inject more liquidity into supply chains, buyers' extension of payment terms stays as the primary concern. This concept can be related to clusters 1 and 4, where the Cohen et al. (2022*b*), Badakhshan and Ball (2022), and Wetzel and Hofmann (2019) state the high need for cash from upstream suppliers is a primary concern during disruptive times. Cash management and payment delays remain one of the main issues that suppliers face during disruptive times (Badakhshan and Ball 2022). However, the optimal payment term extension during disruptive times so suppliers can stay financially stable is still unclear.

Financial stability, especially for financially constrained suppliers, is one of the main needs during disruptive times and for enhancing supply chain resilience. Clusters 2 and 3 describe different financing solutions as a financial risk mitigation strategy during disruptive events. For example, trade credit and reverse factoring are classical risk management solutions for financial management in supply chains (Wu et al. 2019, Babich 2010, Yang and Birge 2018). However, neither reverse factoring nor trade credit is stated as a solution for supply chain resilience explicitly and whether and how it can serve is yet to be demonstrated extensively.

Clusters 1 and 4 can be connected in many aspects. For example, one way to improve supply chain resilience is by investing in improving capabilities and flexibility in supply chains (Pettit et al. 2010, Jüttner and Maklan 2011) by having backup suppliers (Salama and McGarvey 2023). In the same way, Qiao and Zhao (2023) state, in cluster 4, that supply chain participants need to invest more in flexibility by being able to switch to other suppliers and by having better communications between them. It can be created by having more suppliers signed up for the supply chain finance program and for buyers to be able to switch between them. This aspect is also well supported in cluster 2, which states that buyers under financial distress should increase their supplier size and diversify their supplier base (Aral et al. 2022).

In sum, the cluster analysis shows considerable overlap of the approaches within each cluster and that the clusters are related. However, it also shows that approaches typical for one cluster may be improved by considerations and premises typical of another cluster. Building on this logic, we will next derive ten novel research ideas.

## 2.4 Discussion and research gaps

Our analysis in the previous section reveals some high-level recommendations. Researchers in cluster 1 could strongly consider financial dimensions in achieving resilience. Researchers in clusters 2 and 3 could examine further objectives besides profit maximization and bankruptcy risk minimization, such as the recovery time. Researchers in cluster 4 could expand the scope of their work. We formulate ten research opportunities to distill our detailed and specific observations based on the content analysis.

1. **Optimal payment terms for fast recovery.** Cluster 3 examines reverse factoring and typically revolves around payment term extensions to maximize buyer profit subject to participation constraints for suppliers (Kouvelis and Xu 2021*a*, Wu et al. 2019, Moretto et al. 2019). However, when the objective is not only to

maximize profit and free cash flow for focal firms but also to increase upstream supply chain resilience, this trade-off shifts, raising the question of how the supply chain resilience consideration affects the optimal payment terms extension decision. Should buyers offer supply chain finance to their suppliers during crises to expand payment terms, as they do during non-crises times (Kouvelis and Xu 2021*a*)? Should they offer supply chain finance without extending payment terms, only as a tool for injecting more liquidity into their upstream supply chain? Or should they even consider crises as catalysts to increase the otherwise still slow adoption of supply chain finance in their upstream supply chain, and even extend payment terms more than usual (Wuttke et al. 2019)?

2. **Supplier selection for resilience in the presence of market imperfections.** Supplier selection is a central theme in many cluster 1 studies (Babich et al. 2007, Salama and McGarvey 2023, Wissuwa et al. 2022, Hosseini et al. 2019). However, many researchers assume perfect markets, with full transparency and no further transaction or bankruptcy costs. But those costs exist; markets are imperfect, and particularly during crises, those imperfections become manifest. How would they affect supplier selection? How does bankruptcy cost impact whether to use a single or dual source? Do imperfections favor or prevent novel approaches to resilience? Interesting studies could emerge by focusing on select approaches (e.g., using multiple-sourcing or near-shoring) and introducing market imperfections (Babich and Birge 2020).

3. **Market imperfections and the flexibility versus redundancy balance.** Related to the former recommendation, we note that literature in cluster 1 recommends focusing on redundancy and flexibility and provides recommendations on the relative importance of each (Mackay et al. 2020, Pettit et al. 2010, Piprani

et al. 2022, Sáenz et al. 2018). But how do market imperfections, as typically discussed in cluster 2 (Babich 2010, Peura et al. 2017, Tang et al. 2018), inform this trade-off? Will imperfections render redundancies more relevant, or will they favor flexible solutions? One might conjecture that inflexible markets characterized by high setup and transaction costs will mitigate the power of flexibility, shifting the trade-off towards redundancy. On the other hand, market imperfection causes financing costs, which renders the financing of redundancies, often causing inefficiencies, more expensive. Whether or not this is the case is an open research question.

4. **Challenges of financing more diversified, more resilient supply chains.** It is true that diversification can stabilize supply chains, as put forth by several cluster 1 studies; as one form of redundancy, it can thus enhance resilience (Knemeyer et al. 2009, Vega et al. 2023, Chowdhury and Quaddus 2017, Mackay et al. 2020). However, if firms seek to support suppliers financially, they might prefer lean and straightforward settings. Analytical studies in cluster 2 thus often depart from assuming one buyer and one supplier; this perspective is much more tractable than assuming one buyer and $n$ suppliers. Exposing themselves to a broader range of suppliers will accentuate the difficulties in negotiating financing terms and finding optimal, often individual, solutions. Therefore, when introducing market imperfections and financing transaction costs into analytical models, the question arises as to whether firms should focus on a few suppliers, analyze them better offer financing support, or diversify their supplier base even when this implies fewer opportunities to find individual financing arrangements. Related, this reinforces the trade-off of gathering significant information on a few suppliers and managing them better based on the improved set of information or exerting efforts instead of diversifying the supplier base towards some portfolio approach.

5. **Flexibility aspects of supply chain finance for the enhancement of supply chain resilience**. Cluster 2 is concerned about financial flexibility (Babich 2010, Kling et al. 2014, Tang et al. 2018, Nigro et al. 2021). In the case of supply chain resilience, the question arises whether supply chain resilience and supply chain finance can reinforce each other to increase flexibility. For instance, having more cash available improves a firm's ability to react to crises quickly. Is this the pure provision of more liquidity to supply chain partners than sufficient for increasing their effort towards resilience? Or must focal firms, to increase resilience, combine supply chain finance offers with specific target expectations? For instance, should a buyer only offer supply chain finance if the supplier commits to investing more into resilience, or would this be in the supplier's interest anyway? Put differently, how could a coordinating contract to increase supply chain resilience based on supply chain finance look like? Can a simple contract without specific targets be optimal?

6. **The impact of payment delay on supply chain resilience.** It is common to pay suppliers after payment terms, and many studies examine trade credit, which features payment terms (Babich and Tang 2012, Peura et al. 2017). Whereas some studies examine trade credit from a risk management strategy perspective (Babich 2010, Yang and Birge 2018, Kling et al. 2014), we identify a gap between trade credit and the ability to recover. Are trade credits good or bad for suppliers? On the one hand, they are likely bad as they reduce the supplier's liquidity; many authors argue along these lines when motivating reverse factoring as mitigation to risks. On the other hand, they cause a delay. For instance, suppliers that get paid after 90 days still obtain substantial (i.e., pre-crisis) cash flows after the outbreak of a crisis. They then have 90 days to react and readjust their cost structure before witnessing the cash flow reduction following a disruptive event. It

would be exciting to model this to understand whether and when payment terms in the form of trade credit can strengthen a supplier's ability to return to normal, that is, its resilience, as they provide some buffer allowing the supplier to react. This argument somewhat echoes the argument of redundancies. Lean scholars would naturally oppose redundancies, which are virtually the opposite of leanness. Likewise, one might intuitively object to the idea of payment terms positively impacting resilience. After all, they often cause inefficiencies. And so examining this apparent contradiction might lead to exciting results. If demonstrated, it could indicate that payment terms create slack, which can become helpful in crisis times.

7. **The role of digital technology to enhance supply chain resilience and using financial incentives such as accelerated cash flows to motivate suppliers.** Some studies, mainly in cluster 4, consider blockchain technology to enhance supply chain financing arrangements (Dong et al. 2022). The current focus is primarily on increasing visibility and cash flows across multiple tiers. Dong et al. (2022), in cluster 4, then emphasize that this can lead to risk mitigation. However, going a step further, it would be exciting to see how blockchain technology might enable both supply chain financing and resilience. In this context, supply chain financing could even serve as an incentive. To see this, consider the following dilemma. A focal firm might seek to introduce blockchain to create more transparency for better resilience. However, sharing sensitive information might harm the supplier, but without adoption by all players, blockchains will not unfold their full potential (Babich and Hilary 2020). Focal firms can then offer to finance constrained parties as an incentive for blockchain adoption.

8. **Information sharing between all involved parties in supply chain finance as**

**a collaborative approach for enhancement of supply chain resilience.** The role of information is vital in many studies on supply chain resilience and supply chain finance (Ma et al. 2020, Li et al. 2023, Chowdhury and Quaddus 2016, Münch and Hartmann 2023, Scholten et al. 2014). However, it is likely even more exciting when combining both. Ultimately, the idea of supply chain management is to manage the flows of goods, information, and finance (Mentzer et al. 2001). Supply chain resilience adds the focus on recovery after crises, and supply chain finance emphasizes the importance of the financial flow. Therefore, we expect the study of technology that enhances the flow of information to become central to finding novel solutions.

9. **Potentially adverse impacts of supply chain finance on supply chain resilience.** In cluster 4, supply chain finance sometimes appears to be a silver bullet for increasing resilience (Moretto et al. 2019, Wetzel and Hofmann 2019, Qiao and Zhao 2023). However, there are certain limits. For instance, particularly reverse factoring (cluster 3) (Liebl et al. 2016, Grüter and Wuttke 2017, Wuttke et al. 2019) is known to shift dependencies such that (weak) suppliers could depend even more on their focal customers. Such a dependency increase typically indicates more vulnerability and, thus, less resilience. This raises the question of the boundaries in which supply chain finance increases resilience. Put differently, when does supply chain finance negatively affect resilience?

10. **Overarching framework and theory.** All clusters feature studies with unique contributions. Those studies help understand important aspects of supply chain resilience and supply chain finance . However, we did not identify papers seeking a framework for combining and integrating prior work of both streams. Likewise, an overarching theory is missing. If those gaps persist, they will become problematic.

Supply chain resilience argues that firms should care about the time-to-normal after impact about how quickly systems recover. This often conflicts with profit maximization, mainly when firms use redundancies to cover shortfalls. Unless shocks have a high likelihood (as perhaps just after the first Covid-19-related lockdowns), firms will trade-off: do we want to invest in resilience, which we will need only with probability $p$, or invest in innovation, which we will need regardless? Unless $p$ is sufficiently high and the investment in resilience sufficiently efficient, this conflict does not favor supply chain resilience. We believe that a solid supply chain finance perspective on supply chain resilience will provide the grounds for a new theory. The studies in clusters 2 and 3, the main supply chain finance-related work, emphasize the importance of cash flow uncertainty. Taking this lens can help to reevaluate the investment in supply chain resilience. Building on market imperfections could be an exciting approach to precisely conceptualizing underlying market dynamics and limitations.

## 2.5 Summary

Supply chain resilience and supply chain finance both gain importance and relevance quickly. Whereas those concepts used to be studied in separation, they increasingly interact in industries such as Gucci's approach to leverage supply chain finance during the COVID-19 pandemic. Research started picking up recently on these interactions, as demonstrated in a research cluster (cluster 4) we identified. However, the vast majority of research either examines predominantly supply chain resilience or supply chain finance, but not equally. We believe the more stringent combination of both streams will enhance our understanding of supply chain resilience and ultimately lead to novel and more rigorous resilience-enhancing practices. We hope that the ten research recommendations that we ground in our analysis will inspire future research.

CHAPTER 3

# An Empirical Investigation of the Supply Chain Finance Impact on Resilience

The following chapter explores the impact of supply chain finance on supply chain resilience empirically. For that, we create a theoretical model based on the ideas of Sheffi and Rice (2005) on supply chain resilience and further develop four hypotheses. We employ data on 97 firms that use reverse factoring. Data is obtained from one of the leading supply chain finance providers, a European bank. We compare the revenues of reverse factoring firms to those with general revenues that we retrieved from Bloomberg. We employ the difference-in-difference method and Cox proportional hazard rate model to test our hypotheses. We find support for all our hypotheses. Reverse factoring firms return to normal operations faster than suppliers with general revenues. At the same time, extended payment terms negatively impact the time of returning to normal for firms with general revenues.

## 3.1 Theory and hypotheses development

In this section, we develop a theory based on which we derive our hypotheses for testing. For that, we review the literature on reverse factoring and supply chain resilience and create a theoretical framework from which we derive our hypotheses.

### 3.1.1 Review of related literature

Supply chains constantly face different risks, and traditionally, supply chain risk management practices seek to mitigate those risks (Alexander et al. 2022, Pettit et al. 2019, Centobelli et al. 2020). Supply chain resilience can be seen as an enhancement to supply chain risk management (Pettit et al. 2019), and can be a competitive advantage of supply chains (Blackhurst et al. 2011, Juan and Li 2023). Research on supply chain resilience has examined various drivers of it, with flexibility being perhaps the most important one. The flexibility of supply chains can be enhanced through collaborative approaches between suppliers and buyers (Chowdhury and Quaddus 2016, Scholten and Schilder 2015), and by modifying their existing structure during the disruptive event (Sheffi and Rice 2005).

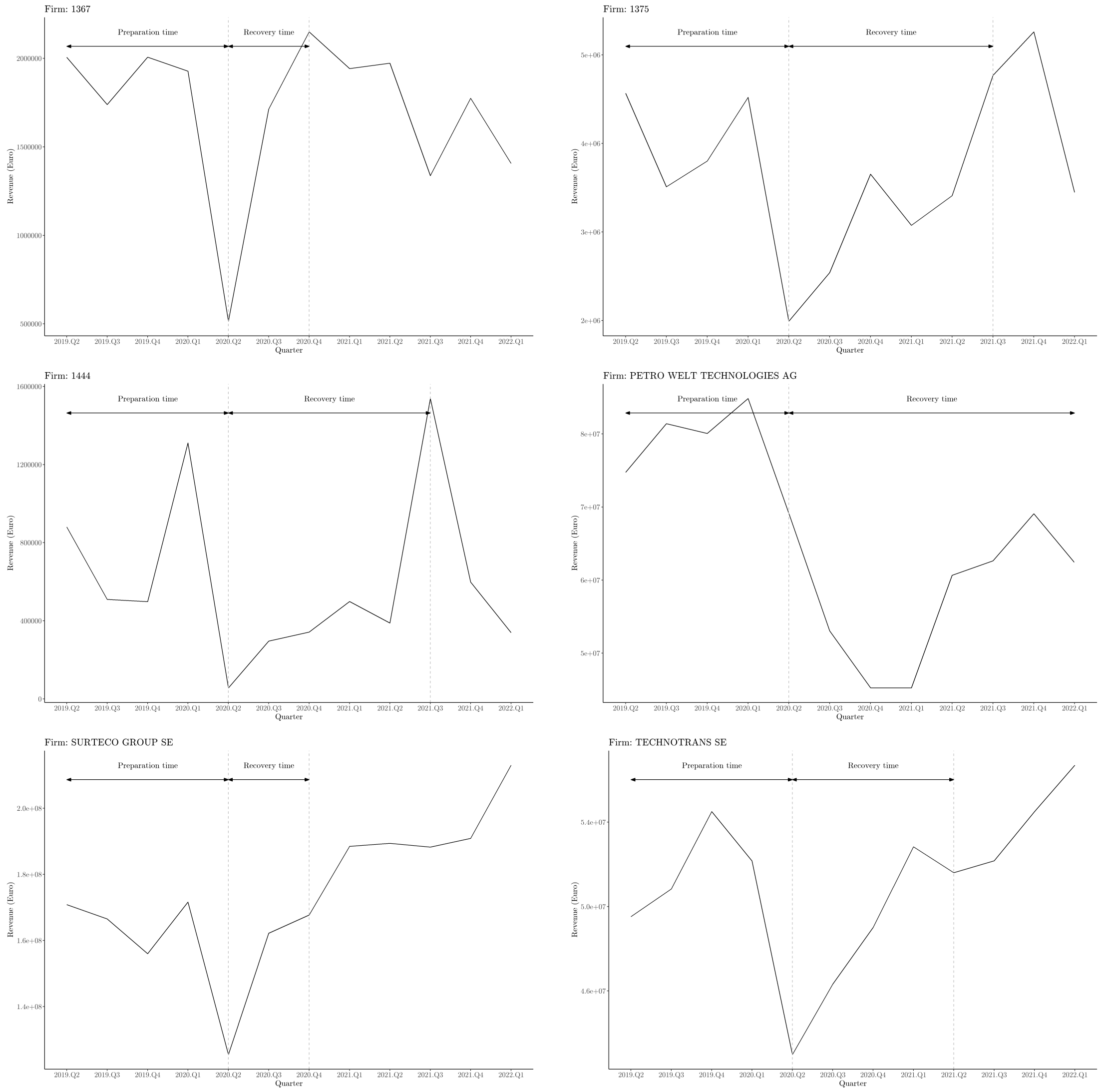
Different strategies can help to mitigate the effect of supply chain disruptions. Recently, Cohen et al. (2022*b*) brought the idea that one of the solutions for supply chain resilience can be the use of reverse factoring as it can bring better liquidity position for small firms. Reverse factoring is a financial solution that brings immediate supplier liquidity (Liebl et al. 2016, Gelsomino et al. 2019) with a discount while the buyers can pay money later to the reverse factoring provider (Kouvelis and Xu 2021*a*). Besides the efficiency of supply chains, reverse factoring aims to reduce the suppliers' risks by giving them financial stability with immediate liquidity (Liebl et al. 2016, Gelsomino et al. 2019, Liu et al. 2021). Other authors such as Lekkakos and Serrano (2016), Phraknoi et al. (2022) find that it can also increase the supply chain's robustness to cash fluctuations during disruptive times.

During disruptive times, suppliers not using reverse factoring might face liquidity issues. Buyers might face decreased sales, resulting in a liquidity shortage. Therefore, these buyers might increase their payment terms to suppliers due to the cash constraints. This might lead to the ripple effect with less cash to upstream suppliers and longer payment terms (Badakhshan and Ball 2022). Cohen et al. (2022*b*) state that one of the ways to resolve this issue might be by ensuring financing programs, such as reverse factoring. Suppliers with reverse factoring do not experience long payment terms as they get their money immediately from the reverse factoring provider. Similarly, Qiao and Zhao (2023) state that reverse factoring can bring more flexibility to supply chains and enhance supply chain resilience. Yang et al. (2019) find that new entrant manufacturers should adopt reverse factoring, especially if they are capital-constrained and might potentially face financial risks. Suppliers do not need to be concerned with their payment terms with reverse factoring as they get their money immediately from the supply chain finance provider.

### 3.1.2 Theoretical framework

As the main idea of reverse factoring is to provide financial efficiency under normal operations, with cash being the most liquid short-term asset, in this paper, we argue that the added liquidity from reverse factoring helps suppliers react faster during crises such as the COVID-19 pandemic and also prepare better for any disruptive events that might occur. Thus, we expect reverse factoring to positively impact resilience, which we define as the ability to resume normal operations quickly (Chopra and Sodhi 2004, Sodhi et al. 2012, Cohen and Kouvelis 2021, Choi et al. 2020).

We build our theoretical framework based on Sheffi and Rice (2005) the disruption profile, where the disruption effect has eight steps: preparation, disruptive event, first response, initial impact, time of full impact, preparation for recovery, recovery, and long-term impact. We use this framework for our study and explore the protection effect of reverse factoring and the recovery phase from the disruption. We consider the preparation time from quarter 2 2019 to quarter 2 2020 and the period from quarter 2 2020 to quarter 2 2022 as the recovery time. Sheffi and Rice (2005) state that disruptive events affect the sales performance of firms; therefore, we assess the performance of revenues of reverse factoring firms. To assess how these firms performed, we compare their revenues with those of comparable size that we retrieved from Bloomberg. Figure 3.1 shows the effect on some firms' revenues, both reverse factoring firms and firms with general revenues.




Firms 1367, 1375, and 1444 are in the reverse factoring group, hence anonymized. The typical time to normal is 2.38 quarters in our sample. The firm Petro Welt Technologies AG illustrates a case that did not return back-to-normal during the study period.

Figure 3.1: Illustration of revenue impact of COVID-19 outbreak

Reverse factoring enables firms to react proactively. Having better access to finance, they can and should be in a better position to cope with an immediate shock. So, we expect that the adverse impact of a crisis like the COVID-19 pandemic has a more minor impact on reverse factoring revenues than general revenues. We call this the protection effect. In addition, there is a recovery effect. The underlying logic relates to the idea that payment terms are one root cause for suppliers' lack of resilience. Because they must wait long to get paid, they lack financial resources and the ability to protect and react quickly. Under reverse factoring, suppliers get paid immediately, regardless of the formal payment terms. Whereas larger payment terms still imply larger costs, this effect might be of secondary concern during a crisis.[1] If this logic applies, we should expect a different impact on payment terms for reverse factoring and general revenues. We create a general framework presented in Figure 3.2. Here, we define how supply chain finance impacts supply chain resilience in general. We define that reverse factoring impacts the preparedness and recovery of firms, and payment terms play a moderating role for supply chain resilience.

