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Is Digital Transformation Tightening SMEs' Access to Debt?

Emilie Håbrekke Hangerhagen & Anna Margrete Kongshaug

Supervisor: José A. Albuquerque de Sousa

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Anna Margrete Kongshaug

Emilie Håbrekke Hangerhagen

Abstract

Is the constantly increasing technology always a blessing, or does it worsen existing challenges? This thesis analyzes how digital transformation in the financial sector affects Small and Medium Enterprises (SMEs) debt. Using the Payment Service Directive No. 2 (PSD2) as a shock into digital transformation, we employ a difference-in-differences (DiD) methodology to analyze the changes in SMEs' debt ratios triggered by digital transformation. First, our study investigates how SMEs are affected by digital transformation in the financial sector. Second, we test whether SMEs experience varying impacts depending on their characteristics. With this approach, we aim to understand the reasons behind the effect of digital transformation on SMEs' debt in the financial sector.

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1. Introduction

This thesis aims to analyze the impact of digital transformation in the financial sector on Small and Medium Enterprises' (SMEs') debt. Using a difference-in-differences methodology, with the Payment Service Directive No. 2 as a shock to digital transformation, we find a statistically significant effect on the debt ratios of SMEs. The difference-in-differences estimators indicate a modest reduction of 0.004 and 0.005 in SMEs' debt ratios in 2019 and 2020, compared to the average decrease in debt ratios of 0.018 and 0.028 in those respective years.

Central to our discussion is the increasing preference for quantifiable (hard) information in lending decisions, a trend accelerated by technological advancements continually redefining what information can be quantified. While this greater reliance on hard information, and the diminishing role of soft information are widely acknowledged, the impact of this shift on Small and Medium Enterprises (SMEs') debt levels is subject to inconsistent evidence. One perspective suggests that the increased availability of hard information can assist lending institutions in enhancing the availability and precision of information and improve the banks' understanding of a firm's creditworthiness, making it easier to provide loans. However, an opposing view points out that SMEs often have less hard information and rely more on soft information. This reliance potentially worsens information asymmetry, making it more challenging for SMEs to secure debt financing from lenders.

In our study, we use PSD2 as a shock into digital transformation in the financial sector to capture the effect of digital transformation on SME debt. PSD2 mandates banks to share third-party access to consumer payment accounts, enabling third-parties to offer financial services independently of conventional banking infrastructure and consumer scale. This shift diversifies financing service providers, reducing SMEs' reliance on only traditional bank financing and offering alternatives that may better suit their needs.

To analyze the effects of digital transformation on SME debt, we employ a difference-in-differences (DiD) approach complemented by the Propensity Score Matching (PSM) technique. With this method, we capitalize on the staggered implementation of PSD2 in Sweden and Norway. We create a control group of Norwegian SMEs, as similar as possible to the treatment group of Swedish SMEs, to isolate the directive's effects from other concurrent economic factors. Furthermore, we use a triple difference-in-differences (DDD) framework to shed light on the underlying reasons for the effects of digital transformation in the financial sector on SMEs by distinguishing them by size, age, and revenue growth. For each model, we present results from regressions three years before and after the treatments and results from detailed year-by-year model regressions.

The year-by-year DiD model finds that digital transformation in the financial sector decreases SMEs' debt ratios. However, in our subsequent triple difference-in-differences (DDD) models, we do not find that firms that we expect to rely more on soft information are disproportionately affected compared to those that do not. We theorize that the lack of distinction between these firms results from the ongoing digitalization. Today's firms are more digitally integrated, facilitating greater accessibility to crucial information through tools like accounting programs. Furthermore, digital transformation may blur the lines between hard and soft information, with more soft data being converted into hard data. Financial innovation and the emergence of fintech, driven by digital transformation and PSD2, provide more tailored tools, such as crowdfunding, enabling them to address the financing needs of SMEs more effectively than traditional banks.

Our unique contribution lies in revealing a more complex understanding of how digital transformation in the financial sector may affect SMEs' debt and analyzing the effect of digital transformation on SMEs in two of the most technology-adapting countries in the world (*World Digital Competitiveness Ranking*, 2022). Existing literature specifically points to the lack of use of soft information as a crucial reason why SMEs may be negatively affected by digital transformation. Through our literature review and discussion, we find that the answer might be more complex by shedding light on how digital transformation may affect market dynamics, changes in the distinction between hard and soft information, and the different effects of digital transformation in banks and fintechs as significant market participants.

The thesis identifies statistically significant outcomes in the year-by-year difference-in-differences model. However, we cannot conclude a causal relationship between digital transformation in the financial sector and SMEs' debt ratios due to constraints within the models and the available data. The presence of omitted variable bias, likely heightened by the COVID-19 pandemic, poses challenges that our analysis cannot sufficiently address.

Additionally, in the three-year average difference-in-difference model, the DiD estimator neither display a consistent negative direction nor achieve statistical significance. This further underscores the complexity of attributing observed effects to a causal relationship between digital transformation and SME debt.

2. Literature Review

This section presents a literature review on hard, soft, and asymmetric information, exploring its shift due to digital transformation in the financial sector and its relation to SMEs' debt ratios. We discuss the impact of digital transformation on market dynamics within the financial sector and elaborate on the role of PSD2 and its potential to reshape SME financing. Additionally, we delve into various SME characteristics and examine how these factors influence the impact of digital transformation on SMEs. Finally, we introduce our hypothesis.

2.1 Technological Impact on Hard and Soft Information and SME Debt

A critical aspect of digital transformation is its influence on the information prioritized by lenders, specifically the shift from soft to hard information. Hard information is characterized by Liberti & Petersen (2018) as standardized and quantifiable data that can be easily gathered, stored, and digitally transmitted. In contrast, soft information encompasses non-quantifiable data that must be collected in person, often through text, ideas, opinions, rumors, and management's plans (Liberti & Petersen, 2018). There is a general agreement that technology enhances the processing of hard information, diminishing the reliance on soft information. However, the literature presents conflicting evidence regarding whether this shift is benefits or harms SMEs' debt ratio.

On the one hand, Sheng's study (2021) supports that fintech effectively facilitates the banking sector's credit supply to SMEs. The information provided by Internet banking platforms has the potential to assist lending institutions in enhancing the availability and precision of information and improve the understanding that banks have of a firm's creditworthiness, making it easier to provide loans.

From a different point of view, Fasano & Cappas study (2022) discovered that SMEs using Internet banking reported less debt than SMEs that did not. The research highlighted that banks rely heavily on hard information from fintech tools, creating a distance between the bank and the firm. This distance hinders the collection of soft information, consequently impacting the credit provision. The study concluded that fintech is exacerbating information asymmetry problems rather than alleviating them. It also emphasizes the importance of soft information, asserting that it cannot be substituted by hard, digital information.

Several studies suggest that the increasing emphasis on data collection and processing could have adverse implications for SMEs. DeYoung et al. (2007) state that prioritizing quantifiable data might hamper gathering soft information. As smaller businesses rely heavily on this qualitative data, as McCann & McIndoe-Calder (2015) demonstrated, a limited collection of soft information might restrict SMEs from accessing credit. Moro & Fink (2013) underscore the significance of soft information in establishing trust between borrowers and lenders, leading to increased access to credit. Thus, the rise of technology and data sharing raises concerns about potential decreases in debt accessibility for SMEs.

The significance of information in financial transactions is closely tied to information asymmetry, which emerges when there is a lack of either hard or soft information. In the context of the banking sector and lending agreements, information asymmetry plays a crucial role. As explained by Bloomenthal (2021), asymmetric information arises when one party in a transaction possesses more or superior information compared to the other. The existence of intermediaries like banks is primarily rooted in their capacities to mitigate asymmetric information (Leland & Pyle, 1977).

Through deposit and transaction services, banks gain access to privileged information about current and potential borrowers, and this information enables banks to assess borrowers' creditworthiness and validate their transactions (Su, 2018). Even though banks strive to handle asymmetric information, eliminating it remains beyond their reach. Borrowers often know more about their financial status and projects, providing them an informational advantage over lenders. Puschmann (2017) highlights that the precision of the information provided fundamentally anchors credit contracts in terms of financial agreements. The evident informational gap between banks and corporate entities is challenging within the banking sector. This disparity complicates the distinction between high-risk and low-risk customers.

Hard information offers a crucial advantage; operations based on standardized data can be easily automated, thanks to its consistent format. This standardization allows the creation of decision rules and computer codes, enabling the delegation of tasks to lower-skilled workers or computers, thereby reducing the reliance on costly labor. Consequently, technology makes it possible to reduce hard information asymmetries due to development in facilitating the collection, processing, and communication of standardized information.

2.2 The Evolving Distinction Between Hard and Soft Information

Based on the research of Liberti & Petersen, introducing new technology triggers a demand for new types of information, which has led to a hardening of soft information. According to Liberti & Petersen (2018), the evolution of financial markets over the past 40 years has partially replaced soft information with hard information as the basis for financial transactions. An old example was the need for credit bureaus when banks started to gain customers within a wider geographical range. Credit bureaus were local and collected soft information about the local firms and made it into two credit scores. In recent years, soft information has been hardened through, for example, textual processing, where text is coded into numerical scores. While this process can make certain soft information more concrete, it likely only captures a portion of the insights a human interpreter could gather from the original text. The fundamental challenge in this context lies in the hardening of soft information. This challenge raises whether the information derived through this process is a substitute or a complement to the bank's hard information (Liberti & Petersen, 2018).

The rise in financial entities recognized as FinTech reflects the adoption of technology to address enduring financial issues with a mix of novel and traditional approaches. Their business models increasingly rely on hard information, leveraging numeric data and systematized decisions to replace the nuanced judgment typically provided by humans. Automation has led to more efficient and cost-effective loan processing. This efficiency likely contributed to the rise in market share for fintechs from 2% in 2010 to 8% in 2016, as Fuster et al. (2019) reported. Because the lenders' ability to cross-verify submitted financials against databases helps to detect and prevent inaccuracies and fraudulent claims, the rate of defaults is unexpectedly low compared to predictions based on credit metrics such as FICO scores and loan-to-value ratios.

Technological advancements and online data have fueled the drive to transform text and figures into quantitative indices. Coupled with decreasing computational costs, there has been a significant shift towards automated decision-making. Information processing is at the core of financial institutions and markets; therefore, the dichotomy between hard and soft information is intrinsic to the ongoing transformation of the financial sector, shaping its future path (Liberti & Petersen, 2018).

2.3 Technological Impact on Market Dynamics and SME Debt Accessibility

The rise of fintech companies in the banking sector has increased market participants, subsequently enhancing the market density. Heightened competition influences the market power of established banks, which again affects the access to debt for SMEs. Existing literature presents conflicting evidence on the effect of market dynamics on SMEs. The theoretical grounding for these mixed results lies in the Market Power and Information-Based hypotheses.

The more competition in the banking landscape, the better the access to finance is for companies, as demonstrated by the study of Love & Pería (2015). A decrease in banks' market power enhances competition and increases the overall efficiency of the banking industry, therefore facilitating credit access. These findings support the Market Power Hypothesis (MPH) that suggests increased competition within the banking sector leads to lower financing costs and enhances SMEs' accessibility to credit.

