Digitalization, a Firm's COVID-19 Vaccination?

Do more digitalized firms outperform less digitalized firms during the pandemic?

Julie Enge-Olsen & Nils-Fredrik Solem

Supervisor: Aline Bütikofer

NHH

Master Thesis, Department of Economics

Majors in Economics & Business Analytics

NORWEGIAN SCHOOL OF ECONOMICS

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Bergen, May 2021

Julie Enge-Olsen

Julie Enge-Olsen

Nils-Fredrik Solem

Nils-Fredrik Solem

Abstract

This paper examines how the first nine months of the COVID-19 pandemic have impacted more and less digitalized firms in Norway. Our main hypothesis is that more digitalized firms outperform their less digitalized counterparts in response to the pandemic. We merged detailed business data on 1,351 Norwegian firms with data from two surveys from May and December 2020 regarding the firms' COVID-19 responses to shed light on this hypothesis. The specific areas studied are (1) development of new products, logistics, or distribution, (2) changes in planned investments, (3) temporary and permanent layoffs, and (4) use of government aid.

We use the Random Forest algorithm to identify the most important variables for our regressions. For each area studied, we run standard WLS regressions based on one-time sampled cross-sectional data with these variables as inputs. Additionally, we exploit the fact that 185 firms answered both surveys to conduct a difference-in-differences strategy on layoffs.

Our findings show that being more digitalized increases firms' propensity to develop new products, logistics, and distribution in response to the pandemic. However, being more digitalized does not seem to impact investments, permanent and temporary layoffs, or the use of government aid. Thus, we only find weak empirical evidence for our main hypothesis claiming that more digitalized firms outperform their counterparts in the first nine months of the pandemic.

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1 Introduction

1.1 Motivation and Purpose

The COVID-19 pandemic arrived as an unexpected shock to the world in 2020. The virus was first discovered in Wuhan, China, in late December 2019 (World Health Organization [WHO], 2020b). By April 1, 2020, more than one million cases were confirmed worldwide (WHO, 2020a). The fast spread of the virus and its threat to public health led several countries to shut down their societies: many businesses and institutions closed. As a result, "The Great Lockdown" brought on the worst recession since the Great Depression (International Monetary Fund, 2020). Worldwide, societies faced deteriorating health, deaths, reduced life quality and learning (Bjertnæs et al., 2021).

Norway, being a small, open economy participating in the globalized world, could not avoid the pandemic's dire consequences. The first lockdown was introduced on March 12, 2020 (Statsministerens kontor & Helse- og omsorgsdepartementet, 2020), and the following months were affected by several more, leading to reduced economic activity and increased unemployment (Bjertnæs et al., 2021). For many, the lockdowns forced work habits to move to digital platforms to abide the mandated social distancing. Hence, as 78% of the Norwegian workforce belongs to the service sector (Statistisk sentralbyrå, n.d.), a large proportion of its workers were able to digitalize their work habits.

Following this, Norway has seen an increased pace of implementation of digital solutions (Innovasjon Norge, 2020). Naturally, digital platforms and workers' ability to use them efficiently became increasingly important during the pandemic. We wanted to find out if the advantages gained from being digitalized could serve as a buffer against financial hardships caused by the pandemic.

The literature we review makes a case for the advantages generated by being a more digitalized firm. In short, higher levels of digitalization have been shown to increase competitive ability, financial results and agility (Kim et al., 2011; Lu & Ramamurthy, 2011; Mikalef & Pateli, 2017). In turn, more agile firms adapt better to turbulent environments (Pavlou & Sawy, 2006), which can be likened to the one created by the pandemic. Therefore, this thesis aims to apply the findings of relevant literature highlighting the advantages of digitalization on a real-life example offered by the COVID-19 pandemic.

The data we use to investigate this stems from two surveys regarding Norwegian businesses' responses to the COVID-19 pandemic, collected in May and December 2020. From those surveys, we find information that allows us to distinguish between more and less digitalized firms. Additionally, the surveys allow us to examine if the firms, in response to the pandemic, have: (1) developed new products, logistics, and distribution, (2) changed their planned investments, (3) used permanent or temporary layoffs, and (4) if they have used government aid.

In our analyses, we use the Random Forest (RF) model to identify the most important variables in deciding how well businesses performed, before using them in standard weighted least squares (WLS) regressions. We seek to explain differences in firm performance during the pandemic based on their pre-pandemic level of digitalization, while at the same time controlling for other relevant firm characteristics. In addition, we use a difference-in-differences (DiD) strategy to seek the causal effect of digitalization on firms' propensity to lay off employees in the first nine months of the pandemic.

1.2 Research Question and Hypotheses

As the pandemic is a recent event, the literature covering its effects on digitalized businesses is still limited. Due to the many assumed benefits of digitalization, we wanted to investigate whether being more digitalized affected how well firms performed during the pandemic. Our main hypothesis is that *more digitalized firms perform better than less digitalized firms during the first nine months of the COVID-19 pandemic.* This hypothesis is extensive, and thus we split it into four sub-hypotheses based on the available survey data. These are the following:

1. *More digitalized firms developed new processes, products, logistics, or distribution to a greater extent than less digitalized firms during the first nine months of the COVID-19 pandemic.*

2. *More digitalized businesses increased their planned investments more than less digitalized firms during the first nine months of the COVID-19 pandemic.*

3. *Compared to less digitalized firms, more digitalized firms have laid off fewer employees*

during the first nine months of the COVID-19 pandemic.