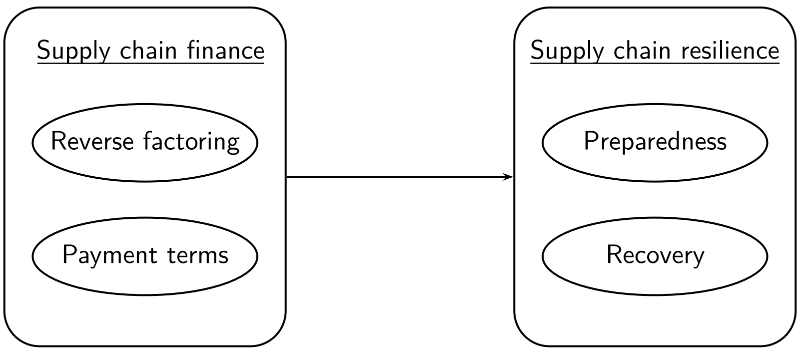



Figure 3.2: Theoretical framework.

[1]Consider a typical reverse factoring program with an annual interest rate of 2% in 2020. For payment terms of 90 days, a supplier would incur a cost of 0.5%, which is negligible relative to the impact of the COVID-19 pandemic.

### 3.1.3 Hypotheses development

Sheffi and Rice (2005) consider the preparation as the period before the disruption occurs. Small suppliers signed up for the reverse factoring program before the COVID-19 pandemic have an additional financial buffer. Suppliers under reverse factoring program get liquidity immediately from the reverse factoring provider (Wuttke et al. 2019, Kouvelis and Xu 2021*b*), while firms not under reverse factoring might have other terms with their partners. Thus, reverse factoring firms are better prepared financially for the disruption and might experience less financial impact. Sheffi and Rice (2005) state that their performance drops significantly when firms experience full impact from the disruption. We measure the full impact of the COVID-19 pandemic on firms based on their revenues. The disruptive event immediately affects firms' sales; thus, this is a full impact that firms experience. Fast access to liquidity via reverse factoring gives small suppliers better standing during disruptive times, as they can continue their operations with the same conditions as they had before disruptive times. This also implies that suppliers' revenue under the reverse factoring program stays the same or is impacted less than the revenues of comparable firms. With that, we propose the following hypothesis:

**Hypothesis 1** *Reverse factoring mitigates the immediate adverse impact of crises on revenue.*

Further, firms must recover from the impact and return to their regular operations levels (Sheffi and Rice 2005). This can be done by producing more than they used to cover up the lost sales at the beginning phase of the disruptive event. As reverse factoring provides fast liquidity for small suppliers, these suppliers can use their liquidity to improve their operations by producing additional stock or restoring operations by research and development to replace missing product components. By having liquidity faster with reverse factoring, firms might not experience a significant impact on their revenues. However, this additional liquidity might not be available for firms without reverse factoring as they need to wait longer for money from their buyers, and they might experience the impact of the disruption for a longer time. As a result, we hypothesize:

**Hypothesis 2** *Reverse factoring accelerates the recovery.*

Further, we explore the mechanisms of reverse factoring and their performance during the COVID-19 pandemic. Payment terms are the main component and mechanism of reverse factoring. The length of the payment terms depends on the conditions between a buyer and its suppliers. In such a case, these suppliers wait for their money from the buyers, which might be 30, 60, or 90 days. However, payment terms might increase during disruptive times due to the liquidity shortage of firms (Badakhshan and Ball 2022). As a result, these longer payment terms also lead to a liquidity shortage for upstream suppliers and thus negatively affect their revenues. With that, we propose the following hypothesis:

**Hypothesis 3** *Payment terms decelerate the recovery.*

The role of payment terms differs substantially between general revenues and reverse factoring revenues. The former is heavily affected by payment terms; each additional day implies necessary waiting time for suppliers. Getting paid just a week later can make a significant difference during a crisis. And so, we expect that payment terms are associated with a slower recovery. Conversely, suppliers do not consider payment terms under reverse factoring as they receive their money immediately from the reverse factoring provider (Wuttke et al. 2019, Kouvelis and Xu 2021*a*). By getting money immediately, their revenue does not have a substantial negative long-term effect, and they can return to their normal business operations faster. Oppositely, suppliers without reverse factoring, due to the longer payment terms, might have a more significant effect on their revenue, and having longer payment terms leads to a slower process of returning to normal operations. Overall, in reverse factoring, payment terms have different meanings. For suppliers, they reflect the financing costs. In a typical program in 2020, suppliers would face annual financing costs of about 2%. That is, one week more payment terms corresponds to about $\frac{2\%\times 7}{365} = 0.038\%$; considering a revenue of \$ 1mn, this is \$ 383. We argue that such an amount will not impede the recovery process to the same extent, leading to our moderation hypothesis.

**Hypothesis 4** *Reverse factoring attenuates the adverse impact of payment terms on the recovery speed.*

We provide how our framework describes our hypotheses in Figure 3.3. Based on the hypotheses outlined above, we show that reverse factoring positively impacts the preparedness and recovery of firms. While overall, extensive payment terms during disruptive times negatively affect the supply chain resilience . However, payment terms moderate the impact of reverse factoring on supply chain resilience and accentuate the recovery speed.

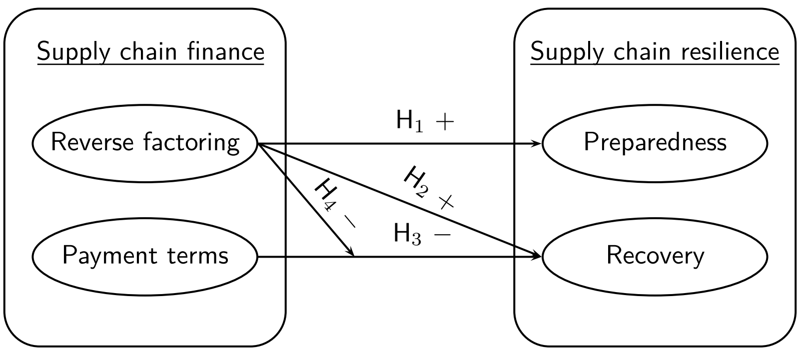



Figure 3.3: Theoretical framework and hypotheses.

## 3.2 Sample and method

### 3.2.1 Reseach sample and data

In our study, we leverage three essential datasets. The first dataset comprises data on reverse factoring revenues of a European bank, recorded daily. The second dataset contains data on general revenues serving as a baseline, recorded on a quarterly level. The third dataset comprises data on the stringency of governmental responses to the COVID-19 pandemic, recorded daily. Since governmental responses differed globally significantly and the COVID-19 pandemic affected firms differently, we focus the regional scope on the Eurozone, all countries whose official currency is the Euro. Explicitly, this focus avoids heterogeneity and exchange rate fluctuations.

Consistent with the most recent data available in our dataset, the time frame of our study is from quarter 1 2019 until quarter 2 2022. Section 2 describes the theoretical framework presented in Figure 3.2. In addition, we present Figure 3.4, which depicts the timeline details of our model. We consider the time before quarter 2 2020 as preparation time and the time after quarter 2 2020 to quarter 2 2022 as a crisis time. The World Health Organization declared COVID-19 a pandemic on March 11, almost coinciding with the start of the quarter 2 of 2020. For example, Sim et al. (2022) assessed the impact of the COVID-19 pandemic on music consumption by taking weeks from March 11, 2020, until May 29, 2020. They aggregated the data weekly, while we aggregated the data quarterly. Consistent with our aggregation on the quarterly level, we thus consider quarter 2 of 2020 as the outbreak of the COVID-19 pandemic. Whereas some countries like China and the U.S. were affected in March 2020, the more severe governmental responses started in quarter 2 of 2020 in the Eurozone. Further, we argue that the impact of the pandemic is slightly delayed: shipments on the route did not stop on the sea or the train. We contend that quarter 2 of 2020 captures the start of the impact of COVID-19 on the industry.

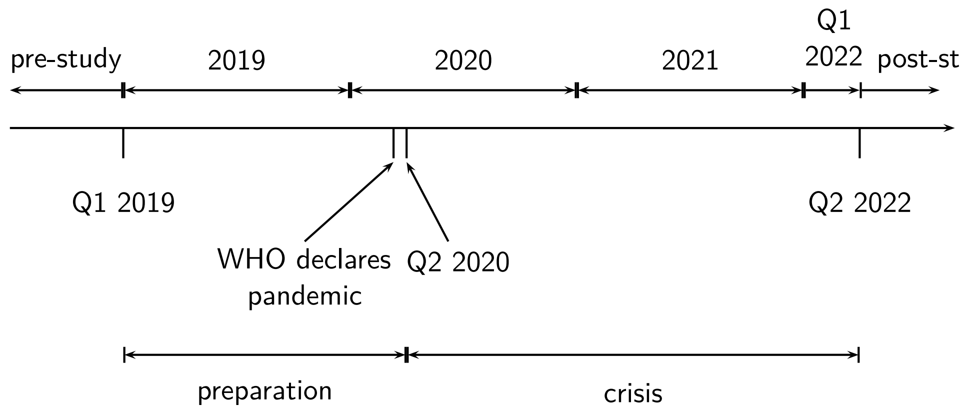



Figure 3.4: Timeline

We obtained the first dataset from a bank that offers reverse factoring. This dataset comprises data on suppliers and buyers at the transaction level. Those transactions are exactly the ones handled in the reverse factoring program, but they neither contain data before a supplier joined the program nor about suppliers not in the reverse factoring program. For the period between January 2019 and May 2022, it features a total of 52,372 transactions by 192 suppliers. However, as one might surmise, some of those suppliers adopted reverse factoring after the outbreak of COVID-19 during the crisis time. Since we lack a clear baseline, we decided to omit those suppliers. While this leads to a drop in the number of suppliers remaining in the sample to 97, those suppliers account for the vast majority of transactions, with a total of 44,659 or 85%. This dataset features information about the transaction volume and payment terms of each transaction. It further features the supplier's country and the supplier's industry. We aggregated this dataset on the quarterly level by summing up the overall transaction volume of all transactions and taking the average of payment terms. If there was no transaction in a specific quarter for a particular supplier, we coded the revenue as 0 and linearly interpolated the payment terms using data from adjacent quarters. We consider revenues in a reverse factoring program as the treatment group.

We complement this dataset with publicly available data collected through Bloomberg. Our bank data set features revenues in the supply chain finance program but not general revenues. Still, we learned from the bank that the suppliers' revenues in their program range between 5mn and 100bn. Therefore, to construct the control group, we sampled all firms in the Eurozone with a revenue range between 5mn and 100bn. We collected data on their quarterly revenues and accounts receivables, which allowed the calculation of average payment terms. We only included firms that report their revenue on a quarterly base. There were some cases where values were missing for accounts receivables or revenues. Consistent with our approach to reverse factoring payment terms, we used linear interpolation from the adjacent quarters. We consider the general revenues as the control group comprising 412 firms.

Third, we collected data from the Oxford government response tracker[2], which measures the stringency of responses per country and time. Specifically, we were interested in the variable stringency, a compound score for several measures such as mandatory work-from-home policies or closure of certain businesses. We aggregated the severity measure for each country every quarter by taking the average. Finally, we obtained further data on macroeconomic control variables from the World Bank[3] and on the Euribor from the German Bundesbank[4]. For quarter 1 2022 we used the latest available data, which is 2021 for the World Bank data. We present the summary statistics for continuous variables in Table 3.1.

[2]https://www.bsg.ox.ac.uk/research/COVID-19-government-response-tracker

[3]https://databank.worldbank.org/source/world-development-indicators#

[4]we use three-month rates, as they have a similar time horizon as receivables, source: https://www.bundesbank.de/de/statistiken/geld-und-kapitalmaerkte/zinssaetze-und-renditen/geldmarktsaetze-650668

Table 3.1: Summary statistics for continuous variables.

| Variable Name | Min. | Max. | Mean | Std. dev. | Count |
|---|---|---|---|---|---|
| **Panel A** | | | | | |
| GDP Growth (GDPG, %) | $-11.325$ | 2.849 | 0.471 | 2.174 | 1664 |
| Stringency | 0.000 | 83.206 | 34.336 | 33.925 | 1664 |
| Adverse impact | $-5.395$ | 1.000 | 0.097 | 0.655 | 1664 |
| Log(revenue) | 0.000 | 21.440 | 14.911 | 3.997 | 1664 |
| Payment terms (days) | 0.333 | 303.000 | 82.273 | 50.509 | 1664 |
| **Panel B** | | | | | |
| Time-to-normal (quarters) | 1.000 | 8.000 | 2.837 | 2.392 | 208 |
| GDP Growth (GDPG, %) | $-1.976$ | 1.736 | $-0.008$ | 0.985 | 590 |
| Stringency | 25.051 | 83.206 | 63.246 | 11.216 | 590 |
| Adverse impact | $-0.953$ | 0.821 | 0.294 | 0.352 | 590 |
| Log(revenue) | 0.000 | 19.983 | 15.113 | 3.632 | 590 |
| Payment terms (days) | 0.523 | 447.548 | 85.865 | 53.974 | 590 |

Summary statistics for continuous variables. Values reported in this table are not transformed. Panel A reports data for the difference-in-difference models; N=1,664 corresponds to 8 quarters of 208 firms. Panel B provides data for the survival regression. N=208 corresponds to 208 firms (each has one time-to-normal), N=590 corresponds to 208 firms and 2.837 quarters, the average time to recall.

### 3.2.2 Propensity score matching

To compare two types of firms and revenues we use propensity score matching. This method is adequate to have a balanced sample for comparative methods (Cunningham 2021). For that, we define the treatment group, which is the reverse factoring group, and the control group, which is a group with general revenues. The treatment group and control group differ in stringency, where the treatment firms have faced more rigorous restrictions ($p < 0.001$, $t = -11.55$), differ in GDP growth ($p < 0.001$, $t = -11.55$), and differ in industry ($p < 0.001$,$\chi^2 = 33.38$). Particularly, the former may affect the impact of COVID-19 on revenues.

To reduce the heterogeneity for testing our Hypotheses 1 and 2, which relate to the impact of COVID-19 on revenue, we use propensity score matching and match on stringency, GDP growth, and industry. The matching is effective, as it renders differences in stringency ($p > 0.1$, $t = 0.13$) and GDP growth ($p > 0.1$, $t = 0.13$) insignificant, and industry differences become insignificant, too ($p > 0.1$,$\chi^2 = 6.45$). This leads to a sample of 194 firms.

Recall that Hypotheses 3–4 relate to reverse factoring and payment terms to the time-to-normal. If it is true that reverse factoring revenues are less affected than general revenues (i.e., if Hypothesis 1 finds support), then we need to re-match the firms based not only on stringency and industry but also on adverse impact. We conceptualize the latter as the negative difference between the revenue in the second quarter of 2020 minus the average revenues between the second quarter of 2019 and the first quarter of 2020 relative to the average revenues between the second quarter of 2019 and the first quarter of 2020. The larger the variable adverse impact, the more a firm suffers.

Again, we find the matching procedure efficient as it leads to no differences regarding stringency ($p > 0.1$, $t = 1.59$), adverse impact ($p > 0.1$, $t = 1.61$), GDP growth ($p > 0.1$, $t = 1.61$), and industry ($p > 0.1$,$\chi^2 = 5.85$). Matching effectiveness is presented in Table 3.2 and 3.4. We also present summary statistics for Industry after matching in Table 3.3. Overall, we conclude that the matching procedure is effective for both tests.

Table 3.2: Matching effectiveness (continuous variables)

| **Panel A** | | Condition (mean) | | | | |
|---|---|---|---|---|---|---|
| Variable | Matched | Treatment | Control | Difference | S.E. | T-statistic |
| Stringency | Unmatched | 59.925 | 54.893 | 5.032 | 0.482 | −10.44 *** |
| | Matched (1) | 34.201 | 34.471 | −0.27 | 0.201 | 1.34 |
| | Matched (2) | 59.925 | 59.704 | 0.22 | 0.364 | −0.61 |
| GDPG | Unmatched | 0.304 | 1.608 | −1.304 | 0.086 | 15.16 *** |
| | Matched (1) | 0.469 | 0.473 | −0.004 | 0.033 | 0.11 |
| | Matched (2) | 0.304 | 0.208 | 0.097 | 0.051 | −1.91 + |
| Adverse impact | Unmatched | 0.096 | 0.111 | −0.015 | 0.089 | 0.17 |
| | Matched (2) | 0.184 | 0.104 | 0.08 | 0.062 | −1.29 |

Unmatched captures the entire control group, matched (1) corresponds to the difference-in-difference models, and matched (2) corresponds to survival regression models. The unmatched sample comprises N=562 firms and matched (1) and matched (2) comprise 208 firms, respectively.

Table 3.3: Summary statistics for industry (after matching)

| Matched sample (1) | Count | Percentage | Matched sample (2) | Count | Percentage |
|---|---|---|---|---|---|
| Automotive | 7 | 3.37% | Automotive | 8 | 3.85% |
| Consumer goods | 36 | 17.31% | Consumer goods | 31 | 14.90% |
| Industrial goods | 63 | 30.29% | Industrial goods | 61 | 29.33% |
| Raw materials | 46 | 22.12% | Raw materials | 48 | 23.08% |
| Services | 56 | 26.92% | Services | 60 | 28.85% |
| **Total** | 208 | 100% | **Total** | 208 | 100% |

Summary statistics for the industry variable after matching. The first matching did not account for adverse impact and serves for the difference-in-difference models on impact. The second matching considers the adverse impact and supports the time-to-normal analysis.

Table 3.4: Matching effectiveness (industry)

**Panel A**

| Control (pre-matching) | Count | Percentage | Treatment (pre-matching) | Count | Percentage |
|---|---|---|---|---|---|
| Automotive | 7 | 1.53% | Automotive | 4 | 3.85% |
| Consumer goods | 133 | 29.04% | Consumer goods | 15 | 14.42% |
| Industrial goods | 148 | 32.31% | Industrial goods | 29 | 27.88% |
| Raw materials | 47 | 10.26% | Raw materials | 30 | 28.85% |
| Services | 123 | 26.86% | Services | 26 | 25.00% |
| **Total** | 458 | 100% | **Total** | 104 | 100% |
| Control (post-matching 1) | Count | Percentage | Treatment (post-matching 1) | Count | Percentage |
| Automotive | 3 | 2.88% | Automotive | 4 | 3.85% |
| Consumer goods | 21 | 20.19% | Consumer goods | 15 | 14.42% |
| Industrial goods | 34 | 32.69% | Industrial goods | 29 | 27.88% |
| Raw materials | 16 | 15.38% | Raw materials | 30 | 28.85% |
| Services | 30 | 28.85% | Services | 26 | 25.00% |
| **Total** | 104 | 100% | **Total** | 104 | 100% |
| Control (post-matching 2) | Count | Percentage | Treatment (post-matching 2) | Count | Percentage |
| Automotive | 4 | 3.85% | Automotive | 4 | 3.85% |
| Consumer goods | 16 | 15.38% | Consumer goods | 15 | 14.42% |
| Industrial goods | 32 | 30.77% | Industrial goods | 29 | 27.88% |
| Raw materials | 18 | 17.31% | Raw materials | 30 | 28.85% |
| Services | 34 | 32.69% | Services | 26 | 25.00% |
| **Total** | 104 | 100% | **Total** | 104 | 100% |

The matching algorithm does not change the treatment group composition (right column) but takes a subset of all control-group firms (pre-matching) for inclusion in the matched sample (post-matching). The first matching did not account for adverse impact and serves for the difference-in-difference models on impact. The second matching considers the adverse impact and serves for the time-to-normal analysis.

### 3.2.3 Econometric specifications

To test hypothesis 1, we implement the difference-in-difference method to assess whether the reverse factoring revenues faced a less negative impact during the COVID-19 pandemic than general revenues. Difference-in-difference is a model under a quasi-experimental design that helps identify the causality in the sample compared to a control group (Cunningham 2021). Specifically, it helps to see the effect of certain interventions on the treatment group, which is a COVID-19 pandemic. We define the treatment group, reverse factoring revenues, and control groups, general revenues. We define the treatment group as one and the control group as zero. In addition, we created a "post" variable, which is a period from quarter 2 2020 until quarter 2 2022, $t$, for supplier $i$. Our dependent variable is revenue. We take a logarithm of revenue to avoid skewness of the distribution. We define it as $log(Revenue)_{it}$, revenue for a firm $i$, and a period $t$. We define $Treatment_i$ variable for a firm $i$, $Post_t$ variable for period $t$, $\sigma_{it}$ is a firm-specific fixed effect, and $\epsilon_{it}$ is an error term. We define the econometric model as follows:

$$log(Revenue)_{it} = \alpha_i + \beta_1 * Treatment_i + \beta_2 * Post_t + \beta_3 * Post_t * Treatment_i + \sum \sigma_{it} + \epsilon_{it}.$$

As the data on time to normal is normally distributed and censored, we use a proportional hazard rate model as our analytical framework (Melnyk et al. 1995). We do not measure the time to normal directly, but we measure its effect on the hazard rate. Decreased hazard rate means a longer time to return to normal. In addition, the Cox proportional hazard rate model studies recurrent events. In our case, recurrent events are quarters of the year. To answer our hypotheses 2, 3, and 4, we use the Cox proportional hazard rate model with fixed effects to assess the time variable - time to normal. Instead of directly estimating the effect on duration, we measure the hazard rate of the time to normal. We assume that suppliers' revenue has a distribution of $F(t)$ with density $f(t)$, where $t$ is the time from quarter 2 2020 to quarter 2 2022. Specifically, we estimate

$$\lambda_{ij}(t) = \lambda_0(t)\exp(\alpha_i + x_{it}\beta + z_{it}\gamma),$$

where $\alpha_i$ is the dummy variable that captures fixed effects.