Conversely, other findings suggest that increased competition harms SMEs' debt situation. The study by Wang et al. (2020) concludes that low bank market power and high competition increase SMEs' debt costs at a disaggregate level and that the impact is particularly significant for smaller SMEs with higher levels of informational opacity. The smaller the firm is, the more effective investing in relationship-based lending techniques becomes. These findings support the Information-Based Hypothesis (IBH) that intensified competition might reduce banks' motivation or increase the expense of investing in private information gathering, subsequently lowering the standards of screening and monitoring. Wang's findings support the information-based hypothesis that SME credit conditions worsen when competition in the banking market increases.

2.4 The Role of PSD2 in Transforming SME Financing

Traditional banks have often been slow to adapt to the specific financing needs of SMEs, as highlighted by Bahillo et al. (2022). This lagging adaptation is partly due to the challenges in traditional banking systems to align their services with the actual needs of SMEs, a mismatch underscored by Kumar et al. (2023). McKinsey's (2022) analysis also indicates that traditional banking processes are often not optimized for SMEs, leading to uncertainty and delays in funding. The OECD (2022) further emphasizes these challenges, particularly during economic downturns, noting SMEs' over-reliance on bank financing and vulnerability to changing credit conditions. This situation underscores the need for banks to rebuild their SME lending approach, encompassing streamlining processes, digitizing credit procedures, and establishing clear segmentation rules to enhance efficiency and improve the customer experience for SMEs.

Over the last decades, the slow-moving innovation processes in the financial sector have been due to established banks not facing significant competitive pressures to attract and retain customers. This lack of competition led to regulatory authorities, like the Competition & Markets Authority (2016) seeking ways to enhance market dynamics. In response, the European Union (EU) introduced Payment Service Directive No. 2 (PSD2). PSD2, applicable in EU and EEA member states, fosters innovation in the financial sector. It requires banks to grant third-party providers, mainly fintechs, access to consumer payment accounts. This access enables fintechs to offer financial services without traditional banking infrastructure. It addresses the scalability challenges new financial service providers previously faced, allowing them to expand their customer base more easily. Consequently, fintechs can now challenge traditional banks in every service segment, from front to back office, capturing a significant market share (Cortet et al., 2016).

2.5 Which Characteristics Affect SMEs Lending Opportunities?

A significant constraint when accessing credit for SMEs is a lack of information, a challenge mitigated through enduring relationships between banks and clients. Consequently, the company's age emerges as a crucial characteristic, initially shaping the relationship between the company and the bank and subsequently affecting the quantity and expense of debt. Prior research, including studies by Dewaelheyns & Van Hulle, (2010), Sakai et al. (2010), and Ezeoha & Botha (2012), has demonstrated a significant correlation between a company's age and its capital structure. Companies with longer track records tend to have enhanced borrowing opportunities because their established reputations and long-term relationships with lenders enable efficient information exchange, reducing information asymmetries and improving credit allocation efficiency.

Research done by Czerwonka & Jaworski (2021) has shown that firm size is a positive determinant of debt for SMEs, a conclusion supported by Chatterjee & Eyigungor (2022). The latter study indicates that the increase in maximum feasible leverage concerning firm size occurs because larger firms experience lower fluctuations in sales growth rates. Their cash flows are less volatile, reducing the risk of default on their debt obligations. Due to this decreased risk, larger companies can borrow more than smaller, riskier ones. Furthermore, McCann & McIndoe-Calder (2015) reveal a noteworthy trend wherein discriminatory power consistently rises with firm size, substantiating that smaller firms tend to become more opaque. Their study also suggests that banks dealing with larger firms can effectively differentiate between sound and risky investment proposals by employing credit scoring models essential to transaction lending technologies. In contrast, banks lending to smaller firms must gather additional qualitative information about borrowers to complement these transaction banking technologies, as credit scoring is less effective for evaluating smaller firms.

The significance of size is also highlighted by Wang et al. (2020). Their research demonstrated that high market power in banks led to reduced debt costs for SMEs at a disaggregate level. Due to high market power, this reduction was attributed to relationship-based lending, relying on qualitative, soft information. This approach favored smaller, less transparent firms that depend heavily on exchanging such information. Consequently, the study suggests that enhanced digitalization might adversely affect smaller SMEs. Increased digitalization diminishes market power and raises market competition, causing banks to invest less in relationship-based lending techniques.

2.6 Hypotheses

The literature review has provided insights into how the use of soft and hard information, market dynamics in the financial sector, and SME characteristics influence their debt levels. While the findings are sometimes inconsistent, there is a general understanding that digital transformation in the financial sector tends to decrease SME debt.

Hypothesis 1: Digital transformation in the financial sector leads to a reduction in SME debt.

To understand why SMEs potentially experience a reduction in debt due to digital transformation, we use a difference-in-difference-in-differences (DDD) model. Evaluating these three characteristics, size, age, and growth, provides insight into the effect of digital transformation. As highlighted in the literature review, soft information plays a crucial role in SME lending decisions. By examining these characteristics, we can understand how firms with varying dependence on soft information differ.

The second hypothesis posits that larger companies experience smaller decreases in debt ratio due to digital transformation. This is grounded in the literature emphasizing that smaller firms face more significant opacity-related challenges and rely more heavily on soft information. Also, a larger company experiences fewer fluctuations in its sales growth and cash flows, reducing the risk of default on its obligations and making its projects more attractive to lenders.

Hypothesis 2: Larger companies experience smaller decreases in debt ratio due to digital transformation in the financial sector.

The following hypothesis asserts that older companies experience smaller decreases in debt ratio due to digital transformation. It is presumed that more established companies, having had time to develop a relationship with their lenders, will be less impacted by the shift from soft to hard information in the lending process.

Hypothesis 3: Older companies experience smaller decreases in debt ratio due to digital transformation in the financial sector.

The last hypothesis states that growth companies experience a larger decrease in debt ratio. As the literature suggests, lower fluctuations in sales growth rates and cash flows can impact a firm's access to debt. Our analysis of growth firms in our sample serves two purposes. First, we examine if digital transformation makes securing financing harder for these firms, as they often have different needs than older or medium-sized firms. Second, we focus on growth firms because they are more likely to seek funding, to address the fact that we do not know if the SMEs in our dataset are seeking new financing.

Hypothesis 4: Growth companies experience larger decreases in debt ratio due to digital transformation in the financial sector.

3. Methodology

In this section, we outline the methodology employed in our analysis. Initially, we present the reasoning for incorporating PSD2 as an exogenous shock in our difference-in-difference (DiD) models. A detailed explanation of the DiD methodology itself follows this. Finally, we introduce our specific DiD models and extend the discussion to our triple difference-in-difference (DDD) models, elaborating on their structure and application in our analysis.

3.1 PSD2: a quasi-exogenous shock

Intending to uncover the actual influence of digital transformation on SMEs' debt, we introduce the implementation of PSD2 as the treatment, Swedish SMEs as the treatment group, and Norwegian SMEs as the control group.

We employ PSD2 as a shock into digital transformation. Following the rollout of PSD2, a significant increase in the adoption of digital financial services is anticipated. We argue that PSD2 acts as an exogenous shock to digital transformation, based on that it is an external factor not influenced by the internal participants of the banking industry. However, other macroeconomic or regulatory changes could correlate with the implementation of PSD2 and influence our outcome variable. We use Norway and Sweden as control and treatment groups to reduce this potential issue.

Moreover, the banking sectors in Norway and Sweden were likely undergoing digitalization transitions before PSD2 implementation. This indicates that banks were already adapting to digital solutions and technology, challenging the definition of PSD2 as a purely exogenous shock. Therefore, it may be more accurate to consider PSD2 as a quasi-exogenous factor, acknowledging that PSD2 originates from outside the financial sector, but it is not the only driver of all digital transformation observed during the specified period.

3.2 The Difference-In-Difference Method

One commonly employed method for assessing the impact of a reform or a policy is the difference-in-difference approach, hereby referred to as DiD. This model measures the causal impact of a treatment on a specific outcome of concern (Hansen, 2022). Employing the DiD method, one group (the treatment group) experiences a change in treatment while the other group (the control group) remains unaffected. Given that both groups exhibit a similar trend in the dependent variable before the treatment is implemented, we can attribute the effect of the policy to the difference in the difference in after vs. before the treatment for the two groups.

The control group in our study comprises Norwegian SMEs, where firms are selected through propensity score matching, while the Swedish SMEs constitute our treatment group. By analyzing the differences between Swedish SMEs' debt ratio and Norwegian SMEs' debt ratio across the periods before and after the treatment, the DiD method aims to isolate the causal effect of digital transformation on SMEs' debt levels.

An essential aspect of our study is that both Norwegian and Swedish firms will fall under the treatment as the implementation of PSD2 takes place in both countries. The key distinction lies in the timing of PSD2 implementation: it was enforced in Sweden in 2018 and in Norway in 2019, resulting in a one-year lag. Consequently, we expect Norwegian firms to adopt the same trend as Swedish firms, with a one-year delay. The exact timing of the directive's effects is uncertain; banks may need time to adjust to PSD2, and third-party providers may gradually launch their products and services. Alternatively, the directive could catalyze rapid digital transformation if the infrastructure for banks and third-party providers is already in place. To ensure we capture the effects, we employ two different DiD models.

The first DiD analysis is to understand the overall impact of digital transformation, as the effect may roll out over the years. This model incorporates year dummies to assess the impact spanning three years before and after the PSD2 directive's implementation. This approach allows us to observe whether a significant shift occurs after the directive. We aim to capture any immediate substantial effects and more distributed impacts over the following three years.

In addition, to gain a more nuanced understanding and to pinpoint the temporal dynamics of this impact, we employ a yearly DiD analysis. This method allows us to test the impact's significance immediately following the directive and to track the interaction term's path over subsequent years. We anticipate the most significant effect to manifest post-implementation in Sweden and expect Norway to mirror Sweden's pattern with a one-year delay. In other words, we predict the interaction term will reach its maximum in 2019, one year after implementation in Sweden. If Norway adopts a similar trend, this will be reflected in the interaction term, moving towards zero in 2020.

Our analysis employs the within-group fixed effects estimator, as recommended by (Wooldridge, 2020). This estimator effectively controls for unobserved heterogeneity within panel data. By capturing group-level variations of the dependent variables, the model seeks to account for those aspects of the dependent variable not explained by other independent variables. Additionally, we use clustered robust standard errors to address potential heteroscedasticity and autocorrelation within groups. This integration enhances the accuracy and robustness of our standard error estimates, with clustering specifically at the firm level.