The covariates are treatment ($Treatment_i$), and payment terms ($PT_{it}$):

$$x_{it}\beta = \beta_1 * Treatment_i + \beta_2 * PT_{it}.$$

The control variables are GDP growth ($GDPG_i$), stringency ($Stringency_{it}$), adverse impact ($Impact_i$), and Industry ($Ind_i$):

$$z_{it}\gamma = \gamma_1 * GDPG_i + \gamma_2 * Stingency_{it} + \gamma_3 * Impact_i + \gamma_4 * Ind_i.$$

We also provide the correlation table for our difference-in-difference (Panel A) and Cox proportional hazard rate (Panel B) models in Table 3.5. In Panel A, we see that the stringency variable negatively correlates with GDP growth, as the higher the stringency, the lower the GDP growth. In addition, we can observe that Revenue negatively correlates to treatment, meaning that revenues are lower for the treatment group, while the payment terms are positively correlated with the treatment group. In contrast, payment terms negatively correlate to revenue, meaning that the lower the revenue, the higher the payment terms.

In Panel B, we can observe that stringency negatively correlates to GDP growth. Similarly to Panel A, treatment negatively correlates with Revenue but positively correlates to adverse impact and payment terms. This means the treatment group has longer payment terms and a higher adverse impact on their revenue. Payment terms positively correlate with stringency, meaning that the higher the stringency, the more prolonged the payment terms. We also provide alternative specifications and conduct several robustness checks in the robustness checks section.

Table 3.5: Correlation matrix

**Panel A**

| | 1. | 2. | 3. | 4. | 5. | 6. |
|---|---|---|---|---|---|---|
| 1. Time | 1 | | | | | |
| 2. GDPG | −0.53* | 1 | | | | |
| 3. Stringency | 0.90* | −0.47* | 1 | | | |
| 4. Treatment | 0.00 | 0.00 | 0.00 | 1 | | |
| 5. Log(revenue) | 0.06* | −0.01 | 0.04 | −0.70* | 1 | |
| 6. Payment terms | 0.01 | −0.01 | 0.02 | 0.41* | −0.35* | |

**Panel B**

| | 1. | 2. | 3. | 4. | 5. | 6. | 7. |
|---|---|---|---|---|---|---|---|
| 1. Time | 1 | | | | | | |
| 2. GDPG | 0.76* | 1 | | | | | |
| 3. Stringency | −0.45* | −0.20* | 1 | | | | |
| 4. Treatment | −0.08* | 0.04 | 0.00 | 1 | | | |
| 5. Log(revenue) | 0.05 | −0.05 | 0.03 | −0.73* | 1 | | |
| 6. Payment terms | −0.07 | −0.09* | 0.14* | 0.32* | −0.31* | 1 | |
| 7. Adverse impact | 0.21* | 0.13* | −0.16* | 0.14* | −0.13* | 0.10* | |

Panel A presents the correlation matrix for the difference-in-difference model; time includes the year before the outbreak and the year after, hence the positive correlation between time and stringency; panel B shows the correlation matrix for survival regression; period includes two years after the pandemic outbreak, hence the negative correlation between time and stringency. $^{*}p < 0.05$.

## 3.3 Results

Results for hypothesis 1 is presented in Tables 3.7, 3.6, and 3.8. Our results support the hypothesis 1. Here, the coefficient of interest is the interaction of "post" and "treatment" variables. We chose the model with the lowest Akaike Information Criterion value for results interpretation. We need the lowest Akaike information criterion value because it implies that the model requires less information to predict almost the same level of prediction for models (Cavanaugh and Neath 2019). From Table 3.7, Model 2, we find that the reverse factoring firms are substantially less affected by the COVID-19 pandemic. For a 1% increase in the interaction of "post" and "treatment" variables, the revenue of reverse factoring firms increases by 0.535%. These results are also supported in the model without control variables, presented in Table 3.6, Model 2. We observe that for a 1% increase in the interaction of "post" and "treatment" variables, the revenue of reverse factoring firms increases by 0.551%. Though we tested the "post" time from quarter 2 2020 to quarter 2 2022, we also assessed the immediate effect of the COVID-19 pandemic. We define the "post" variable as quarter 2 2019 and quarter 2 2020. From Table 3.8, Model 2, it is seen that for a 1% increase in the interaction of "post" and "treatment" variables, the revenue of reverse factoring firms increases by 2.446%. These results are aligned, meaning that reverse factoring firms experience less effect on their revenue from the COVID-19 pandemic.

Table 3.6: Difference-in-difference model estimates omitting control variables

| | 1 | 2 |
|---|---|---|
| (Intercept) | 18.467*** | 18.607*** |
| | 0.251 | 0.256 |
| Time | 0.480*** | 0.480*** |
| | 0.066 | 0.066 |
| Post | −0.897*** | −1.172*** |
| | 0.214 | 0.238 |
| Payment terms | −0.214 | −0.208 |
| | 0.164 | 0.164 |
| Treatment | −5.446*** | −5.720*** |
| | 0.291 | 0.309 |
| Time × Post | −0.390*** | −0.390*** |
| | 0.094 | 0.093 |
| Payment terms × Treatment | 0.032 | 0.017 |
| | 0.223 | 0.223 |
| Post × Treatment | | 0.551** |
| | | 0.209 |
| Number of Observations | 1664 | 1664 |
| AIC | 7674.2 | 7670.5 |

Dependent variable = log(revenue). $^{+}p < 0.10, ^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$.

Table 3.7: Difference-in-difference model estimates

| | 1 | 2 |
|---|---|---|
| (Intercept) | 18.650*** | 18.796*** |
| | 0.330 | 0.335 |
| Industry: Automotive | −0.069 | −0.067 |
| | 0.788 | 0.788 |
| Industry: Consumer goods | −1.010* | −1.010* |
| | 0.413 | 0.413 |
| Industry: Raw materials | −0.056 | −0.052 |
| | 0.393 | 0.393 |
| Industry: Services | −0.144 | −0.145 |
| | 0.363 | 0.363 |
| Stringency | 0.003 | 0.003 |
| | 0.008 | 0.008 |
| GDPG | 0.046 | 0.039 |
| | 0.039 | 0.039 |
| Time | 0.475*** | 0.475*** |
| | 0.068 | 0.067 |
| Post | −1.160* | −1.392** |
| | 0.533 | 0.539 |
| Payment terms | −0.220 | −0.215 |
| | 0.164 | 0.164 |
| Treatment | −5.492*** | −5.758*** |
| | 0.291 | 0.309 |
| Time × Post | −0.318** | −0.330** |
| | 0.113 | 0.113 |
| Payment terms × Treatment | 0.019 | 0.005 |
| | 0.224 | 0.224 |
| Post × Treatment | | 0.535* |
| | | 0.210 |
| Number of observations | 1664 | 1664 |
| AIC | 7689.7 | 7686.5 |

Dependent variable = log(revenue). $^{+}p < 0.10, ^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$

Table 3.8: Difference-in-difference model estimates (emphasis on immediate shock)

| | 1 | 2 | 3 |
|---|---|---|---|
| (Intercept) | 18.796*** | 17.544*** | 18.827*** |
| | 0.335 | 0.733 | 0.574 |
| Industry: Automotive | −0.067 | −0.172 | −0.212 |
| | 0.788 | 1.116 | 0.901 |
| Industry: Sonsumer goods | −1.010* | −1.356* | −1.288** |
| | 0.413 | 0.585 | 0.472 |
| Industry: Raw materials | −0.052 | 0.251 | −0.031 |
| | 0.393 | 0.561 | 0.451 |
| Industry: Services | −0.145 | −0.003 | −0.064 |
| | 0.363 | 0.516 | 0.415 |
| Stringency | 0.003 | 0.051 | −0.046 |
| | 0.008 | 0.084 | 0.041 |
| GDPG | 0.039 | 0.245 | 0.385 |
| | 0.039 | 0.418 | 0.297 |
| Time | 0.475*** | | 0.592*** |
| | 0.067 | | 0.097 |
| Post | −1.392** | −3.593 | 1.367 |
| | 0.539 | 5.862 | 2.650 |
| Payment terms | −0.215 | −0.173 | −0.202 |
| | 0.164 | 0.324 | 0.228 |
| Treatment | −5.758*** | −7.430*** | −5.978*** |
| | 0.309 | 0.527 | 0.361 |
| Time × Post | −0.330** | | |
| | 0.113 | | |
| Payment terms × Treatment | 0.005 | −0.561 | −0.246 |
| | 0.224 | 0.418 | 0.300 |
| Post × Treatment | 0.535* | 2.446*** | 0.890** |
| | 0.210 | 0.571 | 0.334 |
| Number of Observations | 1664 | 416 | 1040 |
| AIC | 7686.5 | 2212.1 | 5188.5 |

For comparison, (1) is the original model, featuring eight quarters from quarter 2, 2019, to quarter 1, 2021. (2) only features quarter 1 2019 and quarter 2 2020; time is colinear with post and omitted. (3) captures five quarters quarter 2 2019 to quarter 2 2020, and places double weights on quarter 2 2019 and quarter 2 2021; time $times$ post is omitted since there is only one-time observation for this period.

The results for hypotheses 2, 3, and 4 are reported in Tables 3.10 and 3.9. Our Models 3 and 4 in Table 3.10 are the main outputs for the analysis. We chose them because these models give the lowest Akaike information criterion value. We include industry and payment terms as control variables. We find support for hypothesis 2 in Table 3.10, Model 4. Reverse factoring firms return to normal faster than those with general revenues by exp(-0.389)-1 $\approx$ 32%. This is also supported in Table 3.9, Model 3, where reverse factoring revenues return to normal faster by exp(-0.296)-1 $\approx$ 26%.

In addition, we find support for our hypothesis 3 in Table 3.10, Model 3, where the payment terms decelerate the process of returning to normal for firms with general revenues by exp(0.099)-1 $\approx$ 10%. Regarding hypothesis 4, we find in Table 3.10 Model 4 that firms with general revenues are more impacted by the payment terms extension, meaning that their extension slows down their recovery more than the reverse factoring firms. Their recovery is slowed by exp(0.272)-1 $\approx$ 31%. This is also supported in Table 3.9 Model 3, where payment terms of firms with general revenues slow down their recovery by exp(0.252)-1 $\approx$ 29%.

Table 3.9: Survival regression models omitting controls

| | 1 | 2 | 3 |
|---|---|---|---|
| industry | | | |
| (ind. goods=baseline) | | | |
| Treatment=1 | −0.195 | −0.258* | −0.296* |
| | 0.122 | 0.131 | 0.141 |
| Payment terms | | 0.097 | |
| | | 0.071 | |
| Treatment=0 × Payment terms | | | 0.252* |
| | | | 0.123 |
| Treatment=1 × Payment terms | | | −0.012 |
| | | | 0.094 |
| Number of Observations | 590 | 590 | 590 |
| AIC | 803.5 | 803.5 | 802.4 |

Smaller values (i.e., more negative values) imply a faster time to normal. Control variables were excluded from the estimation.
$^{+}p < 0.10, ^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$.

Table 3.10: Survival regression models

| | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| industry (ind. goods=baseline) | | | | |
| Industry: Automotive | 0.196 | 0.147 | 0.145 | 0.153 |
| | 0.234 | 0.224 | 0.220 | 0.217 |
| Industry: Consumer goods | 0.028 | −0.005 | 0.017 | 0.047 |
| | 0.127 | 0.122 | 0.121 | 0.119 |
| Industry: Raw materials | 0.010 | 0.023 | −0.015 | −0.024 |
| | 0.110 | 0.106 | 0.106 | 0.104 |
| Industry: Services | 0.040 | 0.018 | 0.018 | −0.038 |
| | 0.104 | 0.099 | 0.098 | 0.097 |
| GDPG | 0.328*** | 0.370*** | 0.381*** | 0.388*** |
| | 0.038 | 0.040 | 0.040 | 0.039 |
| Stringency | −0.052 | −0.060 | −0.071+ | −0.074+ |
| | 0.044 | 0.042 | 0.042 | 0.041 |
| Adverse impact | 0.933*** | 0.884*** | 0.867*** | 0.899*** |
| | 0.102 | 0.093 | 0.092 | 0.090 |
| Treatment=1 | | −0.300*** | −0.353*** | −0.389*** |
| | | 0.081 | 0.083 | 0.090 |
| Payment terms | | | 0.099* | |
| | | | 0.046 | |
| Treatment=0 × Payment terms | | | | 0.272*** |
| | | | | 0.078 |
| Treatment=1 × Payment terms | | | | −0.039 |
| | | | | 0.063 |
| Number of Observations | 590 | 590 | 590 | 590 |
| AIC | 708.0 | 696.6 | 693.6 | 685.0 |

Smaller values (i.e., more negative values) imply a faster time to normal. Control variables included, Weibull distribution is estimated.
$^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

## 3.4 Robustness checks

To assess the robustness of our models, we conduct several robustness checks such as a placebo test for the difference-in-difference model and other robustness checks with several interaction effects for the treatment variable, subset of the treatment group, and with the addition of reverse factoring specific variables. We perform robustness tests to support our main models further and indicate that external effects do not drive our results.

### 3.4.1 Placebo test for difference-in-difference model

Several tests validate the difference-in-difference strategy. One of them is the placebo test (Cunningham 2021). A placebo test is performed using the fake outcome or the time period not assessed in the model. This test reveals that the zero effect supports the trend assumption of the initial model. The same difference-in-difference model has to be performed using the different comparison group, in some cases, or time (Cunningham 2021). In our case, we take the time period and test whether the non-significant effect supports the idea of the impact of the COVID-19 pandemic.

Here, we take the period from 2018 to 2019 as a comparison time and the period in 2019 as the post-period. In our initial difference-in-difference model, this post period is from quarter 2 2020 to quarter 2 2022. We leave the same sample of firms from reverse factoring firms and firms with general revenues. This way, we want to see how reverse factoring firms performed before the COVID-19 shock.

From the analysis, we see, in Table 3.11, Model 2, that the interaction effect of "Post=True" and "Treatment" variables does not have a significant effect, which supports our assumption of the effect of the COVID-19 pandemic on the firms that use reverse factoring.

Table 3.11: Placebo robustness-test: difference-in-difference model estimates

| | 1 | 2 |
|---|---|---|
| (Intercept) | 16.942*** | 16.918*** |
| | 0.498 | 0.500 |
| Industry: Automotive | −0.129 | −0.129 |
| | 0.630 | 0.630 |
| Industry: Consumer goods | −0.316 | −0.316 |
| | 0.419 | 0.419 |
| Industry: Raw materials | −0.329 | −0.329 |
| | 0.348 | 0.348 |
| Industry: Services | −0.025 | −0.025 |
| | 0.330 | 0.330 |
| GDPG | $0.329^{+}$ | $0.325^{+}$ |
| | 0.182 | 0.182 |
| Time | 0.064 | 0.064 |
| | 0.052 | 0.052 |
| Post=True | 0.512 | 0.567 |
| | 0.438 | 0.448 |
| Treatment | −4.143*** | −3.930*** |
| | 0.260 | 0.448 |
| Payment terms | −0.158 | −0.184 |
| | 0.132 | 0.140 |
| Time × Post=True | $-0.125^{+}$ | $-0.125^{+}$ |
| | 0.074 | 0.074 |
| Treatment × Payment terms | 0.418*** | 0.640 |
| | 0.090 | 0.391 |
| Post=True × Treatment | | −0.426 |
| | | 0.732 |
| Number of Observations | 1056 | 1056 |
| AIC | 3949.0 | 3949.5 |

Dependent variable = log(revenue). Period 2018-2019, placebo event takes place 01/01/2019; post = observations in 2019. Non-significance supports the idea that the specification captures the COVID-19 impact. The sample size, $N = 1056$, corresponds to 8 quarters of 132 firms since not all firms in the sample transacted already in 2018. $^{+}p < 0.10, ^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$.

### 3.4.2 Robustness tests for Cox proportional hazard rate model

In addition, we performed several other robustness tests to assess the reliability of estimates for the Cox proportional hazard rate model. The results are presented in Table 3.12. In Model 1, we interact the "treatment" variable with "adverse impact". We observe that this interaction has a positive coefficient. We also observed that the treatment group returned to normal faster than the control group. We observe that reverse factoring firms return to normal faster than suppliers with general revenues by exp(-0.483)-1 $\approx$ 38%.

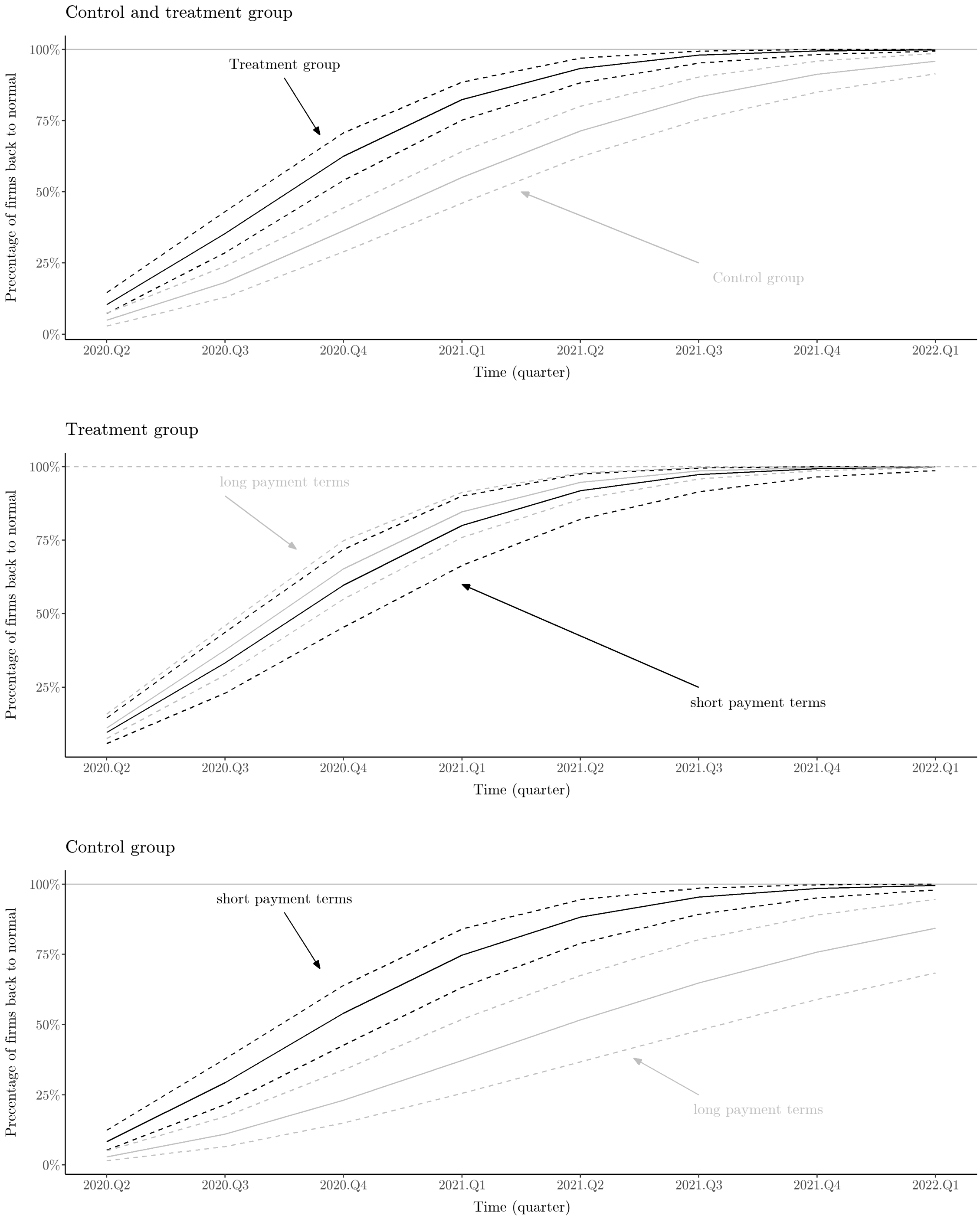
This is also aligned with Model 2, where we use the interaction effect of the "treatment" variable with the "stringency" variable. We use this interaction effect to understand how the stringency variable affects the treatment group. Here, reverse factoring firms return to normal faster by exp(-0.388)-1 $\approx$ 32%. We also find that the payment terms for firms with general revenues slow the process of returning to normal by exp(0.273)-1 $\approx$ 24% in Model 1, for the control group, and based on Model 2, it slows by exp(0.270)-1 $\approx$ 24%. We also present Figure 3.5, where we visually show how the treatment group returns to normal faster than the control group.

In Models 4 and 5, we present only a subset of the treatment firms only. We observe that adverse impact still holds a positive sign for the treatment group, which means that the treatment group had less impact. In addition, we add supply chain finance firms specific variables such as same country, same industry, and annual program size. We still observe that the adverse impact holds the positive coefficient.

Table 3.12: Robustness checks for survival regression

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| industry | | | | | |
| (ind. goods=baseline) | | | | | |
| Industry: Automotive | 0.070 | 0.152 | −0.370 | −0.187 | −0.196 |
| | 0.215 | 0.216 | 0.431 | 0.238 | 0.226 |
| Industry: Consumer goods | 0.047 | 0.048 | −0.010 | −0.219 | −0.330* |
| | 0.118 | 0.119 | 0.235 | 0.147 | 0.148 |
| Industry: Raw materials | 0.013 | −0.026 | 0.042 | −0.050 | −0.129 |
| | 0.103 | 0.104 | 0.208 | 0.123 | 0.120 |
| Industry: Services | −0.037 | −0.038 | 0.073 | 0.052 | 0.047 |
| | 0.096 | 0.097 | 0.194 | 0.128 | 0.137 |
| GDPG | 0.381*** | 0.390*** | −0.020 | 0.608*** | 0.654*** |
| | 0.039 | 0.040 | 0.181 | 0.068 | 0.074 |
| Stringency | $-0.068^{+}$ | | 0.058 | $-0.086^{+}$ | $-0.099^{+}$ |
| | 0.040 | | 0.208 | 0.052 | 0.051 |
| Treatment=1 | −0.483*** | −0.388*** | 0.396* | | |
| | 0.096 | 0.090 | 0.185 | | |
| Treatment=0 × Adverse impact | 0.447*** | | | | |
| | 0.053 | | | | |
| Treatment=1 × Adverse impact | 0.259*** | | | | |
| | 0.039 | | | | |
| Treatment=0 × Payment terms | 0.273*** | 0.270*** | −0.398* | | |
| | 0.079 | 0.078 | 0.160 | | |
| Treatment=1 × Payment terms | −0.029 | −0.037 | 0.108 | | |
| | 0.061 | 0.063 | 0.122 | | |
| Adverse impact | | 0.316*** | −1.498*** | 0.658*** | 0.655*** |
| | | 0.032 | 0.196 | 0.100 | 0.098 |
| Treatment=0 × Stringency | | −0.062 | | | |
| | | 0.059 | | | |
| Treatment=1 × Stringency | | −0.084 | | | |
| | | 0.054 | | | |
| Payment terms | | | | 0.029 | −0.045 |
| | | | | 0.060 | 0.063 |
| Same country | | | | | $-0.285^{+}$ |
| | | | | | 0.165 |
| Same industry | | | | | −0.007 |
| | | | | | 0.111 |
| Annual program size | | | | | −0.076* |
| | | | | | 0.036 |
| Number of Observations | 590 | 590 | 590 | 273 | 273 |
| AIC | 678.9 | 686.9 | 1686.4 | 333.2 | 330.6 |

(1): Treatment interaction with adverse impact
(2): Treatment interaction with stringency
(3): Cox proportional hazard rate model (larger values imply faster time-to-normal)
(4): Subset of treatment firms only
(5): SCF-program-specific variables added.




Counter-factual analysis based on the main Weibull model. Solid lines are estimated survival graphs and dashed lines capture estimated 95%-confidence intervals.

Figure 3.5: Estimations for the percentage of firms back-to-normal

## 3.5 Discussion and summary

Supply chain resilience is one of the essential concepts in supply chain management as it ensures a reliable working state for all supply chain participants. This paper explored reverse factoring as a facilitator of supply chain resilience and its impact on it. We build a theoretical framework based on Sheffi and Rice (2005) and employ data from one of the leading banks that provide supply chain finance platforms for buyers and their suppliers. As one of the most fragile participants in supply chains is small suppliers that might suffer from a liquidity shortage during disruptive times (Kouvelis and Xu 2021*a*, Wuttke et al. 2016), we explore the effect of supply chain disruption from the suppliers' side. We use suppliers from the supply chain finance provider and compare these suppliers with a comparable group of small firms that we retrieved from Bloomberg. The former group we label as our treatment group as they are the ones who use the reverse factoring program, and the latter group is the control group, which is not under the reverse factoring program. Specifically, we compared the impact of the COVID-19 pandemic on the performance of firms' revenue and tested whether firms that use reverse factoring recover faster from the disruptive event.

We used a difference-in-difference model to test the impact of the COVID-19 pandemic on firms that use reverse factoring. We find that firms that use reverse factoring are less impacted by the disruption than comparable firms with general revenues. In addition, we used the Cox proportional hazard rate model to assess whether suppliers using reverse factoring return to normal operations faster than the comparable firms. Based on the analysis, suppliers using the reverse factoring program return to their operations as before the COVID-19 pandemic faster than firms that do not use reverse factoring. This finding aligns with the propositions from Cohen et al. (2022*b*) stating that reverse factoring facilitates supply chain resilience by giving suppliers immediate liquidity to keep up with their daily operations. In addition, we find that payment terms play an essential role for supply chain resilience and decelerate the process of returning to normal overall. Suppliers that do not use reverse factoring tend to have extended payment terms. In essence, payment terms negatively affect the recovery of suppliers with general revenues, and it takes them longer to get back to normal operations.

In summary, our study analyzes the impact of supply chain finance on supply chain resilience . This study makes the following contributions. First, supply chain finance promotes supply chain resilience as these suppliers' revenues return to normal faster than suppliers with general revenue. We also find that payment terms play a crucial role in this setting as payment terms decelerate the process of returning to normal for suppliers with general revenues. This makes reverse factoring an attractive solution to implement by supply chain participants. The managers can also use this finding as they can see that supply chain finance can help their suppliers to be stable during disruptive times and they most likely will not go out of business. This means that buyers and suppliers can fulfill their operations, thus also resulting in more stable supply chains.

Finally, we test our hypotheses using data from a leading bank's reverse factoring platforms containing sensitive information about small firms. It is fairly difficult to obtain such data and to analyze the impact of the COVID-19 pandemic on small firms. This study is one of the early empirical studies on the impact of reverse factoring on supply chain resilience . At the same time, we would recommend to explore this topic with analytical methods.

CHAPTER 4

# Enhancing Supply Chain Flexibility through Reverse Factoring

In an era characterized by pervasive uncertainty and rapidly evolving environmental dynamics, supply chains require heightened flexibility to sustain their competitiveness. Extant research has demonstrated that operational flexibility enhances supply chain resilience (Kim et al. 2015, Shen and Sun 2023), purchase volume flexibility improves e-procurement performance (Nair et al. 2013), labor flexibility boosts plant performance (Sawhney 2013), and manufacturing flexibility enhances firm performance, especially in uncertain conditions (Patel et al. 2012). Additionally, strategic flexibility has been linked to improvements in operational efficiency (Kortmann et al. 2014). From a finance-operations interface perspective, a comprehensive examination of financial flexibility in supply chains and other forms of flexibility is essential for understanding how organizations navigate and thrive in today's volatile business landscape.

This chapter explores the enhancement of supply chain flexibility through reverse factoring. This study draws from extant research on operational flexibility (Shen and Sun 2023, Patel et al. 2012, Kortmann et al. 2014). We argue that dynamic discounting in reverse factoring enhances the suppliers' flexibility as they can decide whether and when to convert receivables into cash. This would explain why even firms with financing costs below the reverse factoring interest rate adopt it if demonstrated. Testing this flexibility idea empirically is borderline tautological when accounting for idiosyncratic cash needs. One might be inclined to pre-suppose that whenever firms discounted an invoice, it was because they needed the money. To find consistent patterns, we thus focus on regular, exogenous cash shocks, times at which all firms need liquidity most and thus more likely draw the option to convert receivables into cash. Several expenses, such as rent and other regular installments, are due at quarter ends. Moreover, investors assess a firm's financial health based on quarterly financial reports (Allen et al. 2011). Investors prefer cash to accounts receivable because cash is more fungible. Therefore, our main conjecture is that suppliers using dynamic discounting in reverse factoring adopt reverse factoring to increase their performance reflected in end-of-quarter effects (our independent variable). We build on the research framework of Jack and Raturi (2002) to examine reverse factoring flexibility in supply chains, expecting a positive impact of reverse factoring flexibility on end-of-quarter effects. They propose two moderating effects: size and importance. Accordingly, we expect that larger suppliers use more sophisticated cash management approaches (Cooley and Pullen 1979, Soenen and Aggarwal 1989) and rely more on their investors' opinions (Melander et al. 2017). We thus hypothesize an accentuating impact of supplier size on the effect of reverse factoring on end-of-quarter effects. We further hypothesize that managers are more attentive to more important transactions, so we hypothesize that transaction importance accentuates the effect of reverse factoring on end-of-quarter effects, too.

To test this mechanism, we use a unique dataset with 64,434 transactions of 268 suppliers from one of the leading reverse factoring providers with data on suppliers that use dynamic discounting in reverse factoring . Our key predictions relate to the time from invoice approval (the earliest possible time to discount an invoice) to the discounting decisions (which can be as late as maturity); we refer to this duration as time-to-discount. We test how factors, such as the remaining days until the end of the current quarter, supplier size, importance, and interactions, affect the time to discount. To that end, we use a semi-parametric Cox proportional hazard rate model (Cox 1972). Our analysis shows suppliers are likelier to discount their invoices close to quarter ends. Consistent with our interaction hypotheses, this effect is stronger for larger suppliers and more important invoices. We also report several robustness tests and address potential collinearity issues.

Our results inform operations managers. First, whereas former literature emphasizes the importance of financial flows in supply chains to provide cheaper and better access to financially-constrained partners (Kouvelis and Zhao 2012, Tanrısever et al. 2012, Lekkakos and Serrano 2016), we shift the focus towards financial flexibility for upstream partners. Based on a counterfactual analysis, we argue that it is often not the financing cost reduction that makes supply chain finance attractive but the liquidity increase. Second, in contrast to the widespread belief that buyers with mediocre credit ratings should refrain from reverse factoring because their suppliers will not benefit enough, our results indicate that even those buyers can benefit by improving financial flows in their supply chains using reverse factoring. They must, however, partner with an reverse factoring provider that allows for dynamic discounting in reverse factoring. Third, we examine the underlying mechanism empirically. We demonstrate that dynamic discounting in reverse factoring is particularly relevant for large suppliers with important transactions. Exactly those suppliers are relevant during crises like the recent pandemic. Against the background that many important, large firms recently faced severe production constraints (e.g., the semiconductor industry) and had to ration their capacity, we expect buyers offering reverse factoring programs to be prioritized in some allocation decisions. Finally, we add more broadly to studies on operational flexibility by highlighting how operations managers of downstream firms can use reverse factoring to increase their upstream supply chain's financial flexibility.

## 4.1 Theoretical background and hypotheses

We review reverse factoring literature before we discuss the theoretical background and derive five hypotheses.

### 4.1.1 Related research on reverse factoring

Analytical reverse factoring studies mainly revolve around lowering financing costs for financially constrained suppliers and buyers wanting longer payment terms. Kouvelis and Xu (2021*a*) compare reverse factoring to factoring and predict when reverse factoring benefits all involved players. Modeling financial friction in the form of dead-weight information loss, Tanrisever et al. (2015) explores the impact of reverse factoring on operational and financial decisions. Both studies assume that suppliers that adopt reverse factoring do so to lower their interest rates. This assumption is also a key premise of Wuttke et al. (2016) and Van der Vliet et al. (2015). Van der Vliet et al. (2015) is very explicit about the notion that suppliers do not adopt reverse factoring for free. Whereas there is no formal fee, buyers only offer reverse factoring to suppliers if they are willing to extend payment terms. Although suppliers can receive their revenue immediately through reverse factoring, this extension still matters. The longer the payment terms, the higher the discount charge. Consequently, Van der Vliet et al. (2015) considers extended payment terms as the price for reverse factoring . Lekkakos and Serrano (2016) provide a numerical study to demonstrate the often substantial value that suppliers can generate by using reverse factoring. They emphasize the importance of supplier size and posit that mainly smaller suppliers benefit from reverse factoring since they tend to have higher financing costs, a prerequisite for reverse factoring adoption in their study. In sum, these analytical studies consistently assume that suppliers adopt reverse factoring to reduce financing costs. Therefore, suppliers always discount invoices immediately in the corresponding equilibria.

There is one exception, which considers suppliers with potentially lower financing costs without reverse factoring. Grüter and Wuttke (2017) study flexibility aspects of reverse factoring in the form of a real option. In their study, suppliers face randomly evolving cash needs. Typically, they prefer other, cheaper sources of financing, such as their corporate credit lines. However, when the liquidity needs are high enough, Grüter and Wuttke (2017) find that these suppliers use reverse factoring to discount outstanding invoices. We also assume suppliers may benefit from postponing the discounting decision to reduce interest payments. However, we take an empirical approach to complement their game-theoretic model. Further, we focus on end-of-quarter effects to make clear predictions across firms.

Several studies examine reverse factoring empirically. Liebl et al. (2016) studies antecedents of reverse factoring adoption and Wuttke, Blome, Foerstl and Henke (2013) the reverse factoring adoption process by buyers. Whereas both papers use case studies, Banerjee et al. (2021*b*) uses conjoint-based experiments to study adoption decisions. Those authors presented subjects with different offers, asking which they preferred. Wuttke et al. (2019) uses secondary data to test hypotheses on supplier reverse factoring adoption. Those authors find that efficiency and legitimacy motive drivers explain how quickly suppliers adopt reverse factoring. They report that 212 suppliers, about 15% in their sample, use dynamic discounting in reverse factoring. This number is relatively large, given that extant research mainly predicts immediate discounting. Studying exactly those firms that use dynamic discounting, our study differs from Wuttke et al. (2019). Whereas they consider adoption speed as the dependent variable, we consider the time-to-discount for each invoice as the dependent variable. Further, their study is on the dyad level with $N = 1,403$ dyads, whereas we study the transaction level with multiple observations per dyad, leading to $N = 64,521$. They build on theory related to technology adoption; we build on the idea of real options value and calendar effect.

### 4.1.2 Theoretical background and hypotheses

We ground our theory development in the extensive research on flexibility in operations management. Whereas there is no single definition of flexibility (see, Sawhney 2006, for a good discussion), we contend that there is agreement that operations management is inherently subject to uncertainty. For instance, even a single project faces multiple forms of uncertainty related to project expectations (Balachandra and Friar 1997), user needs (Brockhoff 1994), and the funding source (Pate-Cornell et al. 1990). Managers identified several forms of flexibility to mitigate uncertainty, which differ by industry. Nair et al. (2013), for instance, find that clinical flexibility enables hospitals to serve patients better, reducing the average cardiology unit length of stay. Devaraj et al. (2012) examine the effects of purchase volume flexibility and purchase mix flexibility in e-procurement and find both to improve cost, quality, and delivery. Jack and Raturi (2002) note a positive impact on short- and long-term volume flexibility sources on performance. Broadly, those studies agree that operational flexibility provides managers with real options; the underlying mechanism essentially features the ability to delay or adjust important decisions when more information becomes available.

Turning to the theoretical underpinning, no single grand theory comprehensively explains the impact of flexibility on performance. Instead, scholars build on different theories depending on their specific views. For instance, Devaraj et al. (2012), in their study on the effects of purchase volume flexibility and purchase mix flexibility in the e-procurement context, leverage transaction costs economics and social exchange theory. Sandberg (2021) link dynamic capabilities to creating logistics flexibility, whereas Jack and Raturi (2002) argues based on the resource-based view.

Kim et al. (2020) take a resource dependence theory perspective on enhancing the logistics capabilities of firms. They find that firms improve their operational performance in their supply chains by building flexibility in logistics and strategic relationships between manufacturers. Resource dependence theory has been viewed as a value-creation mechanism for organizations as organizations are social entities that create values by bringing together resources to achieve their goals (Daft 2015). According to resource dependence theory, every firm depends on every other firm for their critical resources, and this dependence is often reciprocal (Pfeffer and Salancik 2006). The critical resources can be financial, information, or human resources (Tremblay et al. 2003). They are usually scarce or made scarce, and the organizations that allocate and distribute critical resources are usually influential in their environment (Salancik and Pfeffer 1977).

### 4.1.3 Research framework

Reverse factoring is a technological solution that optimizes working capital and liquidity for small firms. One of the critical resources of small suppliers is their financial resources (Tremblay et al. 2003), precisely their cash flow. The cash flow statement is the most critical statement for firms as it shows the strength of the firm and its ability to manage its operations healthily. It shows investors that firms can pay for their expenses and will not go out of business. Firms that can allocate and distribute their cash resources are one of the strong firms in business (Salancik and Pfeffer 1977).

The flexibility that reverse factoring provides through dynamic discounting can help suppliers properly manage their cash flows. Suppliers can discount their invoices anytime but before the maturity date. One of the periods to discount their invoices might be close to the end of the quarter. For instance, many firms consider the end of the quarter in their cash flow decisions to suggest more significant returns by displaying more cash values (Jacobs and Levy 1988). Higher cash values in firms' financial statements are crucial as they signal investors of a healthy financial situation of firms (Melander et al. 2017). It also indicates lower financial risks and a firm's growth potential (Chen and Shane 2014, Harford et al. 2014, Opler et al. 1999). We build on these studies and argue that reverse factoring provides a formidable opportunity to convert receivables into cash at quarter ends.

However, most of the time, small supplier discount their invoices quickly due to the high need for liquidity to run their operations (Grüter and Wuttke 2017, Lekkakos and Serrano 2016, Tanrısever et al. 2012) as they are the ones that have difficulties in accessing the financing. This might not be the case for bigger suppliers. Larger firms can be more flexible with their finances, especially with their cash management practices (Denis 2011). Those firms can choose how to navigate their cash balance and when to show specific amounts. Moreover, larger firms tend to have better access to financing through banks as they publish their statements publicly, which allows those banks to have a clear picture of the financial situation of firms. Thus, large firms might prefer to discount their invoices close to the reporting period, showing a better balance sheet position in their financial statements. This idea is aligned with Jack and Raturi (2002), emphasizing the moderating effect of size on the operational flexibility of firms.

The importance of transactions plays another important role in cash flow flexibility. We hypothesize that the larger invoice values are more likely to be discounted close to the reporting period, accentuating the effect of reverse factoring on the end-of-quarter effects. As the larger values bring substantial liquidity to firms, firms are more prone to discount these invoices to show a better liquidity position on their balance sheets. The research framework we develop in Figure 4.1 builds on this logic.

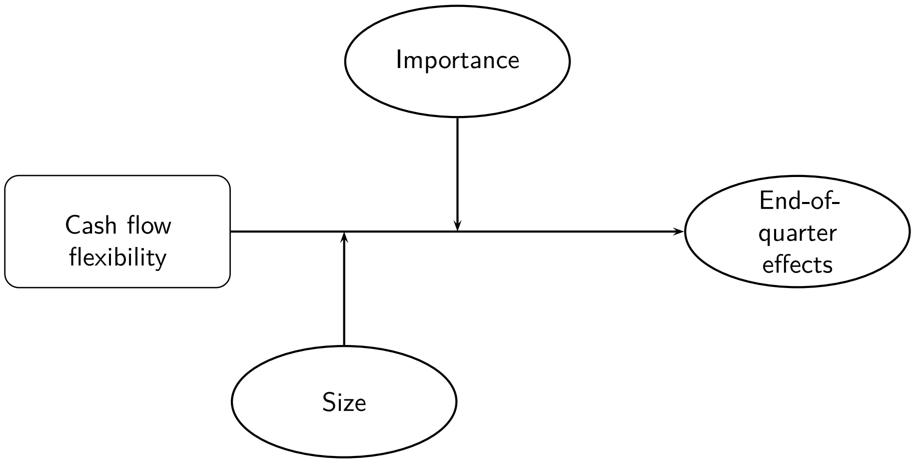



Figure 4.1: Research framework

### 4.1.4 Hypotheses

Liquidity management is among the most important financing decisions (Orgler 1969). Precisely, firms face a newsvendor-like problem (Gitman et al. 1979, Allen et al. 2011). Most cash flows are random (e.g., when customers pay), and there are costs associated with too much cash (opportunity costs and financing costs) as well as costs associated with too little liquidity (default risks). To balance this tradeoff, firms must decide on the optimal level. Reverse factoring is a helpful financial arrangement for suppliers. Instead of waiting for customers to pay at a random time, it allows them to decide when to be paid (Hu et al. 2018). Whereas the specific random needs for each firm are unobservable, we test our theory using general, predictable liquidity needs corresponding to quarter ends.