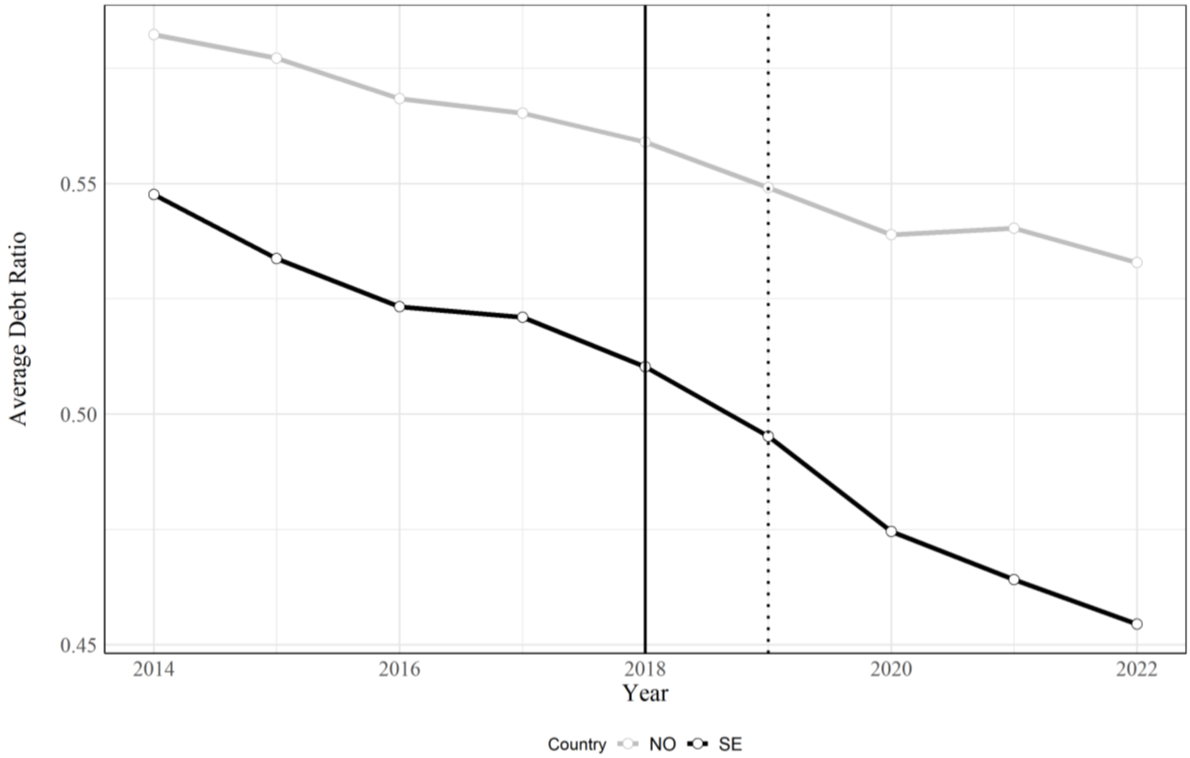
3.3 Assumptions

A fundamental assumption must be satisfied to interpret the DiD estimate as a valid causal effect. This assumption is the parallel trend, which asserts that the treatment group would have evolved similarly without the reform. In other words, the dependent variable must demonstrate a consistent trend in the treatment and control groups during the period preceding the policy change. The DiD estimator mitigates biases in the post-period comparisons between the treatment and control groups by relying on the parallel trend assumption. These biases could arise from lasting distinctions between the groups and temporal trends within the treatment group (Imbens & Wooldridge, 2007).

The anticipation effect and composition of the groups are crucial to ensure no violation of the parallel-trend assumption. Regarding anticipation effects, the established timeline for the directive's implementation was known, allowing banks to adapt to the directive criteria before the implementation date. However, we have not found any sources indicating this is a significant problem. Consistent composition of treatment and control groups is ensured across all years by dividing SMEs into groups based on their legal and operational presence in either Sweden or Norway.

To check if the parallel trend assumption is satisfied, we evaluate the trend of the debt level for SMEs in Norway and Sweden with a visual inspection. These trends are presented in Figure 3.1. Examining the debt ratio trends for Norway and Sweden, the graphs before matching show the two countries moving in a similar direction over the years, indicating parallel trends. This observation aligns with the parallel trend assumption necessary for the difference-in-differences analysis.

Figure 3.1: Debt Ratio Trends Before Matching



3.4 The DiD Regression Models

Our primary regression is designed to capture the effect of digitalization, considering that its influence might unfold progressively rather than instantaneously. To accommodate this, our model incorporates a dummy variable that averages the effect over three years before and after the treatment. This approach enables us to observe emerging effects over the three years following the directive's introduction. The regression is presented in Model 1, where $Post_t$ takes the value of 1 if the observations are from 2018, 2019, or 2020 and 0 if the observation is from 2015, 2016, or 2017.

$$\boldsymbol{Model\ 1}:$$

$$SME\ debt\ level_{i,t} = \alpha + \beta Sweden_i + \gamma Post_t + \delta\ (Sweden_i * Post_t) + \rho X_{i,t} + \varepsilon_{i,t}$$

The coefficient δ corresponds to the interaction term between $Sweden_i$ and $Post_t$ and quantifies the shift in debt level for SMEs influenced by PSD2, the Swedish companies. If this interaction term is statistically significant, it suggests that Swedish SMEs, on average, have experienced a change in their debt level relative to their Norwegian counterparts due to the implementation of PSD2. We anticipate a slight negative impact on the difference-in-differences estimator. Considering the possibility that Norway may follow a trend similar to Sweden's, this impact is expected to be marginal. Consequently, the results might show little statistical significance, particularly if the effects of digital transformation become more pronounced immediately following the directive.

Our subsequent DiD model will examine the effect pattern in more detail. The directive's impact is anticipated to become progressively evident over time, gradually tapering off as Swedish and Norwegian SMEs adapt to the regulatory changes. To comprehensively assess the evolving effects of the directive, we are conducting year-by-year DiD regressions from 2017 to 2020, as detailed by model 1.

In the first model, where 2017 serves as the “pre” period and 2018 as the “post” period, we anticipate the interaction term δ between $Sweden_i$ and $Post_t$ to be zero. This expectation arises from the understanding that the directive’s impact is not immediate; banks may require time to adapt to the new requirements. An insignificant interaction term in the first model confirms the presence of a parallel trend prior to the directive’s influence. In the following model, with 2018 designated as the “pre” period and 2019 as the “post” period, we anticipate the interaction term to reach its peak significance. This anticipation stems from the treatment of Swedish firms while their Norwegian counterparts remain unaffected. As time progresses, we foresee a decline in both the significance and magnitude of the interaction term δ between $Sweden_i$ and $Post_t$. This decline mirrors the diminishing differential impact between Swedish and Norwegian SMEs as they adapt to the new regulatory framework.

3.5 The DDD Regression Models

Intending to explore how different characteristics influence a firm’s vulnerability to the effects of digital transformation, we introduce the “difference-in-difference-in-difference” method. This triple difference, DDD, allows us to measure the specific impact of digital transformation on a particular characteristic within the treatment group. The literature review identified different characteristics that could significantly influence a company's debt level. By incorporating additional interaction terms in the regression analysis, we can capture the specific effect of small/mid-size, young/older, and volatile/non-volatile companies. The triple difference model is presented in Model 2, where $X_{i,t}$ represents the variables of interest: size, age, and CAGR. For each characteristic, we will do a regression averaging out the effect in the three years prior to the treatment and the following three, as well as yearly regressions.

$$\boldsymbol{Model}\ \mathbf{2}:$$

$$SME\ debt\ level_{i,t} = \alpha + \beta Sweden_i + \gamma Post_t + \pi X_{i,t} + \delta\ (Sweden_i * Post_t) + \theta\left(Sweden_i * X_{i,t}\right) + \vartheta\left(Post_t * X_{i,t}\right) + \mu\left(Sweden_i * Post_t * X_{i,t}\right) + \rho X_{i,t} + \varepsilon_{i,t}$$

μ signifies the coefficient for the three-way interaction term involving $Post_t$, $Sweden_i$ and $X_{i,t}$. This interaction term holds the primary focus in Model 2, estimating the combined effect on debt level for medium/old/growth SMEs in the treatment group affected by PSD2.

The literature review identified the reasoning behind incorporating size, age, and CAGR (revenue growth) into our DDD approach. For the first DDD, we introduce the third variable, *Medium, as a proxy for company size*. The variable is defined based on the European Union's criteria for medium-sized companies: it takes the value of 1 for companies with assets equal to or exceeding € 10 M and 0 otherwise (European Commission, 2021). In our sample, the companies categorized as Medium represent the largest size segment. For company age, we incorporate a variable, *old.* We define *old* SMEs as businesses older than 20 years, representing the upper third quartile of our sample. To identify growth firms, we calculate their Compound Annual Growth Rate (CAGR), considering annual average revenue growth. Firms with a CAGR above 20% from 2014 to 2022 are classified as *growth companies.*

4. Data and Sample Description

This section will outline our data collection process and provide an overview of our sample. Following, we will present the reasoning behind our control group, encompassing the propensity score matching method. Finally, we demonstrate the effectiveness and accuracy of the matching process.

4.1 Data Collection and Sample Construction

Our sample of non-financial SMEs from Norway and Sweden is based on the European Commission's definition of SMEs, which includes companies with less than 250 employees and an annual turnover under EUR 50 million. The data is collected from Orbis, a database by Bureau van Dijk that provides comprehensive financial information on companies worldwide. To obtain complete data for all years in the sample, our observations extend from 2014 to 2022.

When filtering our data, we follow a similar approach to the study conducted by Fasano & Cappa (2022). As our study centers on SMEs, excluding companies outside the SME definition is essential. We omit firms from the financial sector, as these typically provide SMEs with debt. Consequently, we exclude companies operating in the financial sectors (NACE[1] codes 64, 65, 66, 68, 77), as well as those involved in public administration, education, human health, residential care, and creative, arts, and entertainment activities (NACE codes 84-90). Membership organizations (NACE code 94), activities related to households as employers, and undifferentiated goods and services produced by households for their use (NACE codes 97-98) are also excluded from our analysis.

Furthermore, we established specific limitations on our dataset. We include only firms with complete data points and exclude any observations that lack meaningful economic relevance concerning accounting information. We remove all firms with a debt ratio of 1 or above and those below 0 from the dataset. Additionally, for companies that exceed the SME definition at any point, we retain only the data from the years when they were classified as SMEs.

[1] NACE is the EU classification of economic activities.

From Orbis, we got data on total assets, non-current debt, current debt, company age, revenue, industry, and EBIT. The dependent variable, debt ratio, is constructed by dividing the sum of current and non-current liabilities by total assets.

Our dataset ended up with a sample of 412 390 firm-year observations over the 2014-2022 period.

4.2 The Propensity Score Matching Model

Propensity Score Matching (PSM) creates an artificial control group that closely aligns with Swedish SMEs. This method reduces selection bias and balances confounding variables, enabling a valid comparison. It allows for a more precise assessment of whether SMEs with similar traits experience the same effects from the digital transformation by comparing 'twins' across the country. PSM confronts the challenge of using Norwegian SMEs as a control group for Swedish SMEs, complicated by Norwegian SMEs receiving treatment one year later.

To perform the propensity score matching, we pair Norwegian and Swedish companies based on a group of characteristics. Given the range of characteristics available, we conduct several matching trials to identify the combination that yields the most precise results. The set of characteristics that provide the most accurate match include assets, non-current debt, current debt, company age, and revenue.

Several key assumptions underlie the use of Propensity Score Matching (PSM). The first assumption is the confoundedness assumption, which posits that the treatment effects are independent of treatment status based on observable variables. This assumption of conditional independence must hold to be sure we make fair comparisons when studying the effect of the treatment. It is based on the idea that we should find the characteristics we base our propensity score on before the treatment happens. This pre-treatment identification ensures that the variables used to estimate the propensity score are independent of the treatment (Pan & Bai, 2015; Rosenbaum & Rubin, 1983).

The second crucial assumption is the common support assumption. For each value of x, there should be one treated and one untreated. This means a range of propensity scores should be shared between both treated and untreated groups (Pan & Bai, 2015; Rosenbaum & Rubin, 1983). Potential pitfalls that violate common support assumptions are having too few or too many matching variables, which can lead to increased standard errors without reducing bias.

We must select either the probit or logit model for propensity score matching. Regarding binary treatment cases, as in our study, the probit and logit models usually yield the same result (Caliendo & Kopeinig, 2008). We use the logit model in the matching because it provides more explicit interpretation through odds ratios, making it easier to understand and communicate how different factors influence the likelihood of a firm being Swedish instead of Norwegian.