At the end of every quarter, firms face recurrent payment obligations. For instance, some pay rent every quarter. Others have revolving credit vehicles and must cover their outstanding debt. Pay role and related monthly expenses add to that, as those are also due at the end of quarters. There are further, less plannable liquidity needs at quarter ends so that elevated cash holdings reduce cash flow risks mainly then (Harford et al. 2014, Chen and Shane 2014). Complementing those operational expenses, there is also a less tangible but perhaps even more important signaling component. Firms that publish quarterly financial statements report their liquidity and free cash flow, among other things. Investors (Jacobs and Levy 1988, Melander et al. 2017, Opler et al. 1999), insurers (Jeenas 2019), and regulators (Kotomin and Winters 2006) pay close attention to reported liquidity. Reporting financial health can thus shape a firm's future. Taken together, those reasons provide strong motives to adopt reverse factoring to discount invoices at the end of quarters or close to the end of a quarter because the positive liquidity effect also arises if suppliers discount invoices just before the quarter end, for instance, a week earlier. Still, suppliers face a tradeoff since they pay the interest rate when discounting invoices. Therefore, we do not expect all firms to discount their invoices at the end of a quarter, but at least to do so more likely. Formally,

**Hypothesis 1 (End-of-quarter effect)** *Suppliers discount their outstanding invoices more likely when the end of the next quarter is closer.*

**Moderating role of supplier size**

To further probe the mechanism underlying Hypothesis 1, we will next examine supplier size's role as a moderator. To that end, we will first hypothesize on its main effect before turning to the interaction. The emphasis on supplier size is common in many analytical studies on reverse factoring that argue how reverse factoring is particularly important for SMEs (Grüter and Wuttke 2017, Lekkakos and Serrano 2016, Tanrısever et al. 2012). In their empirical study on reverse factoring adoption, Wuttke et al. (2019) also connect access to financing to supplier size. They find that smaller suppliers adopt reverse factoring faster. Since larger firms usually adopt novel technology faster (e.g., EDI or the Internet), those authors conclude that the need for liquidity drives the smaller suppliers to adopt reverse factoring faster. Further evidence supports the view that smaller firms tend to have more difficult access to financing (Beck et al. 2005, Berger and Udell 2006, Campello et al. 2010). In part, larger firms can rely on relationship-based rather than transaction-based lending. Publishing quarterly statements, larger firms tend to be more transparent, allowing more efficient borrowing.

The pattern of smaller suppliers lacking access to financing is general, and many exceptions exist. Even small firms can be well-financed. Thus, multiple relatively small firms also use dynamic discounting in reverse factoring. Still, consistent with extant literature, we expect them to have slightly higher financing costs than larger firms using dynamic discounting in reverse factoring. If true, this would shift the smaller suppliers' tradeoff towards faster discounting. Formally,

**Hypothesis 2** *Smaller suppliers are more likely to discount outstanding invoices earlier.*

In addition to the discounting speed that we predict to differ by supplier size, we expect liquidity management approaches to differ by supplier size. Cash flow management practices vary across firms, especially regarding using new technologies (Brinckmann et al. 2011). It is well known that large firms use sophisticated approaches to cash management (Cooley and Pullen 1979, Soenen and Aggarwal 1989). They often deploy dedicated cash management teams engaging in cash forecasting and liquidity planning. Using sophisticated methods and tools, those teams have real-time access to all expected cash flows and needs, limiting cash flow uncertainty. They can strategically delay the discounting of invoices towards the end of a quarter. In addition, larger firms often benefit more from signaling effects to their key stakeholders. They tend to publish more comprehensive reports, focusing on their financial situation. At the same time, they engage more in relationship-based financing (Beck et al. 2005), which means they must signal strength to maintain their strong credit ratings. Smaller suppliers that obtain transaction-based loans engage less in signaling practices. They often obtain loans based on collateralization, such as asset-back loans (Buzacott and Zhang 2004). Therefore, we expect larger suppliers to be more capable of accounting for end-of-quarter effects and also to benefit more from doing so. If true, this leads to,

**Hypothesis 3** *Supplier size moderates the end-of-quarter effect as larger suppliers are more likely to discount invoices at the end of a quarter.*

**Moderating role of invoice value**

We further posit that invoice value affects the decision to discount. Analog to the previous section, we will first hypothesize on its main effect before turning to its expected moderating role. For the main effect, we present an economic and a psychological explanation. To understand the economic impact of invoice value, it is insightful to examine what a "large" amount refers to in our context. For instance, one of the larger invoice values in our sample resulted from a US supplier in the technology sector that sold products or services worth $1,298,956 according to one invoice. Both parties agreed on payment terms of 39 days, and the reverse factoring discount rate was 2.68%. Breaking this amount down to daily values corresponds to $ 95. For this invoice, the supplier delayed the discounting by six days, saving $570. Such an amount is worthwhile checking the need for liquidity, which likely only takes a few minutes. On the other hand, the smallest invoices in our sample correspond to a few cents (amounts that are not uncommon for vendor management inventories with automated billing). In those cases, suppliers can virtually gain nothing by delaying decisions. Then, the question arises whether suppliers will discount outstanding invoices of smaller values fast or slow, given that their decision matters less. Turning to psychological research, Amar et al. (2011) examines how individuals decide on closing accounts (in their case, by paying debt). Those authors find human decision-makers prefer closing accounts whenever possible.

Transferred to our study, we expect the suppliers' managers to discount small invoices whenever possible. This reduces their complexity and future workload (those invoices disappear from the overview screen of open invoices). Therefore, we expect managers to collect debt for small invoices as soon as possible, whereas they take a more nuanced approach for larger invoices, sometimes leading to later discounting. Formally,

**Hypothesis 4** *Suppliers are more likely to discount larger outstanding invoices later.*

Turning to the moderating effect of invoice value, we argue analog to its main effect. Invoices of small value are fairly insignificant and hardly move the investors. Displaying a few Euros more or less on the balance sheet as cash is impactless. However, doing so matters for large invoices. Consider the example above of a single invoice amounting to about $ 1.3mn, which is relatively substantial for that supplier. In this case, it matters more to discount it close to a quarter end, which might be why this specific invoice was discounted on December 23, 2016, instead of closer to its due date in January 2017. Overall, we expect an accentuation of end-of-quarter effects by supplier size.

**Hypothesis 5** *Invoice value moderates the end-of-quarter effect, as suppliers are more likely to discount invoices at the end of a quarter if the invoice value is large.*

We provide how our framework describes our hypotheses in Figure 4.2. Based on the hypotheses elaborated above, we show that suppliers are more likely to discount their invoices close to the end of the quarter. We show the moderating effect of supplier size as a positive sign to the end of the quarter. This means that larger supplier is more likely to discount their invoices close to the end of the quarter. In the same way, we show the moderating effect of the invoice value with importance. This means that larger invoice values are more likely to be discounted close to the end of the quarter.

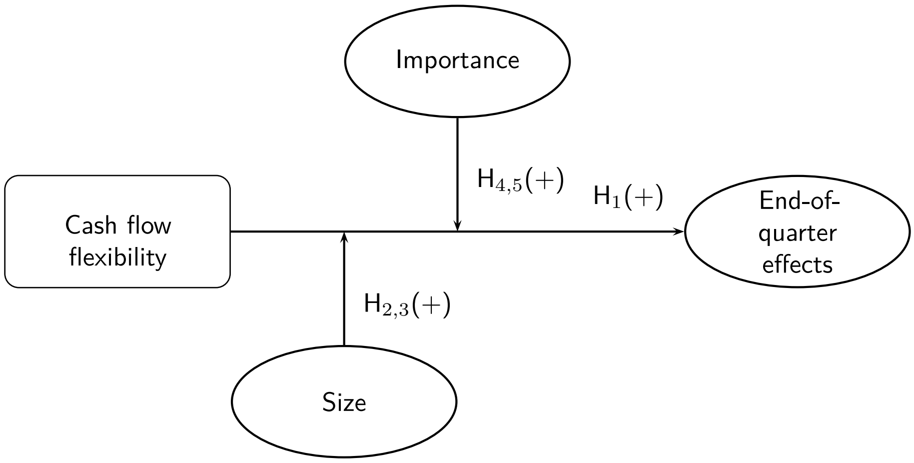



Figure 4.2: Research framework with hypotheses

## 4.2 Sample and method

This section describes our research sample, data operationalization, and economic specifications of analysis.

### 4.2.1 Research sample and data

Our primary data source is our research partner, a leading reverse factoring program provider facilitating transactions between buyers and suppliers. Our sample starts from the 1st of January 2012 until the 31st of December 2017. Every supplier transacts with one buyer; however, one buyer can transact with multiple suppliers in this program.

There are two types of data. The first dataset is on the transaction level generated by the platform. It provides data on transaction value, interest rate, dates of the invoice upload, and discount. This dataset consists of 98,931 transactions. The second dataset is on the supplier and buyer levels, which the buyers manually entered. It provides information on supplier size, country, industry, buyers' size, cost of goods sold, industry, country, and credit ratings. This dataset comprises 3,640 suppliers that use reverse factoring under dynamic discounting. After creating the supplier annual spend values from 2012 to 2017 and merging two datasets, we used list-wise deletion for incomplete cases. We got 64,434 transactions with 268 supplies and 47 buyers as our final dataset for the analysis.

### 4.2.2 Variables definitions and operationalization

To test our hypotheses, we created several variables. $ID_{it}$ is a variable indicating when the particular invoice $i$ was discounted at time $t$. $IA_{it}$ indicates when the particular invoice $i$ was approved by the supplier. We use the duration variable as our dependent variable. We derive duration as $D_{it} := ID_{it} - IA_{it}$, a difference between invoice discount and approved date. We also create a payment terms variable, the difference between invoice due date and invoice approved date. The payment term is an indicator of the maximum length of the repayment by the buyer.

The variable we use as our covariate is the days to the next quarter. We define days to the next quarter by subtracting the date when the invoice was approved from the end of the quarter. We use this variable to operationalize whether the suppliers discounted their invoices close to the next quarter or not. In addition, we calculate the discount rate variable in basis points. We define a discount rate as the invoice charge per year over the duration of the invoice discount. Descriptive statistics on supplier revenue, buyer revenue, and invoice value can be found in Table 4.1. In this table, it can be seen that supplier size varies from 0.110 million USD to 24,400 million USD. It can also be seen that payment terms start from 4 days to 360 days maximum, and the maximum invoice value reaches 20 million USD.

Table 4.1: Summary statistics for continuous variables: these are not transformed variables

| Variable name | Min | Max | Mean | Std.dev. | Count |
|---|---|---|---|---|---|
| Buyer revenue (in mn USD) | 3000.000 | 75 000.000 | 13 457.447 | 15 128.374 | 47 |
| Buyer COGS (in mn USD) | 1000.000 | 45 000.000 | 8606.383 | 10 451.199 | 47 |
| Days to next quarter (in days) | 1 | 92 | 44.465 | 25.965 | 764 820 |
| Discount charge (in USD) | 0.000 | 262 383.200 | 64.015 | 1150.566 | 64 434 |
| Discount rate (in BPS) | 0.000 | 1039.384 | 219.694 | 131.073 | 64 434 |
| Duration (in days) | 1.000 | 176.000 | 10.890 | 19.030 | 64 434 |
| Invoice value (in USD) | 0.010 | 20 064 753.000 | 25 626.130 | 172 393.700 | 64 434 |
| Payment (in USD) | 0.010 | 19 802 370.000 | 25 562.120 | 171 602.800 | 64 434 |
| Payment terms (in days) | 4.000 | 360.000 | 76.011 | 26.894 | 64 434 |
| Supplier revenue (in mn USD) | 0.110 | 24 400.000 | 262.375 | 1761.310 | 268 |

The dataset on the supplier industry, supplier country, buyer industry, and buyer country can be found in Table 4.2. We can observe that the most significant industry in the sample is Industrial goods & services, with 63.06 % of the supplier sample. The second largest industry is Technology, which represents 20.15 % of the supplier sample. For the buyer, the largest industry is Industrial goods & services, with 31.91 %. The second largest industry for buyers is construction and materials, with 25.53 %. The most under-represented industries for suppliers and buyers are consumer goods, food and beverages, automobiles, and parts, retail, media, and personal and household goods.

The largest country representative of suppliers is Germany, with 55.59 % of the sample, and the second largest country, the United States, with 22.76 %. The buyer country goes in a similar trend with 46.80% of Germany, and the second biggest representative of the United States, with 23.40 %. Data on supplier and buyer revenue, cost of goods sold, and their industry was collected by the reverse factoring provider separately and was entered by the buyer. Data on transactions and invoice values are recorded automatically by the reverse factoring database.

Table 4.2: Summary statistics

**Panel A**

| Industry | Supplier Count | Percentage | Buyer Count | Percentage |
|---|---|---|---|---|
| Automobiles & parts | 1 | 0.37% | 0 | 0.00% |
| Basic resources | 13 | 4.85% | 1 | 2.13% |
| Chemicals | 6 | 2.25% | 1 | 2.13% |
| Construction & materials | 2 | 0.75% | 12 | 25.53% |
| Consumer goods | 0 | 0.00% | 1 | 2.13% |
| Food & beverage | 1 | 0.37 % | 0 | 0.00% |
| Health care | 5 | 1.86% | 6 | 12.77% |
| Industrial goods & services | 169 | 63.06% | 15 | 31.91% |
| Oil and gas | 10 | 3.73% | 9 | 19.14% |
| Media | 5 | 1.86% | 0 | 0.00% |
| Personal & household goods | 0 | 0.00% | 1 | 2.13% |
| Retail | 2 | 0.75% | 0 | 0.00% |
| Technology | 54 | 20.15% | 1 | 2.13% |
| Total | 268 | 100.00% | 47 | 100.00% |

**Panel B**

| Country | Supplier Count | Percentage | Buyer Count | Percentage |
|---|---|---|---|---|
| Australia | 4 | 1.49% | 1 | 2.13% |
| Austria | 2 | 0.75% | 0 | 0.00% |
| Belgium | 2 | 0.75% | 1 | 2.13% |
| Canada | 5 | 1.87% | 1 | 2.13% |
| Czech Republic | 3 | 1.12% | 2 | 4.26% |
| Denmark | 5 | 1.87% | 1 | 2.13% |
| Finland | 1 | 0.37% | 0 | 0.00% |
| France | 0 | 0.00% | 1 | 2.13% |
| Germany | 149 | 55.59% | 22 | 46.80% |
| Ireland | 1 | 0.37% | 0 | 0.00% |
| Mexico | 15 | 5.60% | 3 | 6.38% |
| Netherlands | 4 | 1.49% | 0 | 0.00% |
| Poland | 3 | 1.12% | 0 | 0.00% |
| Slovenia | 1 | 0.37% | 0 | 0.00% |
| South Korea | 2 | 0.75% | 0 | 0.00% |
| Spain | 1 | 0.37% | 0 | 0.00% |
| Sweden | 2 | 0.75% | 0 | 0.00% |
| Switzerland | 3 | 1.12% | 1 | 2.13% |
| Turkey | 0 | 0.00% | 1 | 2.13% |
| United Kingdom | 4 | 1.49% | 2 | 4.25% |
| United States | 61 | 22.76% | 11 | 23.40% |
| Total | 268 | 100.00% | 47 | 100.00% |

In addition, we present Figure 4.3, where we present the aggregated values of the transactions on the monthly level. First, we present the monetary volume of the discounted invoices in a specific month. Second, we present the number of invoices discounted in a particular month. We present the month, where the quarter ends with a black color and the other months in grey. From the figure, we can observe that larger values of invoices are discounted in months where the quarter ends, such as March, June, September, and December.

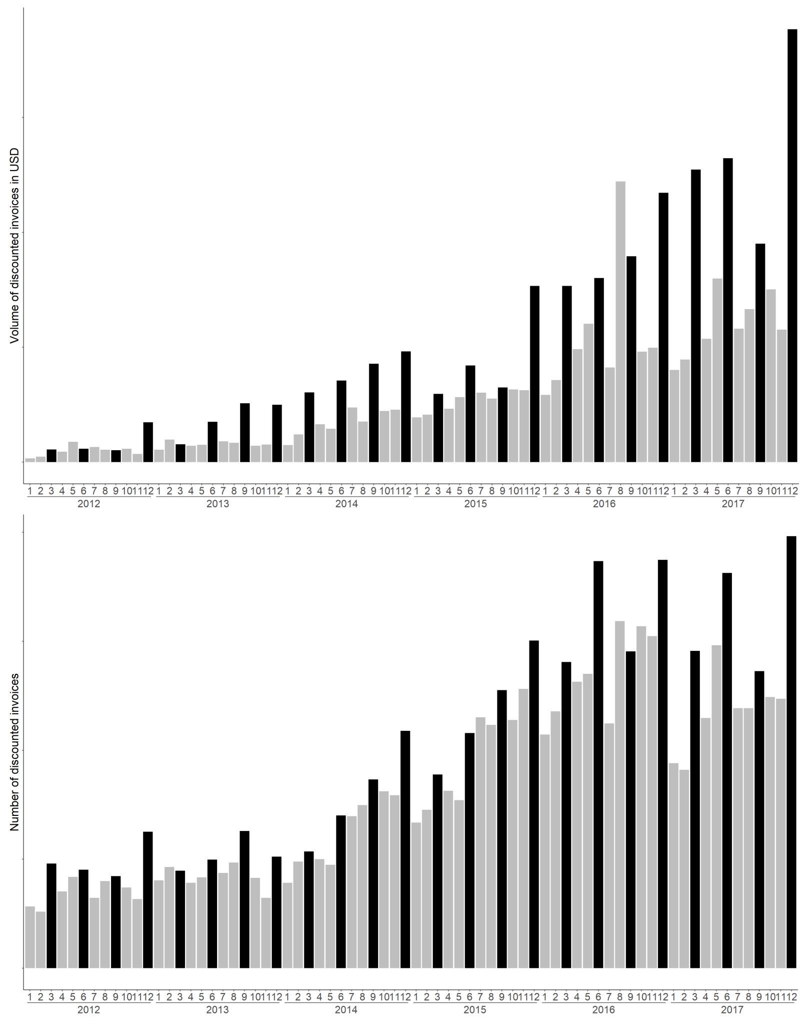



Figure 4.3: Volume and number of discounted invoices per month from 2012 to 2017

### 4.2.3 Econometric specification

As the data on the duration of the invoice discount is normally distributed and censored, we use a proportional hazard rate model as our analytical framework (Melnyk et al. 1995). We do not measure the discount duration directly, but we measure its effect on the duration hazard rate. A decrease in the hazard rate means a longer discount duration. In addition, the Cox proportional hazard rate model studies recurrent events. In this case, transaction discounting is a recurrent event for suppliers. Suppliers have multiple transactions they need to discount; however, buyers do not discount any invoices.

We use the Cox proportional hazard rate model with fixed effects to assess the time variable - duration. Instead of directly estimating the effect on duration, we measure the hazard rate of the duration. We consider that the duration of the invoice discount has a distribution of $F(t)$ with density $f(t)$, where $t$ is the duration from the invoice approval until it is discounted. Specifically, we estimate

$$\lambda_i(t) = \lambda_0(t)\exp(\alpha_i + x_b\beta + z_i\gamma),$$

where $\alpha$ is the dummy variable that captures fixed effects. The covariates are invoice value ($InvVal_{it}$), supplier size ($SupSize_i$), and days to the next quarter ($Days_{it}$):

$$x_{it}\beta = \beta_1 * SupSize_i + \beta_2 * InvVal_{it} + \beta_3 * Days_{it},$$

where we take the logarithm of $SupSize_i$ and $InvVal_{it}$, and mean center all three variables.

Control variables are the discount rate ($Dis_{it}$), supplier industry ($SI_i$), and year $Year_{it}$:

$$z_{it} = \gamma_1 * SI_i + \gamma_2 * Dis_{it} + \gamma_1 * Year_{it}.$$

The correlation matrix table of the variables is included in the analysis (except for the supplier industry and year) and is provided in Table 4.3. The higher the supplier revenue, the higher the invoice value, which is meaningful as larger invoice values bring more revenue for the firms, and lower invoice values bring lower revenue. Also, there is a negative correlation between the discount rate and supplier revenue, implying that the larger suppliers get lower discount rates. Larger suppliers also tend to have shorter days to the next quarter, which implies that they tend to discount their invoices close to the next quarter. Similarly, larger invoice values negatively correlate with days to the next quarter, meaning that larger invoice values are discounted close to the next quarter. We provide an alternative specification and conduct several robustness checks in the robustness check section.