In the matching, we use a combination of 1:1 and nearest-neighbor matching. While our initial intention was to pair each Swedish SME with one unique Norwegian SME, our model permits a Norwegian SME to serve as a match for more than one Swedish SME if it is the closest match within the defined caliper distance of 0.05. This approach ensures that all Swedish SMEs have a corresponding match while also allowing us to maintain the tightest possible balance between the groups, as the caliper indicates. By allowing untreated individuals to be used more than once as a match, we aimed to reduce bias in our sample. However, we were also aware of the increased variance that this method introduces.

4.3 Checking Balance

Propensity score matching often results in a smaller sample than the original. Therefore, it could lead to false nonsignificant differences due to reduced size. Additionally, in larger samples, even minor differences can appear statistically significant. Imai et al. argue that balance is specific to the sample and unrelated to a larger population (Austin, 2011). Therefore, we use alternative methods, such as visual inspection instead of statistical significance, for a more accurate assessment of matching success.

Visualizing helps us compare the distribution of characteristics and propensity scores among individuals in these groups after matching. This approach provides a clear view of the balance achieved through matching (Pan & Bai, 2015). Caliendo and Kopeinig (2008) highlight the importance of balancing precision in estimating treatment effects (efficiency) with the deviation of these estimates from the actual results (bias).

Table 4.1: Matching Summary

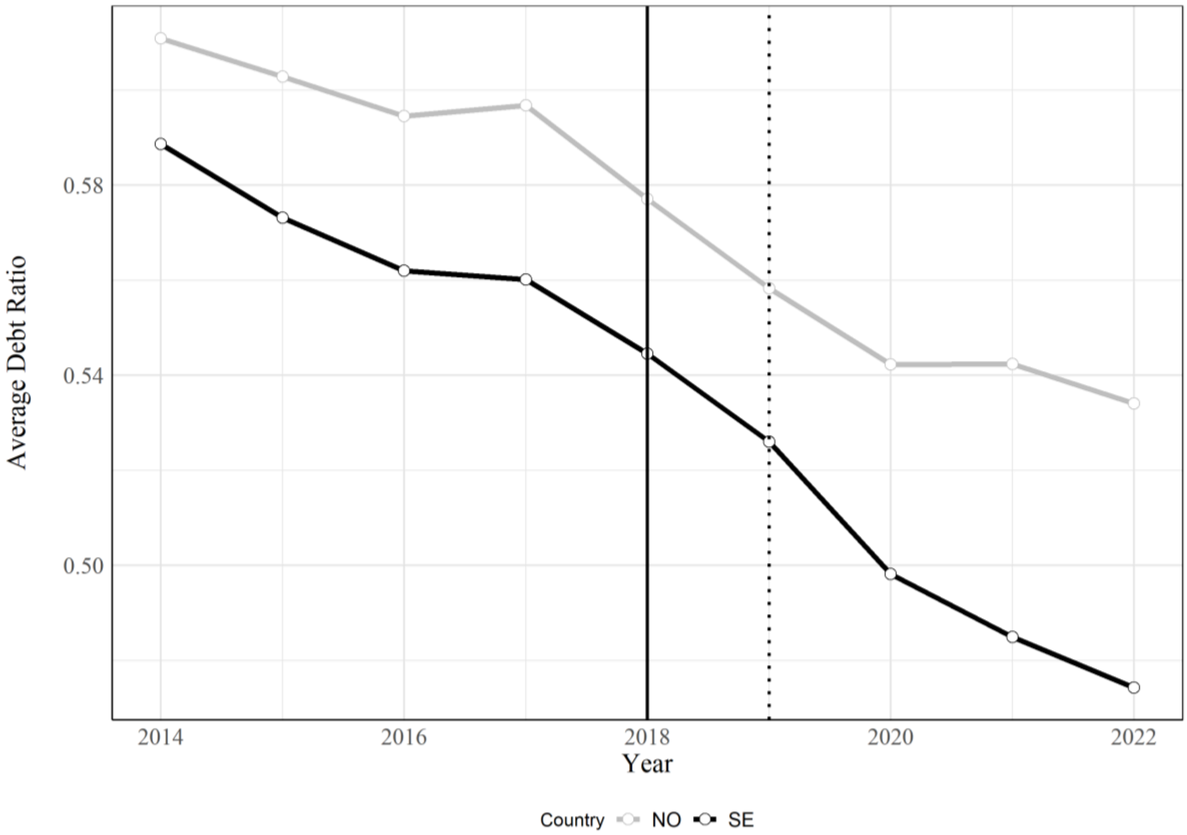
This table presents the means and the standardized mean differences (SMD) for the covariates Assets, Non-current debt, Current debt, Company age, and revenue for the firms opposed to a treatment (Sweden) and control firms (Norway) before and after the matching. Also, it presents the T-values from a two-sample t-test, demonstrating that Company age is the only covariate with no statistically significant difference between the two groups.

	Before PSM		
Variable	Norway	Sweden	SMD
Propensity score (mean)	0.42	0.48	0.424
Non-current debt (mean)	293.23	237.01	-0.059
Current debt (mean)	570.39	411.96	-0.141
Assets (mean)	1434.14	1154.47	-0.099
Company age (mean)	10.68	15.93	0.366
Revenue (mean)	2162.64	1773.05	-0.095

	After PSM			
Variable	Norway	Sweden	SMD	T-value
Propensity score (mean)	0.41	0.41	0.0003	
Non-current debt (mean)	258.47	233.11	-0.037	-6.042
Current debt (mean)	467.63	411.49	-0.050	-4.062
Assets (mean)	1205.28	1086.60	-0.042	-6.676
Company age (mean)	9.90	9.71	-0.014	0.487
Revenue (mean)	1850.51	1728.85	-0.029	-5.130

The matching process has narrowed the gaps between Swedish and Norwegian SMEs. Prior to matching, summary statistics revealed notable differences in standardized mean differences. These differences have significantly diminished following matching, indicating a more balanced alignment of the treatment and control groups. We observe that the standardized mean difference for distance, a composite measure reflecting the overall propensity score balance, has decreased from 0.4096 to 0.0002. This reduction underscores that the matched Norwegian SMEs are now statistically more similar to the Swedish SMEs in their propensity scores than before matching, confirming the efficacy of our matching process.

Figure 4.1: Debt Ratio Trend After Matching



The successful reduction in variance is also illustrated in Figure 4.1, where the parallel trend in debt ratios aligns even more closely after the match.

4.4 Control Variables

Control variables are additional factors that might influence SMEs' debt levels, represented by $X_{i,t}$ in the regressions. By including control variables in our analysis, we can improve the precision of our estimates by adjusting for differences across Sweden and Norway.

Although we employ propensity score matching to eliminate firm-specific characteristics differing between the control and treatment groups, this method cannot eliminate all differences. To address this, we consider incorporating the characteristics from matching as control variables. The matching results reveal a slight yet persistent difference in debt size between countries. Consequently, we introduce non-current and current debts as control variables to mitigate the effects of varying debt ratios across countries, especially given that Norwegian SMEs typically exhibit higher debt ratios. Including debt as a control significantly reduces standard errors, ensuring a stable coefficient across all models. Including revenue as a control variable results in minor changes in the outcome but does not lead to any improvements. Additionally, company age and assets are not employed as controls since the Triple difference-in-differences (DDD) aims to examine the impact of age and size.

EBIT and industry are initially considered for matching but are excluded as they do not enhance the matching results. DiD regressions, which include industry as a control, reveal no significant effects on the coefficients or standard errors. Similarly, using EBIT as a control results in minor changes in the outcomes but does not lead to improvements. Consequently, these variables are excluded from being used as controls in our analysis.

Another control variable we include is the lagged debt ratio, justified due to its statistical significance and consistent influence across various models. Firms typically do not experience drastic changes in their debt ratios annually, making the previous year's debt ratio a reliable predictor for the current year. Incorporating this control enhances our model's explanatory power and significantly reduces standard errors, strengthening the validity of our difference-in-differences estimator's coefficient. This addition helps achieve a more accurate and robust analysis of the factors influencing debt ratios.

Including interest rates as a control variable is particularly relevant given the different interest rates in Norway and Sweden during the sample period. Notably, while Sweden experienced negative rates for a time, Norway's rates followed a similar trend but significantly dropped in

2020/2021. This contrast with Sweden's more consistent rates underscores the need to account for these differences in the financing environments affecting SMEs in both countries. Therefore, end-of-year interest rates for each year in the dataset are included, ensuring a comprehensive capture of these nuances. Interest rates are not affected by the implementation of PSD2 and have shown statistical significance in our year-by-year analysis. Including interest rate increases the precision of the estimators significantly for the year-by-year analysis.

Sweden's economy, driven by service and manufacturing sectors, contrasts with Norway's resource-based economy, reliant on oil and gas (Mæhlum, 2023; Thuesen et al., 2023). Therefore, GDP growth is a suitable control variable for each country's differing macroeconomic factors. It also serves to capture some of the economic impact of the COVID-19 pandemic. Including GDP growth reduces the coefficients of both DiD and DDD estimators, increases the standard errors, and yields statistically significant results. This suggests that its inclusion diminishes bias and enhances precision in the models.

5. Analysis

In the upcoming section, we share the insights gained from our analysis. Initially, we present the development in debt ratios to better interpret the meaning of the estimators. Then, we introduce our results, followed by a discussion of these findings. Finally, we address the limitations inherent in our analysis and summarize this section.

We present the regression models with and without entity fixed effects. In models with fixed effects, we account for company-specific factors that remain constant over time, acknowledging the potential presence of unobservable, time-invariant effects that vary across companies. If these unobserved effects are correlated with debt ratios, relying on the OLS estimator may lead to inconsistent results. Consequently, our preferred model specification includes the adjustment for fixed effects, and our analysis focuses on the results derived from the regressions that incorporate fixed effects.

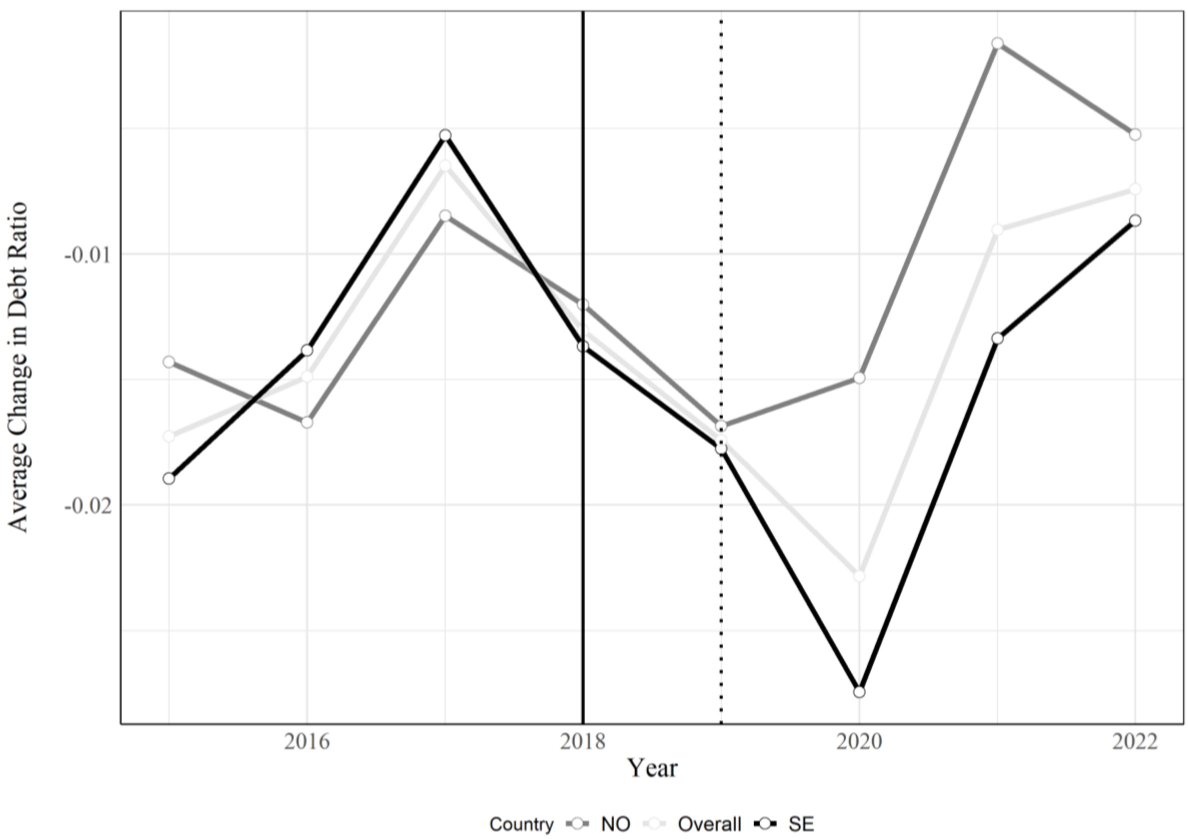
5.1 Development in Debt Ratio

To better understand the economic significance of the estimators, we demonstrate the development in debt ratios from year to year in Table 5.1 and Figure 5.1.

Table 5.1: Average Change in Debt Ratio

Country	2015	2016	2017	2018	2019	2020	2021	2022
NO	−0.01429	−0.01671	−0.00847	−0.01201	−0.01685	−0.01493	−0.00159	−0.00524
SE	−0.01894	−0.01383	−0.00526	−0.01367	−0.01775	−0.02745	−0.01336	−0.00866
Overall	−0.01727	−0.01489	−0.00646	−0.01305	−0.01742	−0.02283	−0.00903	−0.00741

Figure 5.1: Average Change in Debt Ratio



5.2 Hypothesis 1*: Digital transformation in the financial sector leads to a reduction in SME debt.*

First, we aim to assess how the debt ratios of SMEs are affected by digital transformation. The results are presented in Tables 5.2 and 5.3

Table 5.2: Three-years average Difference-in-Difference

	Dependent variable:	
	debt_ratio	
	(FE)	(POLS)
Sweden:post	0.001	−0.003**
	(0.001)	(0.001)
post	−0.014***	0.0004
	(0.001)	(0.001)
Sweden		−0.014***
		(0.001)
interest_rate	−0.008***	−0.009***
	(0.001)	(0.001)
cdebt	0.00004***	0.00001***
	(0.00000)	(0.00000)
ncdebt	0.00004***	0.00001***
	(0.00000)	(0.00000)
GDPgrowth	0.669***	0.306***
	(0.020)	(0.023)
lagged_debt_ratio	0.306***	0.848***
	(0.002)	(0.001)
Fixed Effects	Yes	No
Observations	180,987	180,987
R^2	0.181	0.727
Note:	Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$	

The three-year average DiD results in Table 5.2 reveal a general decline in debt levels among Swedish and Norwegian SMEs from 2018. This trend is evidenced by the negative coefficient of the *post* variable at -0.014 and is statistically significant at the 0.1% level. The *DiD* estimator, however, with a positive coefficient of 0.001, suggests that Swedish SMEs experience a relatively smaller debt ratio reduction than Norwegian SMEs. This coefficient is not statistically significant, and we cannot conclude that there are any statistical differences between Norway and Sweden, nor that an increase in digital transformation negatively affects the debt ratio for SMEs.

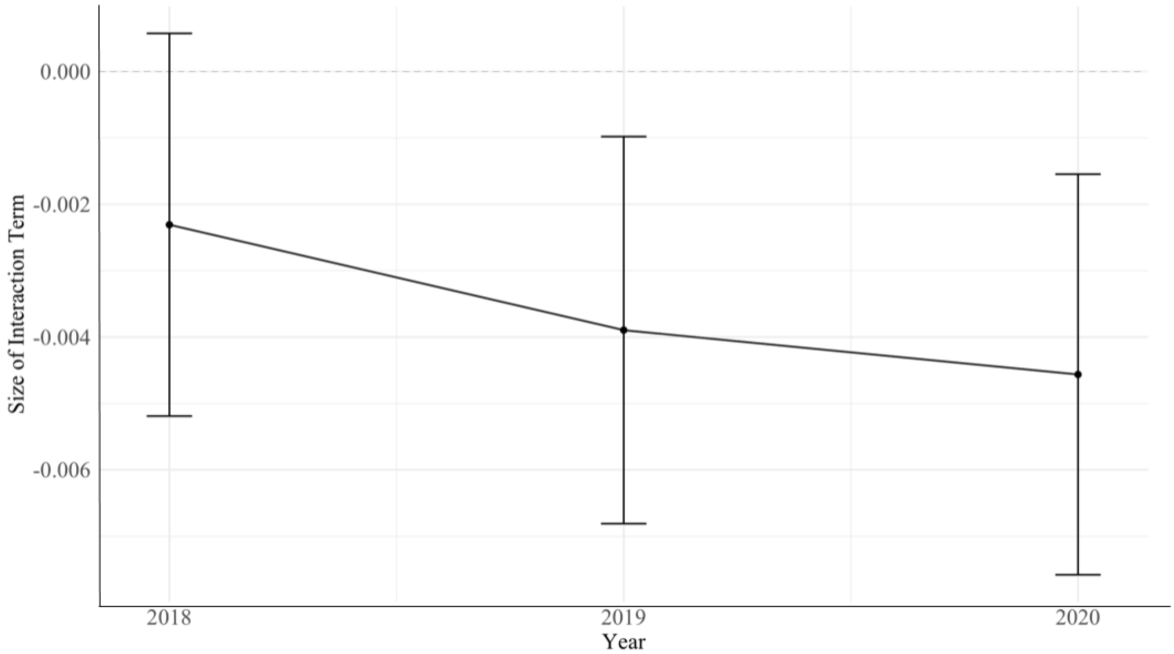
Table 5.3: Year-by-year Difference-in-Difference

	Dependent variable:					
	debt_ratio					
	(FE) 2018	(FE) 2019	(FE) 2020	(POLS) 2018	(POLS) 2019	(POLS) 2020
Sweden:post_2020			-0.005^{**} (0.002)			-0.008^{***} (0.002)
Sweden:post_2019		-0.004^{***} (0.001)			0.002 (0.002)	
Sweden:post_2018	-0.002 (0.001)			0.00003 (0.002)		
post_2018	0.008^{***} (0.001)			0.003^{***} (0.001)		
post_2019		0.002^{**} (0.001)			-0.004^{***} (0.001)	
post_2020			-0.047^{***} (0.001)			-0.013^{***} (0.002)
Sweden				-0.011^{***} (0.001)	-0.011^{***} (0.001)	-0.008^{***} (0.001)
interest_rate	-0.012^{***} (0.0003)	-0.013^{***} (0.0003)	-0.014^{***} (0.0003)	-0.002^{***} (0.0003)	-0.003^{***} (0.0003)	-0.003^{***} (0.0003)
GDPgrowth	0.224^{***} (0.013)	0.215^{***} (0.013)	-0.477^{***} (0.021)	0.202^{***} (0.014)	0.192^{***} (0.014)	-0.054^{**} (0.024)
cdebt	0.00003^{***} (0.00000)	0.00003^{***} (0.00000)	0.00003^{***} (0.00000)	0.00001^{***} (0.00000)	0.00001^{***} (0.00000)	0.00001^{***} (0.00000)
ncdebt	0.00003^{***} (0.00000)	0.00003^{***} (0.00000)	0.00003^{***} (0.00000)	0.00000^{***} (0.00000)	0.00000^{***} (0.00000)	0.00000^{***} (0.00000)
lagged_debt_ratio	0.419^{***} (0.002)	0.419^{***} (0.002)	0.410^{***} (0.002)	0.849^{***} (0.001)	0.850^{***} (0.001)	0.849^{***} (0.001)
Fixed Effects	Yes	Yes	Yes	No	No	No
Observations	242,368	242,368	242,368	242,368	242,368	242,368
R^2	0.241	0.241	0.247	0.731	0.731	0.731

Note: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 5.2: Development of Interaction Term

This graph demonstrates the development of the interaction term, with its confidence intervals in the model from Table 5.3.



When considering the 2018 model, we observe an average reduction in the debt ratio for SMEs from 2017 to 2018. The *DiD* estimator for 2018 is not statistically significant, suggesting no statistical difference in debt trends between the Swedish SMEs and Norwegian SMEs. The result supports the parallel trend assumption, indicating that prior to the policy implementation, the debt paths of the two groups were comparable. We anticipate observing this trend in the following models as well.

In the 2019 analysis, the *DiD* estimator indicates that Swedish companies experienced a relative decrease in debt ratio compared to Norwegian SMEs one year after the implementation of PSD2 in Sweden. Comparing the DiD estimator of -0.004 to the overall change in debt ratio in Sweden from 2019 to 2020 (Table 5.1: -0.0178) demonstrates the economic magnitude of this decrease. The coefficient for *post_2019* indicates, on average, a general increase in debt levels for Swedish and Norwegian SMEs of 0.002. This implies that while Norwegian SMEs saw an increase in their debt levels, Swedish SMEs experienced a decrease. The DiD estimator is significant at 0.1%, while the *post_2019* is significant at 1%.

The 2020 model uncovers an additional decline in the debt ratios of Swedish SMEs compared to their Norwegian counterparts. The *post_2020* coefficient is negative at 0.047, indicating an average debt ratio decrease for Norwegian and Swedish SMEs. The difference-in-differences (DiD) estimator further illustrates that, relative to Norwegian firms, Swedish firms experience an additional 0.005 decrease in their debt ratios. The statistical significance at the 1% level is observed for the *DiD* estimator, while the *post_2020* coefficient attains significance at the 0.1% level.

5.3 Hypothesis 2: *Larger companies experience smaller decreases in debt ratio due to digital transformation in the financial sector.*

In the upcoming model, our objective is to investigate if larger companies demonstrate a less pronounced reduction in their debt levels due to digital transformation. The results are presented in Table 5.4 and 5.5.

Table 5.4: Three-years Average Triple Difference-in-Difference (Size)

	Dependent variable:	
	debt_ratio	
	(FE)	(POLS)
Sweden:post:Medium	−0.003	0.0002
	(0.007)	(0.008)
Sweden:Medium	−0.009	−0.002
	(0.010)	(0.006)
post:Medium	−0.002	0.008
	(0.006)	(0.006)
Sweden:post	0.001	−0.003**
	(0.001)	(0.001)
Medium	−0.123***	−0.121***
	(0.008)	(0.005)
Sweden		−0.014***
		(0.001)
post	−0.013	0.0002
	(0.001)	(0.001)
interest_rate	−0.008***	−0.009***
	(0.001)	(0.001)
cdebt	0.00005***	0.00002***
	(0.00000)	(0.00000)
ncdebt	0.00004***	0.00001***
	(0.00000)	(0.00000)
GDPgrowth	0.664***	0.309***
	(0.020)	(0.023)
lagged_debt_ratio	0.304***	0.840***
	(0.002)	(0.001)
Fixed Effects	Yes	No
Observations	180,987	180,987
R^2	0.185	0.730
Note:	Standard errors in parentheses; * p < 0.05, ** p < 0.01, *** p < 0.001	

Medium-sized companies reduced their debt ratios by 0.009 after 2017, as indicated by the negative coefficient for *post:Medium*. After implementing the directive, the *DDD* estimator suggests that Swedish medium-sized firms experience an additional decrease in their debt ratios of 0.003. However, neither of these coefficients is statistically significant, and therefore, we cannot conclude that there is a difference in debt ratios of medium vs. small-sized companies.