Table 4.3: Correlation matrix

| Variable name | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| 1. Supplier revenue | $1.00$ | | | |
| 2. Invoice value | $0.07$* | $1.00$ | | |
| 3. Discount rate | $-0.08$* | $-0.09$* | $1.00$ | |
| 4. Duration | $-0.08$* | $-0.05$* | $-0.08$* | $1.00$ |
| 5. Days to next quarter | $-0.03$* | $-0.02$* | $0.00$ | $0.03$* |

N = 764 820

## 4.3 Results

The Cox proportional hazard rate model estimation is reported in Table 4.4 and Table 4.5. Our interaction model 3 in Table 4.5 shows the better fit as it has the lowest Akaike Information Criterion value. We need the lowest Akaike information criterion value because it implies that the model requires less information to predict almost the same level of prediction for models (Cavanaugh and Neath 2019). We include year, supplier industry, and discount rate as control variables. We find that the hazard rate of the discount rate decreases by exp(-0.021)-1 $\approx$ 2.07%. We provide more models with each variable to avoid multicollinearity issues with variables such as supplier revenue and invoice value, as these variables are significantly correlated.

In Table 4.4, we create separate models with each variable, and then in Model 5, we have a model with all variables but without interaction effect. This way, we want to demonstrate that the signs of the coefficients of variables stay the same across the models and that we do not face multicollinearity issues. In Table 4.5, Model 5, we can see that the signs of coefficients hold even with the interaction effects.

Our results support hypothesis 1, which can be seen in Table 4.5, Model 5, as the observed relationship between our days to the next quarter variable and the duration hazard rate is negative and significant ($p <$ 0.001). To interpret our coefficients, we measure the duration hazard rate $\lambda_{ij}(t)$, which is assumed to be proportional to exp($\beta_3 Days_{it}$). This means that the duration of a supplier discount close to the quarter decreases by exp(44.465*(-0.105))-1 $\approx$ 99%.

Hypothesis 2 is supported in Model 3 of Table 4.5, where we take the logarithm of the supplier revenue. If supplier revenue increases by a factor of 10, the duration hazard rate is multiplied by $10^{-0.213} \approx$ 61%. The hazard rate is higher for a supplier by $\frac{1}{10}^{-0.031} - 1 \approx$ 7.4% for a supplier with only a tenth of the revenue of another equal supplier. Hypothesis 3 is supported in Model 3 of Table 4.5, where we take the interaction effect of the logarithm of the supplier revenue with days to the next quarter variable. We find that the hazard rate of the supplier discounting close to the next quarter decreases by exp(-

Table 4.4: Main model 1: Cox proportional hazard rate model

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Supplier Industry | | | | | |
| (Omitted from presentation) | | | | | |
| Year | | | | | |
| (Omitted from presentation) | | | | | |
| Discount rate | 0.012*** | −0.001 | −0.007* | −0.014*** | −0.017*** |
| | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 |
| Supplier revenue | | −0.031*** | | −0.015** | −0.018*** |
| | | 0.005 | | 0.005 | 0.005 |
| Invoice value | | | −0.213*** | −0.212*** | −0.212*** |
| | | | 0.004 | 0.004 | 0.004 |
| Days to next quarter | | | | | −0.073*** |
| | | | | | 0.004 |
| Num.Obs. | 764 820 | 764 820 | 764 820 | 764 820 | 764 820 |
| Num. of Events | 64 434 | 64 434 | 64 434 | 64 434 | 64 434 |
| Num. of Sup. | 268 | 268 | 268 | 268 | 268 |
| AIC | 1 291 414.4 | 1 291 370.1 | 1 288 876.5 | 1 288 867.5 | 1 288 535.7 |

Continuous variables are mean-centered. Negative values indicate slower discounting.

0.074)-1 $\approx$ 7.1%.

We find support for hypothesis 4, which can be seen in Model 3 of Table 4.5, where we take the logarithm of the invoice value. The relationship between duration hazard rate and invoice value is negative and significant ($p$<0.001). If the invoice value increases by a factor of 10, the duration hazard rate is multiplied by $10^{-}0.213 \approx$ 0.6. The hazard rate is higher for an invoice by $\frac{1}{10}^{-0.213} - 1 \approx$ 63.3% for an invoice with only a tenth of the invoice of another equal invoice value.

Hypothesis 5 is supported in Model 3 of Table 4.5, where we take the interaction effect of the logarithm of the invoice value with days to the next quarter variable. We find that the hazard rate of the bigger invoice value discounting close to the end of the quarter decreases by exp(-0.046)-1 $\approx$ 4.5%.

Table 4.5: Main model 2: Cox proportional hazard rate model

| | 1 | 2 | 3 |
|---|---|---|---|
| Supplier Industry | | | |
| (Omitted from presentation) | | | |
| Year | | | |
| (Omitted from presentation) | | | |
| Discount rate | −0.008* | −0.008* | −0.021*** |
| | 0.004 | 0.004 | 0.004 |
| Supplier revenue | −0.046*** | | −0.031*** |
| | 0.005 | | 0.005 |
| Days to next quarter | −0.090*** | −0.096*** | −0.105*** |
| | 0.004 | 0.004 | 0.004 |
| Supplier revenue * Days to next quarter | −0.085*** | | −0.074*** |
| | 0.004 | | 0.004 |
| Invoice value | | −0.216*** | −0.213*** |
| | | 0.004 | 0.004 |
| Invoice value * Days to next quarter | | −0.060*** | −0.046*** |
| | | 0.004 | 0.004 |
| Num.Obs. | 764 820 | 764 820 | 764 820 |
| Num. of Events | 64 434 | 64 434 | 64 434 |
| Num. of Sup. | 268 | 268 | 268 |
| AIC | 1 290 529.8 | 1 288 284.7 | 1 287 913.2 |

Continuous variables are mean-centered. Negative values indicate slower discounting.

## 4.4 Robustness checks

For the robustness of our models, we conduct several robustness checks, such as the Accelerated failure test with Weibull distribution and Cox proportional hazard rate models with a discount duration of more and/or equal to 3 days, by removing outliers based on the suppliers' revenue and by applying fixed effects on the supplier level. We perform robustness checks to support our baseline model further and indicate that any internal effects do not drive our analysis.

### 4.4.1 Accelerated failure test

Unlike the semi-parametric model, such as the Cox proportional hazard rate model, we apply a parametric proportional hazard rate model that assumes the shape of the hazard rate. While the Cox proportional hazard rate model has the advantage that we do not need to assume the shape of the baseline hazard rate, accelerated failure tests can lead to more efficient estimates. The estimates are in Table 4.6. The most valid model for the Accelerated failure test is Model 5, which has the lowest Akaike Information Criterion value.

This test further supports hypothesis 1, which can be seen in Table 4.6, Model 5, as the observed relationship between days to the next quarter and duration is positive and significant ($p$<0.001). This means that suppliers discount their invoices close to the next quarter, and it increases by exp(0.152)-1 $\approx$ 16.5%. Hypothesis 2 is further supported, and we find that the larger suppliers tend to discount their invoices longer by exp(0.036)-1 $\approx$ 3.7%. This can also be illustrated in Figure 4.4a, which clearly shows that the percentage of discounted invoices after 30 days increases significantly for larger suppliers close to the end of the quarter. As well, hypothesis 3 is further supported. Larger suppliers have a higher propensity to discount close to the end of the quarter by exp(0.112)-1 $\approx$ 12%.

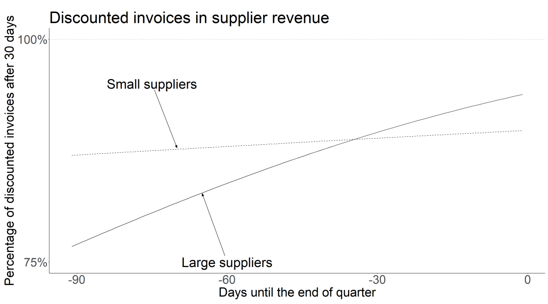
We further find support for hypothesis 4, where suppliers discount the invoices with larger values slower by exp(0.321)-1 $\approx$ 38%. This is well demonstrated in Figure 4.4b, where it can be seen that the percentage of invoices discounted after 30 days increases close to the next quarter. We further find support for hypothesis 5, where larger invoice values tend to be discounted by exp(0.069)-1 $\approx$ 7% close to the next quarter.

In addition, we present Figure 4.5, which displays that most of the invoices are discounted late. We present that the black line is zero days to the next quarter, the blue line is 30 days to the next quarter, the grey line is 60 days next to the quarter, and the red line is 90 days to the next quarter.

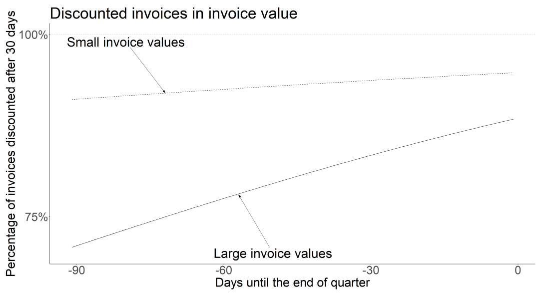
Table 4.6: Accelerated failure test with Weibull distribution

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Shape | −0.276*** | −0.275*** | −0.326*** | −0.273*** | −0.270*** |
| | 0.004 | 0.004 | 0.003 | 0.004 | 0.004 |
| Scale | 3.060 | 3.110 | 2.914 | 3.104 | 3.099 |
| | 3.016 | 3.166 | 2.739 | 3.147 | 3.120 |
| Supplier industry | | | | | |
| (Omitted from presentation) | | | | | |
| Supplier revenue | 0.015* | 0.015* | 0.056*** | | 0.036*** |
| | 0.006 | 0.006 | 0.006 | | 0.006 |
| Year | | | | | |
| (Omitted from presentation) | | | | | |
| Invoice value | 0.318*** | 0.318*** | | 0.325*** | 0.321*** |
| | 0.006 | 0.006 | | 0.006 | 0.005 |
| Discount rate | −0.005 | 0.000 | −0.011+ | −0.009+ | 0.007 |
| | 0.005 | 0.005 | 0.006 | 0.005 | 0.006 |
| Days to next quarter | | 0.108*** | 0.138*** | 0.138*** | 0.152*** |
| | | 0.005 | 0.005 | 0.005 | 0.005 |
| Supplier revenue * Days to next quarter | | | 0.133*** | | 0.112*** |
| | | | 0.005 | | 0.005 |
| Invoice value * Days to next quarter | | | | 0.090*** | 0.069*** |
| | | | | 0.005 | 0.005 |
| Num.Obs. | 764 820 | 764 820 | 764 820 | 764 820 | 764 820 |
| Num. of Events | 64 434 | 64 434 | 64 434 | 64 434 | 64 434 |
| Num. of Sup. | 268 | 268 | 268 | 268 | 268 |
| AIC | 421 568.6 | 421 103.2 | 423 564.0 | 420 715.2 | 420 163.5 |

Continuous variables are mean-centered. Positive values indicate slower discounting.

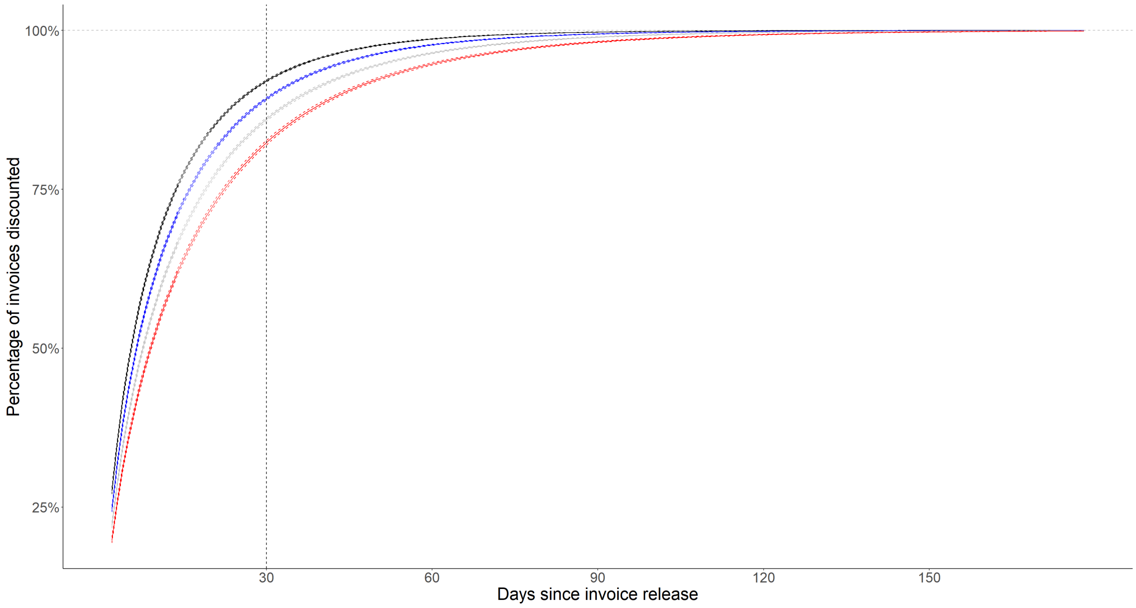



(a) Estimation of the percentage of invoices discounted with plus/minus one standard deviation above average in supplier revenue




(b) Estimation of the percentage of invoices discounted with plus/minus one standard deviation above average in invoice value

Figure 4.4: Estimates on the invoices discounted based on supplier revenue and invoice value.




Black dashed line: 0 days next to the end of the quarter,
Blue dashed line: 30 days next to the end of the quarter,
Grey dashed line: 60 days next to the end of the quarter,
Red dashed line: 90 days next to the end of the quarter.

Figure 4.5: Estimates on the percentage of invoices discounted since the invoice release.

### 4.4.2 Other robustness checks

We perform other robustness checks, such as reduced invoice discount duration of more and/or equal to 3 days, which is displayed in Table 4.7, Model 5. We perform this test to see whether the effect of shorter durations changes the effect in coefficients. With a reduced sample of 257 suppliers and 700,998 observations, our results align with the baseline model's results, meaning that suppliers tend to discount their invoices close to the end of the quarter. Further, we perform robustness checks on our baseline model by removing outliers. We implemented the approach outlined by Albright et al. (2011) by removing only extreme outliers. We perform this test to see whether outliers drive the analysis or not. The estimates can be seen in Table 4.8, Model 5. This analysis of the reduced sample with 263 suppliers and 755,988 observations is aligned with the baseline model.

Table 4.7: Robustness test with a subset of invoice discount duration of more and/or equal to 3 days.

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Supplier industry | | | | | |
| (Omitted from presentation) | | | | | |
| Supplier revenue | 0.042*** | 0.039*** | 0.019** | | 0.015* |
| | 0.007 | 0.007 | 0.007 | | 0.007 |
| Year | | | | | |
| (Omitted from presentation) | | | | | |
| Discount rate | 0.115*** | 0.109*** | 0.122*** | 0.098*** | 0.104*** |
| | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 |
| Invoice value | −0.230*** | −0.228*** | | −0.238*** | −0.235*** |
| | 0.006 | 0.006 | | 0.006 | 0.006 |
| Days to next quarter | | −0.116*** | −0.129*** | −0.127*** | −0.136*** |
| | | 0.005 | 0.005 | 0.005 | 0.005 |
| Supplier revenue * Days to next quarter | | | −0.134*** | | −0.124*** |
| | | | 0.005 | | 0.005 |
| Invoice value * Days to next quarter | | | | −0.082*** | −0.067*** |
| | | | | 0.005 | 0.005 |
| Num.Obs. | 700 998 | 700 998 | 700 998 | 700 998 | 700 998 |
| Num. of Events | 33 939 | 33 939 | 33 939 | 33 939 | 33 939 |
| Num. of Sup. | 257 | 257 | 257 | 257 | 257 |
| AIC | 634 178.0 | 633 683.0 | 634 385.5 | 633 438.3 | 632 803.8 |

Continuous variables are mean-centered. Negative values indicate slower discounting.

Table 4.8: Robustness test based on removing outliers from suppliers based on the suppliers' revenue.

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Supplier industry | | | | | |
| (Omitted from presentation) | | | | | |
| Supplier revenue | 0.055*** | 0.053*** | 0.038*** | | 0.044*** |
| | 0.005 | 0.005 | 0.005 | | 0.005 |
| Year | | | | | |
| (Omitted from presentation) | | | | | |
| Discount Rate | 0.017*** | 0.014*** | 0.025*** | −0.007 | 0.011* |
| | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 |
| Invoice value | −0.206*** | −0.206*** | | −0.207*** | −0.206*** |
| | 0.004 | 0.004 | | 0.004 | 0.004 |
| Days to next quarter | | −0.063*** | −0.082*** | −0.086*** | −0.096*** |
| | | 0.004 | 0.004 | 0.004 | 0.004 |
| Supplier revenue * Days to next quarter | | | −0.075*** | | −0.063*** |
| | | | 0.004 | | 0.004 |
| Invoice value * Days to next quarter | | | | −0.053*** | −0.044*** |
| | | | | 0.004 | 0.004 |
| Num.Obs. | 755 988 | 755 988 | 755 988 | 755 988 | 755 988 |
| Num. of Events | 63 489 | 63 489 | 63 489 | 63 489 | 63 489 |
| Num. of Sup. | 263 | 263 | 263 | 263 | 263 |
| AIC | 1 264 625.2 | 1 264 381.0 | 1 266 361.5 | 1 264 276.8 | 1 263 984.3 |

Continuous variables are mean-centered. Negative values indicate slower discounting.

Another robustness check assesses our baseline model with fixed effects on the supplier level. As we hold a general fixed effect in our baseline model, we perform supplier-level fixed effects to see whether the estimates still hold similarly to the baseline model. The resulting estimates in Table 4.9 align with the estimates in our baseline model. This implies that our initial model is robust and that external factors do not drive coefficients.

Table 4.9: Robustness test with fixed effects on the supplier level

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Supplier industry | | | | | |
| (Omitted from presentation) | | | | | |
| Supplier revenue | −0.015 | −0.016 | −0.045 | | −0.030 |
| | 0.005 | 0.005 | 0.005 | | 0.005 |
| Year | | | | | |
| (Omitted from presentation) | | | | | |
| Invoice value | −0.212*** | −0.212*** | | −0.218*** | −0.215*** |
| | 0.004 | 0.004 | | 0.004 | 0.004 |
| Discount rate | −0.014 | −0.017 | −0.009 | −0.008 | −0.022 |
| | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 |
| Days to next quarter | | −0.080** | −0.097*** | −0.102*** | −0.112*** |
| | | 0.004 | 0.004 | 0.004 | 0.004 |
| Supplier revenue * Days to next quarter | | | −0.093** | | −0.082** |
| | | | 0.003 | | 0.004 |
| Invoice value * Days to next quarter | | | | −0.066*** | −0.048*** |
| | | | | 0.003 | 0.004 |
| Num.Obs. | 764 820 | 764 820 | 764 820 | 764 820 | 764 820 |
| Num. of Events | 64 434 | 64 434 | 64 434 | 64 434 | 64 434 |
| Num. of Sup. | 268 | 268 | 268 | 268 | 268 |
| AIC | 1 288 867.5 | 1 288 425.2 | 1 290 228.0 | 1 288 073.0 | 1 287 554.0 |

Continuous variables are mean-centered. Negative values indicate slower discounting.

## 4.5 Discussion and summary

Reverse factoring is a mechanism that suppliers use to get immediate payments from their buyers (Wuttke et al. 2019). Besides that, reverse factoring brings flexibility to firms by allowing them to discount their invoices dynamically, which is called dynamic discounting (Wuttke et al. 2016). In this study, we explore the motives of suppliers that use dynamic discounting and reverse factoring to enhance supply chain flexibility. Specifically, we explore what drives suppliers to use dynamic discounting, when they discount them, and what type of suppliers use it extensively. We analyzed a dataset with 64,434 transactions and 268 suppliers that use dynamic discounting through reverse factoring. The average supplier size is $ 262 million, and the average invoice value is $ 26,000. The average duration of the invoice discount is 11 days.

We assume that suppliers discount their invoices close to the end of the quarter. In addition, we assume that larger suppliers are more likely to discount their invoices close to the end of the quarter, and larger invoice values tend to be discounted close to the end of the quarter. Based on the analysis, suppliers tend to discount their invoices close to the next quarter. This finding aligns with the literature (Kotomin and Winters 2006, Acharya et al. 2012), where balance sheet items tend to change close to the reporting period. The balance sheet effect matters close to the reporting period because suppliers can signal their investors their healthy financial position and liquidity to run their business (Babich and Sobel 2004).

Complementary to this, we find support for our second hypothesis, where larger suppliers tend to discount their invoices more slowly than smaller ones. This finding aligns with the literature stating that small suppliers tend to discount their invoices immediately as they need cash faster than bigger suppliers (Wuttke et al. 2019, Kim and Bettis 2014, Beck et al. 2005, Lekkakos and Serrano 2016). Complementary to this, larger suppliers tend to discount their invoices close to the end of the quarter. As larger suppliers are more flexible on the discounting period, they can discount their invoices when needed, such as at the end of the reporting period.

We measured discounting patterns of invoice sizes parallel to the suppliers' size. We find that suppliers tend to discount their larger value invoices slower than larger size invoices. This finding is aligned with Amar et al. (2011), who find that firms favor closing smaller accounts faster than the bigger ones. Firms might leave larger accounts to be closed close to the reporting period as this will boost the cash values on their balance sheet.