Table 5.5: Year-by-Year Triple Difference-in-Difference (Size)

	Dependent variable:					
	debt_ratio					
	(FE) 2018	(FE) 2019	(FE) 2020	(POLS) 2018	(POLS) 2019	(POLS) 2020
Sweden:post_2020:Medium			−0.029***			−0.009
			(0.009)			(0.010)
Sweden:post_2019:Medium		0.001			−0.006	
		(0.009)			(0.010)	
Sweden:post_2018:Medium	−0.001			0.007		
	(0.010)			(0.011)		
post_2020:Medium			0.026***			0.009
			(0.007)			(0.008)
post_2019:Medium		0.003			0.004	
		(0.007)			(0.008)	
post_2018:Medium	0.006			−0.005		
	(0.007)			(0.008)		
Sweden:post_2018	−0.002			−0.0002		
	(0.001)			(0.002)		
Sweden:post_2019		−0.004***			0.002	
		(0.002)			(0.002)	
Sweden:post_2020			−0.004**			−0.008***
			(0.002)			(0.002)
Sweden:Medium	−0.001	−0.001	0.001	−0.001	0.00003	0.0004
	(0.007)	(0.007)	(0.007)	(0.004)	(0.004)	(0.004)
Sweden				−0.010***	−0.010***	−0.008***
				(0.001)	(0.001)	(0.001)
post_2018	0.007***			0.004***		
	(0.001)			(0.001)		
post_2019		0.002*			−0.004***	
		(0.001)			(0.001)	
post_2020			−0.047***			−0.013***
			(0.001)			(0.002)
Medium	−0.130***	−0.130***	−0.131***	−0.117***	−0.118***	−0.119***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
interest_rate	−0.012***	−0.013***	−0.014***	−0.003***	−0.003***	−0.003***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
cdebt	0.00004***	0.00004***	0.00004***	0.00002***	0.00002***	0.00002***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
ncdebt	0.00004***	0.00004***	0.00004***	0.00001***	0.00001***	0.00001***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GDPgrowth	0.223***	0.215***	−0.471***	0.201***	0.191***	−0.059**
	(0.013)	(0.013)	(0.021)	(0.014)	(0.014)	(0.023)
lagged_debt_ratio	0.417***	0.417***	0.408***	0.841***	0.841***	0.840***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Fixed Effects	Yes	Yes	Yes	No	No	No
Observations	242,368	242,368	242,368	242,368	242,368	242,368
R^2	0.245	0.245	0.251	0.733	0.733	0.733
Note:	Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$					

The coefficient of 0.003 for *post_2019:Medium* suggests that, on average, both Swedish and Norwegian companies experienced an increase in their debt levels in 2019. The *DDD* estimator for 2019 indicates a slightly smaller decrease for Swedish medium-sized SMEs, reflected in the positive coefficient of 0.001. However, neither of the coefficients in the 2019 model reaches statistical significance. In 2020, the *post_2020:Medium* coefficient reveals that medium-sized SMEs underwent a minor reduction in their debt ratios compared to their smaller counterparts in our sample, registering a value of 0.026, in contrast to 2019. However, Swedish medium-sized SMEs experienced a relative reduction in their debt ratios of 0.029 during this period, as indicated by the *DDD* estimator. Both coefficients for 2020 achieve statistical significance at the 0.1% level. Despite these findings, we cannot conclusively assert that larger companies encountered a lesser decrease in their debt ratios due to digital transformation in the financial sector.

Figure 5.3: The Average Debt Ratio Development of Medium and non-Medium Firms

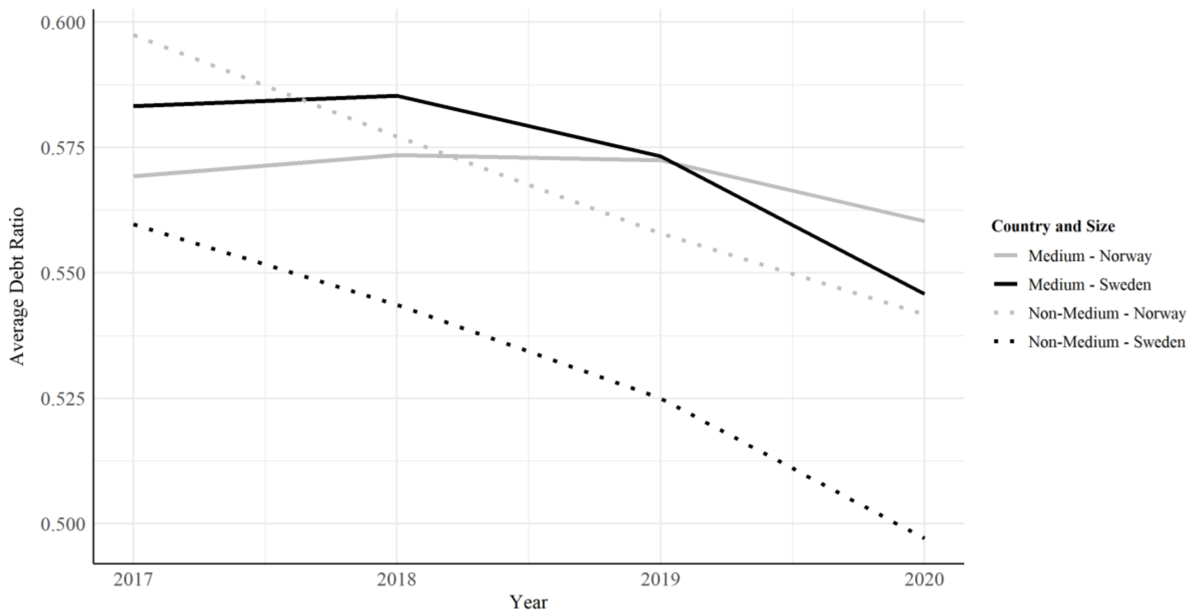


Figure 5.3 illustrates that while Swedish medium and non-medium firms generally follow a similar trend in debt ratio, medium firms consistently maintain a higher debt ratio than their non-medium counterparts, with a slight divergence noted between 2017 and 2018. In contrast, Norwegian firms in 2017 show a distinct split, where non-medium firms experience a much

steeper decline in debt ratios compared to medium firms, highlighting differing financial approaches or market impacts during this period.

5.4 Hypothesis 3: *Older companies experience smaller decreases in debt ratio due to digital transformation in the financial sector.*

The third hypothesis aims to explore how the debt ratios of older companies are affected by digital transformation. The results of this analysis are presented in Tables 5.6 and 5.7.

Table 5.6: Three-years Average Triple Difference-in-Difference (Age)

	Dependent variable:	
	debt_ratio	
	(FE)	(POLS)
Sweden:post:Old	-0.001	0.0004
	(0.003)	(0.003)
Sweden:Old	0.013^{**}	0.004
	(0.004)	(0.002)
post:Old	0.009^{***}	-0.001
	(0.002)	(0.002)
Sweden:post	0.001	-0.004^{**}
	(0.001)	(0.001)
Sweden		-0.015^{***}
		(0.001)
post	-0.015^{***}	0.001
	(0.001)	(0.001)
Old	-0.014^{***}	-0.006^{***}
	(0.003)	(0.002)
interest_rate	-0.008^{***}	-0.009^{***}
	(0.001)	(0.001)
ncdebt	0.00004^{***}	0.00001^{***}
	(0.00000)	(0.00000)
cdebt	0.00004^{***}	0.00001^{***}
	(0.00000)	(0.00000)
GDPgrowth	0.676^{***}	0.304^{***}
	(0.020)	(0.023)
lagged_debt_ratio	0.305^{***}	0.848^{***}
	(0.002)	(0.001)
Fixed Effects	Yes	No
Observations	180,987	180,987
R^2	0.181	0.727
Note:	Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$	

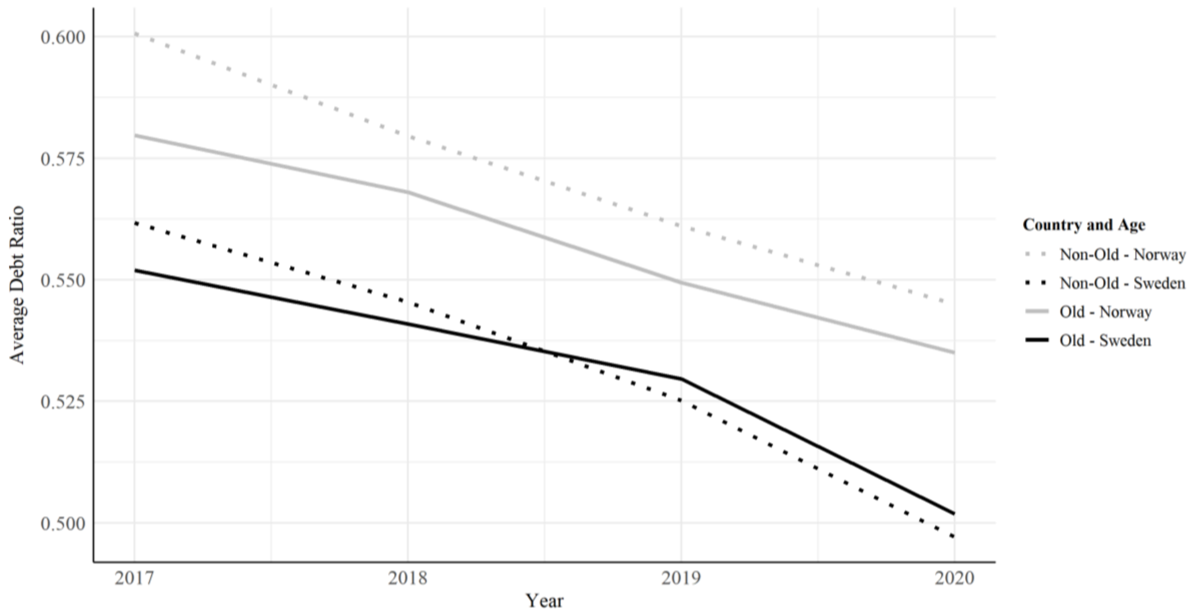
The results from Table 5.6 indicate that, on average, older companies tend to experience less reduction in their debt levels after 2017, as evidenced by the positive coefficient of 0.013 of *post:Old*. However, the findings from the *DDD* estimator present a contrasting view. The negative value of this estimator suggests that older, treated companies experienced an additional decrease in debt ratio of 0.001. While the coefficient of *post:Old* is statistically significant at the 1% level, the *DDD* estimator does not reach statistical significance. These findings suggest that the general trends in debt ratio change for older firms from 2018 align with expectations. Nevertheless, we cannot say that older firms that have undergone treatment experience less decrease in their debt ratio compared to younger firms.

Table 5.7: Year-by-year Triple Difference-in-Difference (Age)

	Dependent variable:					
	debt_ratio					
	(FE) 2018	(FE) 2019	(FE) 2020	(POLS) 2018	(POLS) 2019	(POLS) 2020
Sweden:post_2020:Old			0.003			0.001
			(0.003)			(0.004)
Sweden:post_2019:Old		0.009**			0.011**	
		(0.004)			(0.004)	
Sweden:post_2018:Old	−0.004			−0.002		
	(0.004)			(0.004)		
post_2020:Old			0.004			−0.001
			(0.003)			(0.003)
post_2019:Old		−0.0002			−0.006*	
		(0.003)			(0.003)	
post_2018:Old	0.005*			0.003		
	(0.003)			(0.003)		
Sweden:post_2020			−0.005***			−0.008***
			(0.002)			(0.002)
Sweden:post_2019		−0.005***			−0.001	
		(0.002)			(0.002)	
Sweden:post_2018	−0.001			0.001		
	(0.002)			(0.002)		
Sweden:Old	−0.002	−0.003	−0.008***	0.001	−0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Old	−0.019***	−0.018***	−0.008***	−0.006***	−0.005***	−0.005***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Sweden				−0.011***	−0.011***	−0.008***
				(0.001)	(0.001)	(0.001)
post_2018	0.006***			0.003*		
	(0.001)			(0.001)		
post_2019		0.002			−0.003*	
		(0.001)			(0.002)	
post_2020			−0.047***			−0.012***
			(0.002)			(0.002)
interest_rate	−0.011***	−0.012***	−0.013***	−0.002***	−0.002***	−0.003***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
ncdebt	0.00003***	0.00003***	0.00003***	0.00000***	0.00000***	0.00000***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
cdebt	0.00003***	0.00003***	0.00003***	0.00001***	0.00001***	0.00001***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GDPgrowth	0.217***	0.208***	−0.462***	0.201***	0.190***	−0.048**
	(0.013)	(0.013)	(0.021)	(0.014)	(0.014)	(0.024)
lagged_debt_ratio	0.418***	0.418***	0.410***	0.849***	0.849***	0.848***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Fixed Effects	Yes	Yes	Yes	No	No	No
Observations	242,368	242,368	242,368	242,368	242,368	242,368
R^2	0.242	0.241	0.247	0.731	0.731	0.731
Note:	Standard errors in parentheses; * p < 0.05, ** p < 0.01, *** p < 0.001					

The findings in Table 5.7 suggest that, on average, older companies in Norway and Sweden exhibit no difference in effects compared to their younger counterparts. This is indicated by the statistically insignificant and small coefficients of *post_2019:Old*, measuring at -0.0002. The average difference between older and younger companies remains statistically insignificant in 2020, albeit with a slightly larger coefficient of 0.004. The only coefficient achieving statistical significance in this model is the *DDD* estimator for 2019, revealing a minor reduction in debt ratios (0.009) for older companies compared to their younger counterparts. The *DDD* estimator for 2020 indicates a similar trend to 2019 but with a coefficient of 0.003, which is statistically insignificant. Consequently, we cannot confirm a distinct difference in trends in debt ratios between older companies in Sweden and Norway.

Figure 5.4: The Average Debt Ratio Development for Old and Non-old firms



In Figure 5.4, the observed trend for Swedish firms reveals a steeper path for older firms. Initially, these older firms had a higher level of debt ratio. However, the trend lines cross between 2018 and 2019, resulting in a reversal where the debt ratios of older firms become lower than those of their younger counterparts. In contrast, for Norway, the debt ratios of the two groups exhibit a more parallel trend, with older firms consistently maintaining a higher debt ratio.

5.5 Hypothesis 4: *Growth companies experience larger decreases in debt ratio due to digital transformation in the financial sector.*

Lastly, we aim to assess how the debt ratios of growth companies are affected by digital transformation. The results from the analysis are presented in Tables 5.8 and 5.9.

Table 5.8: Three-years Average Triple Difference-in-Difference (Growth)

	Dependent variable:	
	debt_ratio	
	(FE)	(POLS)
Sweden:post:GrowthCompany	−0.006	0.001
	(0.004)	(0.004)
post:GrowthCompany	−0.004	−0.009**
	(0.003)	(0.003)
Sweden:GrowthCompany		−0.009*
		(0.003)
Sweden:post	0.002	−0.003**
	(0.001)	(0.001)
Sweden		−0.013***
		(0.001)
post	−0.013***	0.001
	(0.001)	(0.001)
GrowthCompany		0.028***
		(0.002)
interest_rate	−0.008***	−0.009***
	(0.001)	(0.001)
GDPgrowth	0.669***	0.307***
	(0.020)	(0.023)
ncdebt	0.00004***	0.00001***
	(0.00000)	(0.00000)
cdebt	0.00004***	0.00001***
	(0.00000)	(0.00000)
lagged_debt_ratio	0.306***	0.846***
	(0.002)	(0.001)
Fixed Effects	Yes	No
Observations	180,987	180,987
R^2	0.181	0.728
Note:	Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$	

This model reveals that growth companies in Sweden and Norway, on average, saw a greater reduction in their debt ratios by a magnitude of 0.004 after 2017, compared to the non-growth firms, as indicated by the positive coefficient of *post:GrowthCompany.* The *DDD* estimator suggests an additional decrease for the treated growth companies of 0.006. However, these findings lack statistical significance, and it is not possible to conclude that growth companies are affected differently by digital transformation in the financial sector.

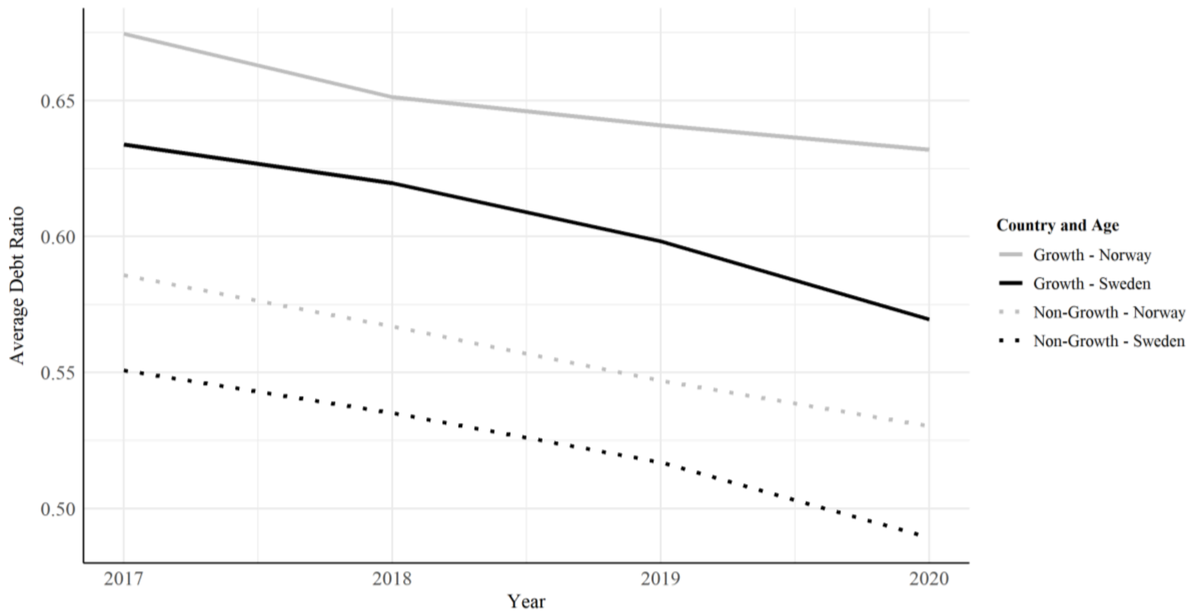
Table 5.9: Year-by-year Triple Difference-in-Difference (Growth)

	Dependent variable:					
	debt_ratio					
	(FE) 2018	(FE) 2019	(FE) 2020	(POLS) 2018	(POLS) 2019	(POLS) 2020
Sweden:post_2020:GrowthCompany			-0.015^{**} (0.005)			-0.010 (0.005)
Sweden:post_2019:GrowthCompany		-0.008 (0.005)			-0.010 (0.005)	
Sweden:post_2018:GrowthCompany	0.006 (0.005)			0.005 (0.005)		
post_2020:GrowthCompany			0.007^{**} (0.004)			0.003 (0.004)
post_2019:GrowthCompany		0.004 (0.004)			0.002 (0.004)	
post_2018:GrowthCompany	-0.002 (0.004)			-0.007^{*} (0.004)		
Sweden:post_2020			-0.003^{*} (0.002)			-0.007^{***} (0.002)
Sweden:post_2019		-0.003^{*} (0.002)			0.003 (0.002)	
Sweden:post_2018	-0.003^{*} (0.002)			-0.001 (0.002)		
Sweden:GrowthCompany				-0.004^{**} (0.002)	-0.002 (0.002)	-0.003 (0.002)
Sweden				-0.010^{***} (0.001)	-0.011^{***} (0.001)	-0.008^{***} (0.001)
post_2018	0.008^{***} (0.001)			0.004^{***} (0.001)		
post_2019		0.002 (0.001)			-0.004^{***} (0.001)	
post_2020			-0.048^{***} (0.001)			-0.013^{***} (0.002)
GrowthCompany				0.021^{***} (0.001)	0.019^{***} (0.001)	0.019^{***} (0.001)
interest_rate	-0.012^{***} (0.0003)	-0.013^{***} (0.0003)	-0.014^{***} (0.0003)	-0.003^{***} (0.0003)	-0.003^{***} (0.0003)	-0.003^{***} (0.0003)
GDPgrowth	0.224^{***} (0.013)	0.215^{***} (0.013)	-0.477^{***} (0.021)	0.204^{***} (0.014)	0.194^{***} (0.014)	-0.056^{**} (0.024)
ncdebt	0.00003^{***} (0.00000)	0.00003^{***} (0.00000)	0.00003^{***} (0.00000)	0.00000^{***} (0.00000)	0.00000^{***} (0.00000)	0.00000^{***} (0.00000)
cdebt	0.00003^{***} (0.00000)	0.00003^{***} (0.00000)	0.00003^{***} (0.00000)	0.00001^{***} (0.00000)	0.00001^{***} (0.00000)	0.00001^{***} (0.00000)
lagged_debt_ratio	0.419^{***} (0.002)	0.419^{***} (0.002)	0.410^{***} (0.002)	0.847^{***} (0.001)	0.847^{***} (0.001)	0.847^{***} (0.001)
Fixed Effects	Yes	Yes	Yes	No	No	No
Observations	242,368	242,368	242,368	242,368	242,368	242,368
R^2	0.241	0.241	0.247	0.731	0.731	0.731

Note: Standard errors in parentheses; * p < 0.05, ** p < 0.01, *** p < 0.001

The data from Table 5.9 suggests that, on average, growth companies in Sweden and Norway undergo a less pronounced decrease in their debt ratios, with Swedish growth companies experiencing a relative decrease. This is illustrated by positive coefficients for *post_2019:GrowthCompany* and *post_2020:GrowthCompany*, measuring 0.004 and 0.007, respectively, with only the latter gaining statistical significance at the 1% level. The *DDD* estimators reveal a relative decrease in debt levels of 0.008 and 0.015 for treated growth companies in 2019 and 2020. Only the *DDD* estimator for 2020 attains statistical significance at the 1% level. Given the lack of significance in the other estimates, we cannot conclude regarding a trend where growth companies experience a more significant decrease in their debt ratios.