In summary, this chapter provides an extensive overview of how suppliers can leverage the flexibility aspect that dynamic discounting through reverse factoring provides. This study makes the following contributions. First, suppliers are more likely to use dynamic discounting close to the reporting period. One of the main motives to discount close to the reporting period might be to show a better balance sheet position, meaning more liquidity, which indicates the healthiness of the operational activities of a firm. This finding can contribute to the research on operational flexibility. From the findings, we can see that reverse factoring allows suppliers to manage their cash balances better and further improve the attractiveness of their businesses.

Second, we test our hypotheses using data from one of the leading supply chain finance providers, which contains sensitive financial information of firms. It is fairly challenging to obtain such data and to have an opportunity to analyze the different motives of suppliers on why they use dynamic discounting. Third, our findings extend beyond the operational flexibility to discount close to the end of the quarter. Supplier and invoice sizes are other distinctive factors when invoices get discounted. This means larger suppliers tend to discount their invoices more slowly, and smaller suppliers tend to discount their invoices faster. This means larger suppliers are more flexible and can decide when and how much to discount. This is the first empirical study on the flexibility that dynamic discounting brings through reverse factoring. Some areas can be further researched, such as the type of firms that discount their invoices close to the reporting period beyond the size.

# CHAPTER 5

# Conclusion

This thesis aims to provide a flexibility perspective on supply chain finance. Until now, little study has explored how supply chain finance can provide financial flexibility to firms. We conducted an extensive literature review on supply chain resilience and supply chain finance in Chapter 2. Further, in Chapter 3, we analyzed the impact of supply chain finance on supply chain resilience and found that supply chain finance firms are more resilient than comparable firms as they return to normal faster.

In Chapter 4, we find that suppliers using reverse factoring leverage dynamic discounting option and discount their invoices close to the end of the quarter. In addition, we find that larger suppliers are more likely to discount their invoices close to the end of the quarter, as larger invoice values are more likely to be discounted close to the end of the quarter. We presented results on these findings in Chapters 3 and 4. This chapter summarizes the key findings of this thesis by answering the research questions and raises suggestions for further research.

## 5.1 Summary

In Chapter 3, using the idea of Sheffi and Rice (2005) on supply chain resilience, we presented a theoretical model with hypotheses and tested these hypotheses with econometric analysis. Specifically, we leveraged difference-in-difference and Cox proportional hazard rate models for analysis. We used data from one of the leading banks in Europe that provides reverse factoring for buyers and their suppliers. We compared suppliers' revenues using reverse factoring with firms with general revenues of the same size. We retrieved data for the firms with general revenues from Bloomberg.

We answered the research question: *Do suppliers under the supply chain finance program suffer less in the first year after a significant shock than comparable suppliers?* Our results indicate that reverse factoring firms experience less effect on their revenue than similar-sized firms. In addition, we performed several robustness tests to verify the results. By using the immediate impact of the COVID-19 pandemic on firms' revenues, we find that firms that use reverse factoring experience less impact on their revenues. In addition, we conducted a placebo test. The test results are aligned with our findings that reverse factoring firms experience less impact on their revenues during the COVID-19 pandemic.

We also answered two other research questions: *Are they back to their operations faster than before the disruption? Are firms that use reverse factoring more resilient than comparable firms?* To answer these questions, we used the Cox proportional hazard rate model for the data analysis. We find that reverse factoring firms return to normal faster than firms with general revenues by around 32%. This finding is also supported by a robustness check, where firms using reverse factoring return faster to normal than suppliers with general revenues by around 38%. This is also aligned with our findings. In addition, we find that payment terms play a moderating effect, and payment terms negatively affect the process of returning to normal for firms with general revenues.

In Chapter 4, we answered the following research questions: *Why do firms using dynamic discounting adopt reverse factoring if it is not for cheaper access to financing? What is driving them?* We grounded our theory on extensive research on operational flexibility. We derived that suppliers can use the cash flow flexibility that reverse factoring provides by discounting their invoices close to the reporting period. We also emphasize the moderating effect of supplier size and invoice value on supplier discounting behavior. We used the Cox proportional hazard rate model to test if suppliers tend to discount their invoices close to the reporting period. In addition, we tested whether the supplier size and invoice value affect when suppliers discount their invoices.

As dynamic discounting through reverse factoring gives more flexibility on when and how many invoices to discount, we find that suppliers are more likely to discount their invoices close to the reporting period. In addition, larger suppliers are more likely to discount their invoices close to the reporting period than smaller suppliers. Similarly, larger invoice values are more likely to be discounted close to the reporting period. By discounting larger invoices close to the end of the quarter, firms can show more cash values on their balance sheet. This way, firms position themselves in a healthy and liquid financial position to their shareholders and potential investors.

In summary, our findings show that the flexibility that supply chain finance brings to firms helps them be resilient during disruptive times and have more financial flexibility in managing their invoices.

## 5.2 Outlook

Our findings bring the following managerial implications. First, based on a literature review, we find that combining supply chain finance and supply chain resilience leads to more rigorous supply chain resilience practices. Suppliers can optimize their liquidity, and supply chain finance can help them operate normally during disruptive times. Second, in Chapter 3, we find that supply chain finance enhances supply chain resilience. Suppliers' revenue returns to normal faster than the ones that have not adopted supply chain finance. This finding can motivate buyers and suppliers to adopt supply chain finance in their businesses. This way, buyers can ensure that small suppliers are not out of business during disruptive times and can operate as usual. Moreover, this finding shows that supporting the weakest links in supply chains creates more robust supply chains for all participants.

Secondly, in Chapter 4, we find that dynamic discounting through reverse factoring allows suppliers to discount their invoices flexibly, meaning when they want to and need to. This way, suppliers can decide on the timing of discounting and discount only when needed but before the maturity date. In addition, we find that larger suppliers that use dynamic discounting through reverse factoring discount their invoices close to the reporting period. Suppliers are also more likely to discount larger invoices close to the end of the quarter. This finding shows that supply chain finance provides not only cheap financing for suppliers but also an ability to be flexible with their cash management practices.

Our findings imply that supply chain finance helps suppliers to manage their operations flexibly. Suppliers recover from disruptive events faster than firms that do not use supply chain finance. Due to the extended payment terms, other suppliers suffer more, and it takes them longer to return to normal operations. This leads to further research opportunities on the impact of payment delays on supply chains. It can also be interesting to explore the optimal payment terms for the fast recovery of small suppliers.

In addition, the effect of supply chain finance on supply chain resilience can be explored analytically. For example, finding the optimal time needed for suppliers to recover from the supply chain disruption would be interesting. From the dynamic discounting perspective, it would be interesting to research factors other than supplier size and invoice value as the drivers to discount invoices close to the end of the quarter.

# Bibliography

Acharya, V., Davydenko, S. A. and Strebulaev, I. A. (2012), 'Cash holdings and credit risk', *The Review of Financial Studies* **25**(12), 3572–3609.

Albright, S. C., Winston, W. L., Zappe, C. J. and Broadie, M. N. (2011), *Data analysis and decision making*, Vol. 577, Citeseer.

Alexander, A., Blome, C., Schleper, M. C. and Roscoe, S. (2022), 'Managing the new normal: the future of operations and supply chain management in unprecedented times', *International Journal of Operations & Production Management* **42**(9), 1061–1076.

Allen, F., Brealey, R. A. and Myers, S. C. (2011), *Principles of corporate finance*, McGraw-Hill/Irwin.

Amar, M., Ariely, D., Ayal, S., Cryder, C. E. and Rick, S. I. (2011), 'Winning the battle but losing the war: The psychology of debt management', *Journal of Marketing Research* **48**(SPL), S38–S50.

Ambulkar, S., Blackhurst, J. and Grawe, S. (2015), 'Firm's resilience to supply chain disruptions: Scale development and empirical examination', *Journal of operations management* **33**, 111–122.

Aral, K. D., Giambona, E. and Wang, Y. (2022), 'Buyers bankruptcy risk, sourcing strategy, and firm value: Evidence from the supplier protection act', *Management Science* **68**(11), 7940–7957.

Babich, V. (2010), 'Independence of capacity ordering and financial subsidies to risky suppliers', *Manufacturing & Service Operations Management* **12**(4), 583–607.

Babich, V. and Birge, J. R. (2020), 'Foundations and trends at the interface of finance, operations, and risk management', *Operations, and Risk Management (December 28,* *2020)* .

Babich, V., Burnetas, A. N. and Ritchken, P. H. (2007), 'Competition and diversification effects in supply chains with supplier default risk', *Manufacturing & Service Operations Management* **9**(2), 123–146.

Babich, V. and Hilary, G. (2020), 'Om forumdistributed ledgers and operations: What operations management researchers should know about blockchain technology', *Manufacturing & Service Operations Management* **22**(2), 223–240.

Babich, V. and Sobel, M. J. (2004), 'Pre-ipo operational and financial decisions', *Management Science* **50**(7), 935–948.

Babich, V. and Tang, C. S. (2012), 'Managing opportunistic supplier product adulteration: Deferred payments, inspection, and combined mechanisms', *Manufacturing & Service Operations Management* **14**(2), 301–314.

Badakhshan, E. and Ball, P. (2022), 'Applying digital twins for inventory and cash management in supply chains under physical and financial disruptions', *International Journal of Production Research* pp. 1–23.

Balachandra, R. and Friar, J. H. (1997), 'Factors for success in r&d projects and new product innovation: a contextual framework', *IEEE Transactions on Engineering Management* **44**, 276–287.

**URL:** *https://api.semanticscholar.org/CorpusID:111098184*

Bandaly, D., Satir, A. and Shanker, L. (2014), 'Integrated supply chain risk management via operational methods and financial instruments', *International Journal of Production Research* **52**(7), 2007–2025.

Banerjee, A., Lücker, F. and Ries, J. M. (2021*a*), 'An empirical analysis of suppliers' trade-off behaviour in adopting digital supply chain financing solutions', *International Journal of Operations & Production Management* **41**(4), 313–335.

Banerjee, A., Lücker, F. and Ries, J. M. (2021*b*), 'An empirical analysis of suppliers' trade-off behaviour in adopting digital supply chain financing solutions', *International Journal of Operations & Production Management* **41**(4), 313–335.

Beck, T., Demirgüç-Kunt, A. and Maksimovic, V. (2005), 'Financial and legal constraints to growth: does firm size matter?', *The journal of finance* **60**(1), 137–177.

Berger, A. N. and Udell, G. F. (2006), 'A more complete conceptual framework for sme finance', *Journal of Banking & Finance* **30**(11), 2945–2966.

Birkie, S. E., Trucco, P. and Fernandez Campos, P. (2017), 'Effectiveness of resilience capabilities in mitigating disruptions: leveraging on supply chain structural complexity', *Supply Chain Management: An International Journal* **22**(6), 506–521.

Blackhurst, J., Dunn, K. S. and Craighead, C. W. (2011), 'An empirically derived framework of global supply resiliency', *Journal of business logistics* **32**(4), 374–391.

Botta, A., Höll, R., Jain, R., Shah, N. and Tan, L. H. (2020), 'Supply-chain finance: A case of convergent evolution?', *The 2020 McKinsey Global Payments Report* pp. 19–26.

Boyabatlı, O., Leng, T. and Toktay, L. B. (2016), 'The impact of budget constraints on flexible vs. dedicated technology choice', *Management Science* **62**(1), 225–244.

Brandon-Jones, E., Squire, B., Autry, C. W. and Petersen, K. J. (2014), 'A contingent resource-based perspective of supply chain resilience and robustness', *Journal of Supply Chain Management* **50**(3), 55–73.

Brinckmann, J., Salomo, S. and Gemuenden, H. G. (2011), 'Financial management competence of founding teams and growth of new technologybased firms', *Entrepreneurship Theory and Practice* **35**(2), 217–243.
**URL:** *https://doi.org/10.1111/j.1540-6520.2009.00362.x*

Brockhoff, K. (1994), 'R&d project termination decisions by discriminant analysis-an international comparison', *IEEE Transactions on Engineering Management* **41**(3), 245–254.

Brusset, X. and Teller, C. (2017), 'Supply chain capabilities, risks, and resilience', *International Journal of Production Economics* **184**, 59–68.

Buzacott, J. A. and Zhang, R. Q. (2004), 'Inventory management with asset-based financing', *Management Science* **50**(9), 1274–1292.

Campello, M., Graham, J. R. and Harvey, C. R. (2010), 'The real effects of financial constraints: Evidence from a financial crisis', *Journal of Financial Economics* **97**(3), 470–487.

Cavanaugh, J. E. and Neath, A. A. (2019), 'The akaike information criterion: Background, derivation, properties, application, interpretation, and refinements', *Wiley Interdisciplinary Reviews: Computational Statistics* **11**(3), e1460.

Centobelli, P., Cerchione, R. and Ertz, M. (2020), 'Managing supply chain resilience to pursue business and environmental strategies', *Business Strategy and the Environment* **29**(3), 1215–1246.

Chakraborty, T., Chauhan, S. S. and Ouhimmou, M. (2020), 'Mitigating supply disruption with a backup supplier under uncertain demand: competition vs. cooperation', *International Journal of Production Research* **58**(12), 3618–3649.

Chakuu, S., Masi, D. and Godsell, J. (2019), 'Exploring the relationship between mechanisms, actors and instruments in supply chain finance: A systematic literature review', *International Journal of Production Economics* **216**, 35–53.

Chen, J. Z. and Shane, P. B. (2014), 'Changes in cash: persistence and pricing implications', *Journal of Accounting Research* **52**(3), 599–634.

Chen, X., Wang, C. and Li, S. (2023), 'The impact of supply chain finance on corporate social responsibility and creating shared value: A case from the emerging economy', *Supply Chain Management: An International Journal* **28**(2), 324–346.

Choi, T.-M. and Shi, X. (2022), 'Reducing supply risks by supply guarantee deposit payments in the fashion industry in the new normal after covid-19', *Omega* **109**, 102605.

Choi, T. Y., Rogers, D. and Vakil, B. (2020), 'Coronavirus is a wake-up call for supply chain management', *Harvard Business Review* **27**(1), 364–398.

Chopra, S. and Sodhi, M. S. (2004), 'Managing risk to avoid supply-chain breakdown', *MIT Sloan management review* .

Chowdhury, M. M. H. and Quaddus, M. (2016), 'Supply chain readiness, response and recovery for resilience', *Supply Chain Management: An International Journal* .

Chowdhury, M. M. H. and Quaddus, M. (2017), 'Supply chain resilience: Conceptualization and scale development using dynamic capability theory', *International Journal of Production Economics* **188**, 185–204.

Cohen, M. A., Cui, S., Doetsch, S., Ernst, R., Huchzermeier, A., Kouvelis, P., Lee, H. L., Matsuo, H. and Tsay, A. (2020), 'Putting supply chain resilience theory into practise', *Management and Business Review, Forthcoming, Georgetown McDonough School of Business Research Paper* .

Cohen, M. A. and Kouvelis, P. (2021), 'Revisit of aaa excellence of global value chains: Robustness, resilience, and realignment', *Production and Operations Management* **30**(3), 633–643.

Cohen, M., Cui, S., Doetsch, S., Ernst, R., Huchzermeier, A., Kouvelis, P., Lee, H., Matsuo, H. and Tsay, A. (2022*a*), Understanding global supply chain and resilience: Theory and practice, *in* 'Creating Values with Operations and Analytics: A Tribute to the Contributions of Professor Morris Cohen', Springer, pp. 287–311.

Cohen, M., Cui, S., Doetsch, S., Ernst, R., Huchzermeier, A., Kouvelis, P., Lee, H., Matsuo, H. and Tsay, A. A. (2022*b*), 'Bespoke supply-chain resilience: the gap between theory and practice', *Journal of Operations Management* **68**(5), 515–531.

Cooley, P. L. and Pullen, R. J. (1979), 'Small business cash management practices', *American Journal of Small Business* **4**(2), 1–8.
**URL:** *https://doi.org/10.1177/104225877900400201*

Cox, D. R. (1972), 'Regression models and life tables (with discussion)', *Journal of the Royal Statistical Society* **34**(2), 187–220.

Cunningham, S. (2021), *Causal inference: The mixtape*, Yale university press.

Daft, R. L. (2015), *Organization theory and design*, Cengage learning.

Dello Iacono, U., Reindorp, M. and Dellaert, N. (2015), 'Market adoption of reverse factoring', *International Journal of Physical Distribution & Logistics Management* **45**(3), 286–308.

Denis, D. J. (2011), 'Financial flexibility and corporate liquidity', *Journal of corporate finance* **17**(3), 667–674.

Devaraj, S., Vaidyanathan, G. and Mishra, A. N. (2012), 'Effect of purchase volume flexibility and purchase mix flexibility on e-procurement performance: An analysis of two perspectives', *Journal of Operations Management* **30**(7), 509–520.

**URL:** *https://www.sciencedirect.com/science/article/pii/S0272696312000551*

Ding, W. and Wan, G. (2020), 'Financing and coordinating the supply chain with a capital-constrained supplier under yield uncertainty', *International Journal of Production Economics* **230**, 107813.

Dong, L., Qiu, Y. and Xu, F. (2022), 'Blockchain-enabled deep-tier supply chain finance', *Manufacturing & Service Operations Management* .

El Baz, J. and Ruel, S. (2021), 'Can supply chain risk management practices mitigate the disruption impacts on supply chains resilience and robustness? evidence from an empirical survey in a covid-19 outbreak era', *International Journal of Production Economics* **233**, 107972.

Friedman, A. (2021), 'Gucci invests in sustainable supply chains with italian bank', `https://sourcingjournal.com/sustainability/sustainability-news/gucci-intesa-sanpaolo-supply-chain-sustinable-esg-italian-suppliers-289276/`. (Accessed on 02/05/2023).

Gelsomino, L. M., de Boer, R., Steeman, M. and Perego, A. (2019), 'An optimisation strategy for concurrent supply chain finance schemes', *Journal of Purchasing and Supply Management* **25**(2), 185–196.

Gelsomino, L. M., Mangiaracina, R., Perego, A. and Tumino, A. (2016), 'Supply chain finance: a literature review', *International Journal of Physical Distribution & Logistics Management* .

Gernert, A., Wuttke, D. A. and Heese, H. S. (2023), 'Sourcing and pricing decisions under upstream competition with a financially distressed supplier, endogenous bankruptcy risk, and a backup supply option', *Production and Operations Management* **Forthcoming, available online**.

Gitman, L. J., Moses, E. A. and White, I. T. (1979), 'An assessment of corporate cash management practices', *Financial Management* pp. 32–41.

Grüter, R. and Wuttke, D. A. (2017), 'Option matters: valuing reverse factoring', *International journal of production research* **55**(22), 6608–6623.

Han, Y., Chong, W. K. and Li, D. (2020), 'A systematic literature review of the capabilities and performance metrics of supply chain resilience', *International Journal of Production Research* **58**(15), 4541–4566.

Harford, J., Klasa, S. and Maxwell, W. F. (2014), 'Refinancing risk and cash holdings', *The Journal of Finance* **69**(3), 975–1012.

Herath, G. (2015), 'Supply-chain finance: The emergence of a new competitive landscape.', *McKinsey on Payments* **8**(22).

Hofmann, E. (2005), 'Supply chain finance: some conceptual insights', *Beiträge Zu Beschaffung Und Logistik* pp. 203–214.

Hohenstein, N.-O., Feisel, E., Hartmann, E. and Giunipero, L. (2015), 'Research on the phenomenon of supply chain resilience: a systematic review and paths for further investigation', *International Journal of Physical Distribution & Logistics Management* **45**(1/2), 90–117.

Hosseini, S. and Barker, K. (2016), 'A bayesian network model for resilience-based supplier selection', *International Journal of Production Economics* **180**, 68–87.

Hosseini, S., Morshedlou, N., Ivanov, D., Sarder, M., Barker, K. and Al Khaled, A. (2019), 'Resilient supplier selection and optimal order allocation under disruption risks', *International Journal of Production Economics* **213**, 124–137.

Hu, M., Qian, Q. and Yang, S. A. (2018), 'Financial pooling in a supply chain (March 5, 2018)'. Rotman School of Management Working Paper No. 2783833. Available at SSRN: https://ssrn.com/abstract=2783833.

Huang, C., Chan, F. T. and Chung, S. (2022), 'The impact of payment term extensions on the working capital management of an automotive supply chain', *International Journal of Production Research* **60**(24), 7360–7383.

Hurtrez, N. and Salvadori, M. G. (2010), 'Supply chain finance: From myth to reality', *McKinsey on Payments* pp. 22–28.

Jack, E. P. and Raturi, A. (2002), 'Sources of volume flexibility and their impact on performance', *Journal of operations management* **20**(5), 519–548.

Jacobs, B. I. and Levy, K. N. (1988), 'Calendar anomalies: Abnormal returns at calendar turning points', *Financial Analysts Journal* **44**(6), 28–39.

Jain, V., Kumar, S., Soni, U. and Chandra, C. (2017), 'Supply chain resilience: model development and empirical analysis', *International Journal of Production Research* **55**(22), 6779–6800.

Jeenas, P. (2019), 'Firm balance sheet liquidity, monetary policy shocks, and investment dynamics', *Work* **5**.

Jia, F., Blome, C., Sun, H., Yang, Y. and Zhi, B. (2020), 'Towards an integrated conceptual framework of supply chain finance: An information processing perspective', *International Journal of Production Economics* **219**, 18–30.

Jiang, S., Yeung, A. C., Han, Z. and Huo, B. (2023), 'The effect of customer and supplier concentrations on firm resilience during the covid-19 pandemic: resource dependence and power balancing', *Journal of Operations Management* **69**(3), 497–518.

Journal Citation Report (2023), 'Journals', `https://jcr.clarivate.com/jcr/browse-journals?app=jcr&referrer=target%3Dhttps:%2F%2Fjcr.clarivate.com%2Fjcr%2Fbrowse-journals&Init=Yes&authCode=ekqkxgWPGhWSnZPhNZkl0SODOqu-q0J9Vwx6LyqiT8Q&SrcApp=IC2LS`. (Accessed on 25/04/2023).

Juan, S.-J. and Li, E. Y. (2023), 'Financial performance of firms with supply chains during the covid-19 pandemic: the roles of dynamic capability and supply chain resilience', *International Journal of Operations & Production Management* **43**(5), 712–737.

Jüttner, U. and Maklan, S. (2011), 'Supply chain resilience in the global financial crisis: an empirical study', *Supply chain management: An international journal* **16**(4), 246–259.

Kähkönen, A.-K., Evangelista, P., Hallikas, J., Immonen, M. and Lintukangas, K. (2023), 'Covid-19 as a trigger for dynamic capability development and supply chain resilience improvement', *International Journal of Production Research* **61**(8), 2696–2715.

Kamalahmadi, M. and Mellat-Parast, M. (2016), 'Developing a resilient supply chain through supplier flexibility and reliability assessment', *International Journal of Production Research*

**54**(1), 302–321.

Kim, C. and Bettis, R. A. (2014), 'Cash is surprisingly valuable as a strategic asset', *Strategic Management Journal* **35**(13), 2053–2063.

Kim, S. T., Lee, H.-H. and Hwang, T. (2020), 'Logistics integration in the supply chain: a resource dependence theory perspective', *International Journal of Quality Innovation* **6**, 1–14.

Kim, Y., Chen, Y.-S. and Linderman, K. (2015), 'Supply network disruption and resilience: A network structural perspective', *Journal of Operations Management* **33-34**, 43–59.
**URL:** *https://www.sciencedirect.com/science/article/pii/S0272696314000746*

Kling, G., Paul, S. Y. and Gonis, E. (2014), 'Cash holding, trade credit and access to short-term bank finance', *International Review of Financial Analysis* **32**, 123–131.

Knemeyer, A. M., Zinn, W. and Eroglu, C. (2009), 'Proactive planning for catastrophic events in supply chains', *Journal of operations management* **27**(2), 141–153.

Kochan, C. G. and Nowicki, D. R. (2018), 'Supply chain resilience: a systematic literature review and typological framework', *International Journal of Physical Distribution & Logistics Management* .

Kortmann, S., Gelhard, C., Zimmermann, C. and Piller, F. T. (2014), 'Linking strategic flexibility and operational efficiency: The mediating role of ambidextrous operational capabilities', *Journal of Operations Management* **32**(7), 475–490. Special Issue on Implementing Operations Strategy for Competitive Advantage.
**URL:** *https://www.sciencedirect.com/science/article/pii/S0272696314000667*

Kotomin, V. and Winters, D. B. (2006), 'Quarter-end effects in banks: preferred habitat or window dressing?', *Journal of Financial Services Research* **29**, 61–82.

Kouvelis, P. and Xu, F. (2021*a*), 'A supply chain theory of factoring and reverse factoring', *Management Science* **67**(10), 6071–6088.

Kouvelis, P. and Xu, F. (2021*b*), 'A supply chain theory of factoring and reverse factoring', *Management Science* **67**(10), 6071–6088.

Kouvelis, P. and Zhao, W. (2012), 'Financing the newsvendor: Supplier vs. bank, and the structure of optimal trade credit contracts', *Operations Research* **60**(3), 556–580.

Kouvelis, P. and Zhao, W. (2016), 'Supply chain contract design under financial constraints and bankruptcy costs', *Management Science* **62**(8), 2341–2357.

Lee, H., Tang, C., Yang, S. A. and Zhang, Y. (2022), 'Dynamic trade finance in the presence of information frictions and fintech', *Manufacturing & Service Operations Management* .

Lekkakos, S. D. and Serrano, A. (2016), 'Supply chain finance for small and medium sized enterprises: the case of reverse factoring', *International Journal of Physical Distribution & Logistics Management* .

Li, L., Wang, Z., Chen, L., Zhao, X. and Yang, S. (2023), 'Supply chain collaboration and supply chain finance adoption: the moderating role of information transparency and transaction dependence', *Supply Chain Management: An International Journal* **28**(4), 710–723.

Liebl, J., Hartmann, E. and Feisel, E. (2016), 'Reverse factoring in the supply chain: objectives, antecedents and implementation barriers', *International Journal of Physical Distribution & Logistics Management* **46**(4).

Liu, F., Fang, M., Park, K. and Chen, X. (2021), 'Supply chain finance, performance and risk: How do smes adjust their buyer-supplier relationship for competitiveness?', *Journal of Competitiveness* .

Liu, H. and Wei, S. (2022), 'Leveraging supply chain disruption orientation for resilience: the roles of supply chain risk management practices and analytics capability', *International Journal of Physical Distribution & Logistics Management* **52**(9/10), 771–790.

Ma, H.-L., Wang, Z. and Chan, F. T. (2020), 'How important are supply chain collaborative factors in supply chain finance? a view of financial service providers in china', *International Journal of Production Economics* **219**, 341–346.

Macdonald, J. R. and Corsi, T. M. (2013), 'Supply chain disruption management: Severe events, recovery, and performance', *Journal of Business Logistics* **34**(4), 270–288.

Macdonald, J. R., Zobel, C. W., Melnyk, S. A. and Griffis, S. E. (2018), 'Supply chain risk and resilience: theory building through structured experiments and simulation', *International Journal of Production Research* **56**(12), 4337–4355.

Mackay, J., Munoz, A. and Pepper, M. (2020), 'Conceptualising redundancy and flexibility towards supply chain robustness and resilience', *Journal of Risk Research* **23**(12), 1541–1561.

Martin, J. and Hofmann, E. (2019), 'Towards a framework for supply chain finance for the supply side', *Journal of Purchasing and Supply Management* **25**(2), 157–171.

Melander, O., Sandström, M. and von Schedvin, E. (2017), 'The effect of cash flow on investment: an empirical test of the balance sheet theory', *Empirical Economics* **53**, 695–716.

Melnyk, S. A., Pagell, M., Jorae, G. and Sharpe, A. S. (1995), 'Applying survival analysis to operations management: Analyzing the differences in donor classes in the blood donation process', *Journal of Operations Management* **13**(4), 339–356.

Mentzer, J. T., DeWitt, W., Keebler, J. S., Min, S., Nix, N. W., Smith, C. D. and Zacharia, Z. G. (2001), 'Defining supply chain management', *Journal of Business Logistics* **22**(2), 1–25.

**URL:** *https://onlinelibrary.wiley.com/doi/abs/10.1002/j.2158-1592.2001.tb00001.x*

Moretto, A. and Caniato, F. (2021), 'Can supply chain finance help mitigate the financial disruption brought by covid-19?', *Journal of Purchasing and Supply Management* **27**(4), 100713.

Moretto, A., Grassi, L., Caniato, F., Giorgino, M. and Ronchi, S. (2019), 'Supply chain finance: From traditional to supply chain credit rating', *Journal of Purchasing and Supply Management* **25**(2), 197–217.

Müller, J., Hoberg, K. and Fransoo, J. C. (2023), 'Realizing supply chain agility under time pressure: Ad hoc supply chains during the covid-19 pandemic', *Journal of Operations Management* **69**(3), 426–449.

Münch, C. and Hartmann, E. (2023), 'Transforming resilience in the context of a pandemic: results from a cross-industry case study exploring supply chain viability', *International Journal of Production Research* **61**(8), 2544–2562.

Nair, A., Nicolae, M. and Narasimhan, R. (2013), 'Examining the impact of clinical quality and clinical flexibility on cardiology unit performancedoes experiential quality act as a

specialized complementary asset?', *Journal of Operations Management* **31**(7), 505–522.
**URL:** *https://www.sciencedirect.com/science/article/pii/S027269631300079X*

Namdar, J., Li, X., Sawhney, R. and Pradhan, N. (2018), 'Supply chain resilience for single and multiple sourcing in the presence of disruption risks', *International Journal of Production Research* **56**(6), 2339–2360.

Nigro, G. L., Favara, G. and Abbate, L. (2021), 'Supply chain finance: The role of credit rating and retailer effort on optimal contracts', *International Journal of Production Economics* **240**, 108235.

Opler, T., Pinkowitz, L., Stulz, R. and Williamson, R. (1999), 'The determinants and implications of corporate cash holdings', *Journal of financial economics* **52**(1), 3–46.

Orgler, Y. E. (1969), 'An unequal-period model for cash management decisions', *Management Science* **16**(2), B–77.

Ozdemir, D., Sharma, M., Dhir, A. and Daim, T. (2022), 'Supply chain resilience during the covid-19 pandemic', *Technology in Society* **68**, 101847.

Pate-Cornell, M., Tagaras, G. and Eisenhardt, K. (1990), 'Dynamic optimization of cash flow management decisions: a stochastic model', *IEEE Transactions on Engineering Management* **37**(3), 203–212.

Patel, P. C., Terjesen, S. and Li, D. (2012), 'Enhancing effects of manufacturing flexibility through operational absorptive capacity and operational ambidexterity', *Journal of Operations Management* **30**(3), 201–220.
**URL:** *https://www.sciencedirect.com/science/article/pii/S0272696311001136*

Pellegrino, R., Costantino, N. and Tauro, D. (2019), 'Supply chain finance: A supply chain-oriented perspective to mitigate commodity risk and pricing volatility', *Journal of Purchasing and Supply Management* **25**(2), 118–133.

Pettit, T. J., Croxton, K. L. and Fiksel, J. (2013), 'Ensuring supply chain resilience: development and implementation of an assessment tool', *Journal of business logistics* **34**(1), 46–76.

Pettit, T. J., Croxton, K. L. and Fiksel, J. (2019), 'The evolution of resilience in supply chain management: a retrospective on ensuring supply chain resilience', *Journal of Business Logistics* **40**(1), 56–65.

Pettit, T. J., Fiksel, J. and Croxton, K. L. (2010), 'Ensuring supply chain resilience: development of a conceptual framework', *Journal of business logistics* **31**(1), 1–21.

Peura, H., Yang, S. A. and Lai, G. (2017), 'Trade credit in competition: A horizontal benefit', *Manufacturing & Service Operations Management* **19**(2), 263–289.

Pfeffer, J. and Salancik, G. R. (2006), *The external control of organizations : a resource dependence perspective*, 1 edn, Stanford Business Books.

Phraknoi, N., Busby, J. and Stevenson, M. (2022), 'The relational focus of small and medium sized actors' understandings of supply chain finance (scf)', *International Journal of Operations & Production Management* **42**(9), 1435–1466.

Piprani, A. Z., Jaafar, N. I., Ali, S. M., Mubarik, M. S. and Shahbaz, M. (2022), 'Multi-dimensional supply chain flexibility and supply chain resilience: the role of supply chain risks exposure', *Operations Management Research* **15**(1-2), 307–325.

Qiao, R. and Zhao, L. (2023), 'Highlight risk management in supply chain finance: effects of supply chain risk management capabilities on financing performance of small-medium enterprises', *Supply Chain Management: An International Journal* .

Queiroz, M. M., Wamba, S. F., Jabbour, C. J. C. and Machado, M. C. (2022), 'Supply chain resilience in the uk during the coronavirus pandemic: a resource orchestration perspective', *International Journal of Production Economics* **245**, 108405.

Raghavan, N. S. and Mishra, V. K. (2011), 'Short-term financing in a cash-constrained supply chain', *International Journal of Production Economics* **134**(2), 407–412.

Raj, A., Mukherjee, A. A., de Sousa Jabbour, A. B. L. and Srivastava, S. K. (2022), 'Supply chain management during and post-covid-19 pandemic: Mitigation strategies and practical lessons learned', *Journal of business research* **142**, 1125–1139.

Revilla, E. and Saenz, M. J. (2017), 'The impact of risk management on the frequency of supply chain disruptions: a configurational approach', *International Journal of Operations & Production Management* **37**(5), 557–576.

Ronchini, A., Moretto, A. and Caniato, F. (2021), 'A decision framework for inventory-and equipment-based supply chain finance solutions', *Journal of Purchasing and Supply Management* **27**(4), 100712.

Sáenz, M. J., Revilla, E. and Acero, B. (2018), 'Aligning supply chain design for boosting resilience', *Business Horizons* **61**(3), 443–452.

Salama, M. R. and McGarvey, R. G. (2023), 'Resilient supply chain to a global pandemic', *International Journal of Production Research* **61**(8), 2563–2593.

Salancik, G. R. and Pfeffer, J. (1977), 'Who gets powerand how they hold on to it: A strategic-contingency model of power', *Organizational dynamics* **5**(3), 3–21.

Salecka, L. (2021), 'Covid-19 turbo charges take-up of supply chain finance', `https://www.theglobaltreasurer.com/2021/10/18/covid-19-turbo-charges-take-up-of-supply-chain-finance/`. (Accessed on 26/04/2023).

Sandberg, E. (2021), 'Dynamic capabilities for the creation of logistics flexibility–a conceptual framework', *The international journal of logistics management* **32**(2), 696–714.

Sawhney, R. (2006), 'Interplay between uncertainty and flexibility across the value-chain: towards a transformation model of manufacturing flexibility', *Journal of operations management* **24**(5), 476–493.

Sawhney, R. (2013), 'Implementing labor flexibility: A missing link between acquired labor flexibility and plant performance', *Journal of Operations Management* **31**(1), 98–108. Behavioral Operations.

**URL:** *https://www.sciencedirect.com/science/article/pii/S0272696312000824*

Scheibe, K. P. and Blackhurst, J. (2018), 'Supply chain disruption propagation: a systemic risk and normal accident theory perspective', *International Journal of Production Research* **56**(1-2), 43–59.

Scholten, K. and Schilder, S. (2015), 'The role of collaboration in supply chain resilience', *Supply Chain Management: An International Journal* **20**(4), 471–484.

Scholten, K., Sharkey Scott, P. and Fynes, B. (2014), 'Mitigation processes–antecedents for building supply chain resilience', *Supply Chain Management: an international journal* **19**(2), 211–228.

Sheffi, Y. and Rice, J. B. (2005), 'A supply chain view of the resilient enterprise', *MIT Sloan management review* .

Shen, Z. M. and Sun, Y. (2021), 'Strengthening supply chain resilience during covid-19: A case study of jd. com', *Journal of Operations Management* .

Shen, Z. M. and Sun, Y. (2023), 'Strengthening supply chain resilience during covid-19: A case study of jd. com', *Journal of Operations Management* **69**(3), 359–383.

Shou, Y., Shao, J. and Wang, W. (2021), 'How does reverse factoring affect operating performance? an event study of chinese manufacturing firms', *International Journal of Operations & Production Management* **41**(4), 289–312.

Siemens (n.d.), 'Supply chain finance - an alternative form of finance', `https://new.siemens.com/global/en/company/about/corporate-functions/supply-chain-management/collaborating-with-siemens/supply-chain-finance.html`. Accessed: 2021-06-24.

Sim, J., Cho, D., Hwang, Y. and Telang, R. (2022), 'Frontiers: virus shook the streaming star: estimating the covid-19 impact on music consumption', *Marketing Science* **41**(1), 19–32.

Sodhi, M. S., Son, B.-G. and Tang, C. S. (2012), 'Researchers' perspectives on supply chain risk management', *Production and operations management* **21**(1), 1–13.

Soenen, L. A. and Aggarwal, R. (1989), 'Cash and foreign exchange management: Theory and corporate practice in three countries', *Journal of Business Finance & Accounting* **16**(5), 599–619.

**URL:** *https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1468-5957.1989.tb00041.x*

Tang, C. S., Yang, S. A. and Wu, J. (2018), 'Sourcing from suppliers with financial constraints and performance risk', *Manufacturing & Service Operations Management* **20**(1), 70–84.

Tanrisever, F., Cetinay, H., Reindorp, M. and Fransoo, J. C. (2015), 'Value of reverse factoring in multi-stage supply chains', *Available at SSRN 2183991* .

Tanrısever, F., Erzurumlu, S. S. and Joglekar, N. (2012), 'Production, process investment, and the survival of debt-financed startup firms', *Production and Operations Management* **21**(4), 637–652.

Tranfield, D., Denyer, D. and Smart, P. (2003), 'Towards a methodology for developing evidence-informed management knowledge by means of systematic review', *British journal of management* **14**(3), 207–222.

Tremblay, M., Côté, J. and Balkin, D. B. (2003), 'Explaining sales pay strategy using agency, transaction cost and resource dependence theories', *Journal of Management Studies* **40**(7), 1651–1682.

Tukamuhabwa, B. R., Stevenson, M., Busby, J. and Zorzini, M. (2015), 'Supply chain resilience: definition, review and theoretical foundations for further study', *International journal of production research* **53**(18), 5592–5623.

Van der Vliet, K., Reindorp, M. J. and Fransoo, J. C. (2015), 'The price of reverse factoring: Financing rates vs. payment delays', *European Journal of Operational Research* **242**(3), 842–853.

Vega, D., Arvidsson, A. and Saiah, F. (2023), 'Resilient supply management systems in times of crisis', *International Journal of Operations & Production Management* **43**(1), 70–98.

Walmart (2021), 'Walmart creates industry first by introducing science-based targets for supply chain finance program', `https://www.crxmarkets.com/nestle-case-study/`. (Accessed on 07/06/2023).

Web of Science (2023), 'Search', `https://www.webofscience.com/wos/author/search`. (Accessed on 25/04/2023).

Wetzel, P. and Hofmann, E. (2019), 'Supply chain finance, financial constraints and corporate performance: An explorative network analysis and future research agenda', *International Journal of Production Economics* **216**, 364–383.

Wissuwa, F., Durach, C. F. and Choi, T. Y. (2022), 'Selecting resilient suppliers: Supplier complexity and buyer disruption', *International Journal of Production Economics* **253**, 108601.

Wu, A. (2021), 'Supporting a capital-constrained supplier with mixed pre-shipment financing facilities', *International Journal of Production Research* pp. 1–14.

Wu, A. (2022), 'Purchasing from multiple capital-constrained suppliers using order financing', *International Journal of Production Research* pp. 1–16.

Wu, S.-M., Chan, F. T. and Chung, S. (2022), 'The impact of buyback support on financing strategies for a capital-constrained supplier', *International Journal of Production Economics* **248**, 108457.

Wu, Y., Wang, Y., Xu, X. and Chen, X. (2019), 'Collect payment early, late, or through a third party's reverse factoring in a supply chain', *International Journal of Production Economics* **218**, 245–259.

Wuttke, D. A., Blome, C., Foerstl, K. and Henke, M. (2013), 'Managing the innovation adoption of supply chain financeempirical evidence from six european case studies', *Journal of Business Logistics* **34**(2), 148–166.

Wuttke, D. A., Blome, C., Heese, H. S. and Protopappa-Sieke, M. (2016), 'Supply chain finance: Optimal introduction and adoption decisions', *International Journal of Production Economics* **178**, 72–81.

Wuttke, D. A., Blome, C. and Henke, M. (2013), 'Focusing the financial flow of supply chains: An empirical investigation of financial supply chain management', *International journal of production economics* **145**(2), 773–789.

Wuttke, D. A., Rosenzweig, E. D. and Heese, H. S. (2019), 'An empirical analysis of supply chain finance adoption', *Journal of Operations Management* **65**(3), 242–261.

Xu, X., Chen, X., Jia, F., Brown, S., Gong, Y. and Xu, Y. (2018), 'Supply chain finance: A systematic literature review and bibliometric analysis', *International Journal of Production Economics* **204**, 160–173.

Yan, B., Chen, Z., Yan, C., Zhang, Z. and Kang, H. (2021), 'Evolutionary multiplayer game analysis of accounts receivable financing based on supply chain financing', *International Journal of Production Research* pp. 1–19.

Yang, H., Sun, F., Chen, J. and Chen, B. (2019), 'Financing decisions in a supply chain with a capital-constrained manufacturer as new entrant', *International Journal of Production Economics* **216**, 321–332.

Yang, S. A. and Birge, J. R. (2018), 'Trade credit, risk sharing, and inventory financing portfolios', *Management Science* **64**(8), 3667–3689.

Yang, S. A., Birge, J. R. and Parker, R. P. (2015), 'The supply chain effects of bankruptcy', *Management Science* **61**(10), 2320–2338.

Zhao, Y., Zhou, H. and Leus, R. (2022), 'Recovery from demand disruption: Two-stage financing strategy for a capital-constrained supply chain under uncertainty', *European Journal of Operational Research* **303**(2), 699–718.