Figure 5.5: The Average Debt Ratio Development for Growth and Non-growth firms



As illustrated in Figure 5.5, Swedish growth firms and non-growth firms exhibit a parallel trend, with growth firms consistently maintaining higher debt ratios than their non-growth counterparts. Similarly, the trend is mirrored among Norwegian firms, where Norwegian firms consistently display higher debt ratios than those observed in the Swedish groups.

5.6 Discussion of results

The outcomes derived from our DiD models could confirm our hypothesis that digital transformation in the financial sector is causing a reduction in SMEs' debt ratios. The year-by-year analysis indicates statistically significant evidence supporting our hypothesis, with a peak effect in 2020. However, the three-year average DiD model has a positive, non-significant coefficient, which does not support the results of the year-by-year DiD.

Suppose the effect we observe in the year-by-year DiD model is a causal effect of digital transformation in the financial sector. In that case, previous studies have indicated that this negative effect on SMEs' debt is due to the diminishing role of soft information. Consequently, we might observe an additional effect on firms more dependent on soft information and a contrasting effect on those with more available hard information.

However, our results contradict the idea that digital transformation in the financial sector disproportionately affects firms reliant on soft information. For instance, we observe no distinct trends between growth and non-growth firms, even though the former are traditionally considered riskier lending cases where soft information plays a crucial role. Similarly, we do not find that digital transformation has a less pronounced negative impact on medium-sized or older firms, which often rely on soft information. These observations can imply a more complex relationship between digital transformation and SME debt that goes beyond the simple exclusion of soft information.

A consequence of increased digital transformation inside and outside the financial sector is the overall increase of new digital tools available to SMEs and other businesses. Today's firms are inherently more digital than in the past. Consequently, more crucial information is now digitally accessible beyond just hard data. For instance, new accounting programs with new technology allow SMEs to manage their finances independently without needing an accountant. This means they have more financial information readily available than before. The shift in digital ability among SMEs themselves could have reduced the information opacity of these firms.

According to the literature, given the recent rise of digital transformation in the financial sector, an appropriate question is whether the distinction between hard and soft information has changed due to this digital shift. The lack of findings that firms reliant on soft information suffer more than those less reliant on soft information could be attributed to new technology effectively converting previous soft information into hard data. While this “hardened” soft information does not directly complement the reduction of all soft information, its combination with the cost-efficient processing of hard data might create a substitute closer to a complement than a direct replacement for soft information.

Based on the literature, the digital transformation within banks is expected to hinder SMEs' access to financing. On the other hand, growing fintech firms with new technology could positively impact SMEs' debt ratios. With their more tailored tools, fintech firms are better suited to address the financing needs of SMEs. Our results can, therefore, have a two-sided explanation. Because of the banks' slow adaptation to the financing needs of SMEs, digital transformation can amplify the typically disadvantaged SMEs by an increased reliance on hard information. In contrast, new fintech is helping to bridge the gap created by traditional banks, creating new lending solutions that are more customized for SMEs.

Our DiD analysis confirms the concept asserted in the IBH, suggesting that SMEs experience a weakening in their debt situations attributable to heightened market density. However, our DDD models diverge from supporting the underlying rationale of this hypothesis. Contrary to expectations, we do not find evidence that firms suffering from higher levels of information opacity are more severely impacted by digital transformation than those encountering lower levels of information opacity.

5.7 Limitations of the study

When interpreting if digital transformation has a causal effect on SME debt, it is essential to shed light on the study's limitations. The risk of a spillover effect presents one limitation: it complicates the isolation of digital transformation's impact on SMEs' debt ratios. Considering PSD2 implementation in 2018, it is a risk that Norwegian banks began to adapt to their requirements before the known implementation in Norway in 2019. This adaptation by Norwegian banks could blur the distinction between Norway's pre- and post-PSD2 periods, making capturing the directive's direct effects challenging.

Moreover, our results can raise questions about the exogeneity of the PSD2 as a shock to the financial sector. Although the sector itself did not create the directive, the impact of these new regulations might not be substantial enough to illuminate the effects of digital transformation significantly. As discussed, Norway and Sweden are known for rapidly adopting new technologies. Therefore, the changes expected from PSD2 may have been less noticeable, as the adaptations it aimed to introduce were likely already underway or initiated in these countries.

Further, the unexpected peak year 2020 might indicate an omitted variable bias. The risk of excluding crucial variables from our model, which could influence the results, is considerable due to the COVID-19 pandemic in 2020 affecting Norway and Sweden differently. This factor makes the interpretation of the 2020 results less reliable. Although we have accounted for differences in GDP growth, the variations in support arrangements and restrictions in the business community may not have been sufficiently controlled. Additionally, there could be other omitted variables, both time-invariant (e.g., unobservable individual characteristics) and time-varying (e.g., time-specific shocks or policy changes). For example, our study does not specifically target companies actively seeking financing. The sample may include many firms not pursuing additional funding and are content with their current financial status. This aspect could bias our understanding of the impact of PSD2 on SMEs' debt levels, as it does not fully capture the experiences of those firms most likely to be affected by changes in the financial sector.

Lastly, our study faces limitations regarding the quality and accessibility of the SME data we obtained. The sample, comprising around 40,000 companies from Norway and Sweden, raises concerns about its representativeness and ability to reflect the broader population of SMEs. Constraints arise from incomplete data and instances of non-applicable or missing information within the dataset. We excluded firms with NA values to ensure a dataset with complete information, and this exclusion introduces a potential risk of selection bias, as it may lead to the omission of SMEs with less available hard information.

6. Conclusion

6.1 Conclusion

Our year-by-year DiD model findings suggest a negative impact of digital transformation on SMEs' debt ratios. The DiD estimators for 2019 and 2020 show a statistically significant reduction in SME debt ratios, with the most substantial coefficient observed in 2020.

However, there is a potential risk of omitted variable bias, lack of significance in the average model, and a possibility that the PSD2 directive might not have constituted a significant shock to digital transformation in the financial sector. These factors make it challenging to confidently attribute the observed effects of digital transformation in our DiD model to be causal to SME debt. Unfortunately, this leaves our main hypothesis unanswered from a causal point of view.

6.2 Further Research

There are two main topics for further research. First, identify the soft information overlooked due to the digitalization of the financial sector and clarify the quality of the hard information that substitutes for the omitted soft information. Research on faster processing efficiency versus the loss of soft information is important because it tells if banks are making better lending decisions and distinguishing between promising and less viable companies more effectively. Further research from a bank perspective could provide insights into whether banks are making better lending decisions. The second topic for further research centers on SMEs actively seeking financing. It is crucial to investigate whether these SMEs face rejections or receive funding below their actual requirements. Further research should be done to understand the impact of digital transformation in the financial sector on SMEs’ debt.

7. Appendix

A.1 Matching Quality

Figure 7.1: Distribution of Propensity Score Before and After Treatment

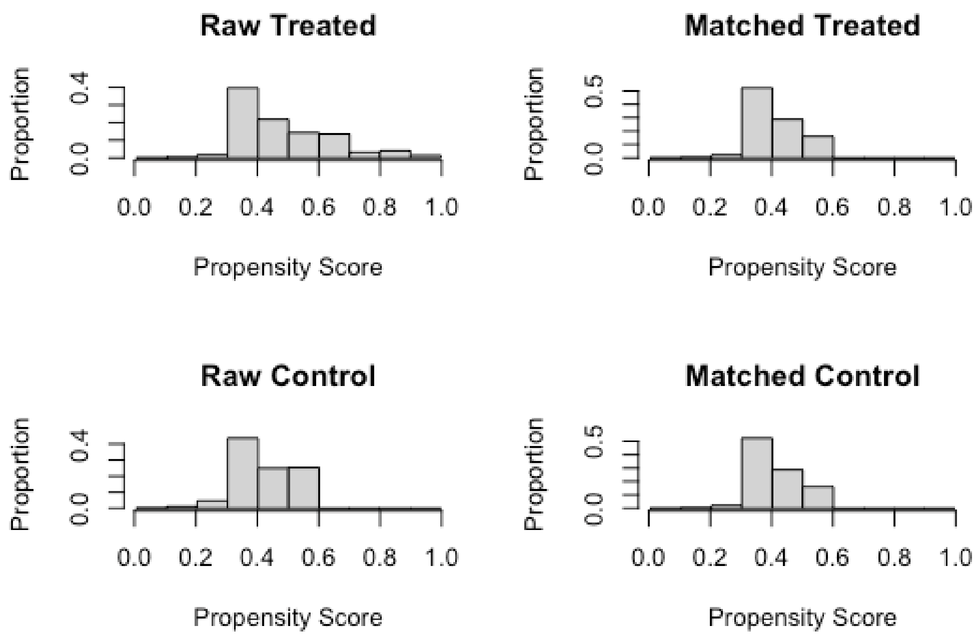
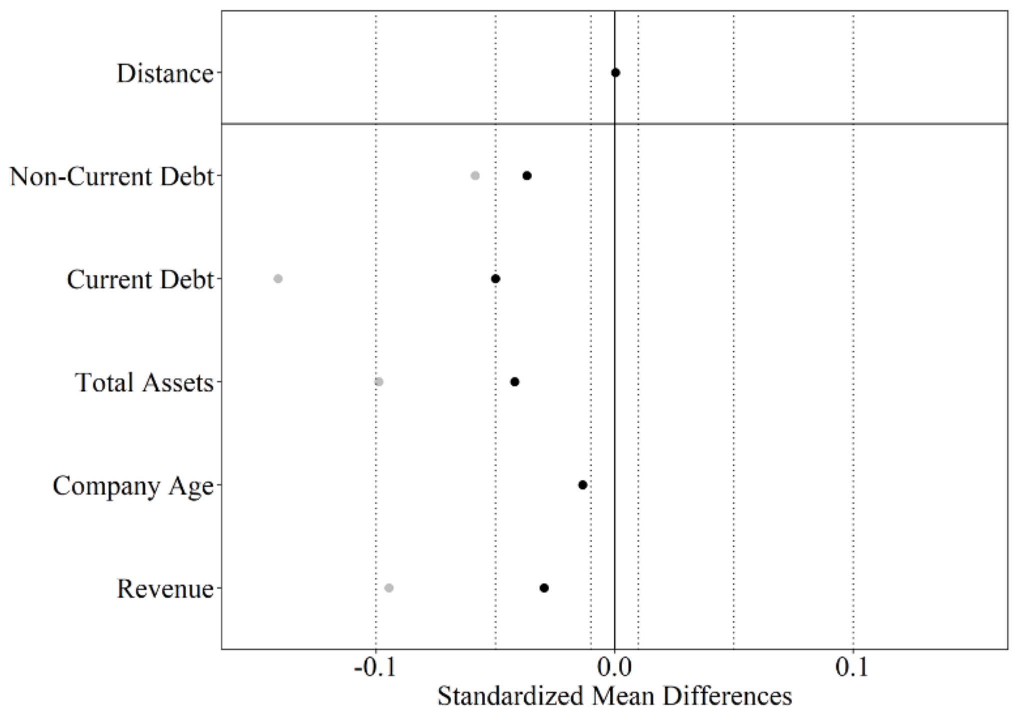


Figure 7.2: Covariates Balance

This figure presents the standardized mean differences between Norway and Sweden for the covariates Total assets, Non-current debt, Current debt, Company age, and Revenue before and after the matching.



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