4. *Compared to less digitalized firms, more digitalized firms have had a lower usage of government aid during the first nine months of the COVID-19 pandemic.*

The thesis is organized in the following structure: we start by presenting the background for the thesis by giving a brief overview of the COVID-19 pandemic and the importance of digitalization. Following this, we review relevant literature and its following implications for our study. In the two following chapters, we present our data and methodology. Then, we show the results of our estimations before discussing our findings and their limitations. Last, we conclude the thesis.

2 Background

2.1 The COVID-19 Pandemic

COVID-19 is an infectious disease primarily spreading through droplets of saliva or liquids released from an infected person's nose (WHO, n.d.-a). The majority of the infected patients follow a mild to moderate infection course (Folkehelseinstituttet [FHI], 2021). This includes symptoms such as fever, dry cough, reduced sense of smell and taste, and tiredness (WHO, n.d.-b). A minority of the infected follow a severe infection course and experience difficulties breathing, chest pain, and loss of speech and movement. This group might need intensive care treatment, and those who become seriously ill might die (FHI, 2021). Worldwide, by December 2, 2020, 64.67 million cases were confirmed. Of these, 1.50 million had died (Center for Systems Science and Engineering [CSSE], 2021). In Norway, by December 2, 2020, 348 people had died, and the confirmed cases added up to 36,135 (FHI, 2020).

Due to the risk of infected patients having a severe infection course and the subsequent pressure brought onto the health system, the Norwegian society closed to maintain adequate vital health and care services (Helsedirektoratet, 2020a). The Norwegian lockdown of March 12, 2020, temporarily closed several parts of the economy (Statsministerens kontor & Helse- og omsorgsdepartementet, 2020): kindergartens, schools, and other educational institutions, gyms, and swimming pools, in addition to service-oriented businesses such as hairdressing and body care (Helsedirektoratet, 2020a). Moreover, all employees were advised to work from home if possible (Helsedirektoratet, 2020b). Following the first lockdown, more lockdowns were mandated. Some were mandated by the national authorities, but as the pandemic progressed, municipalities received more authority to enforce local lockdowns (Helsedirektoratet, n.d.).

As documented by Bjertnæs et al. (2021) in their report for the Norwegian corona commission appointed by the government, the consequences of the lockdowns were dire. Economic activity declined: unemployment rose, household consumption fell, and production decreased. The average unemployment rate rose from 3.7% in 2019 to 4.6% in 2020. Industries such as culture, entertainment, hotels and restaurants, and other service industries were the main drivers of this increase, while the fall in production was mainly driven by service industries affected by infection control measures.

However, a decline in economic activity was not purely a Norwegian phenomenon. As most countries closed their societies, "The Great Lockdown" caused the world economy to suffer. Supply and demand shocks hit economies, and global value chains were disrupted (Sørheim et al., 2020). Industries such as tourism, entertainment, and service-oriented businesses were directly affected by the lockdowns. Most other industries were affected indirectly through unstable financial markets, reduced demand, and disrupted value chains (Steen et al., 2020). Some businesses faced total closure, while most were affected through altered work patterns and changed supply and demand dynamics. Consequently, we will treat the effects of the COVID-19 pandemic as a negative productivity shock to the economy.

The pandemic did not only cause economic losses. In addition to the health problems and deaths by infection, the pandemic may also have introduced indirect health loss and deaths of people with other illnesses caused by the healthcare system's overload. Moreover, the lockdowns may have caused costs related to physical and mental illnesses, in addition to reduced learning and school dropouts (Bjertnæs et al., 2021).

The consequences of the pandemic have been overwhelmingly negative. However, there has been an upside for digitalization through the mandated reduced physical contact - increased use of digital solutions. As a result, Deloitte (2020) claimed that the pandemic probably accelerated the digital work habits by 10 to 15 years. People have embraced digital learning and taken advantage of digital solutions. The home office has increased the possibility of teleworking, bringing efficiency gains by reduced travel time and increased flexibility. Additionally, Innovasjon Norge (2020) reported that some young firms with a high degree of digital competencies exploit the situation by adapting their technologies to the needs created by the crisis.

2.2 Digitalization

2.2.1 Digital Terminology

"Digitalization", the specific word used in the analysed surveys, is a very broad term. Therefore, this section presents relevant terminology regarding digital technologies, as distinctions may be unclear. We will disambiguate the three main terms associated with digitalization: digitization, digitalization, and digital transformation.

Unruh and Kiron (2017) have developed a framework to distinguish between digitization, digitalization, and digital transformation. They define *digitization* as converting products to a digital format and the associated inventions that ensure such a conversion. This differs from *digitalization* which is defined as "the innovation of business models and processes that exploit digital opportunities" (Unruh & Kiron, 2017, Purposeful Digital Transformation section, illustration). Last, *digital transformation* is a restructuring happening at the system level through digital diffusion. This transformation occurs in all societal levels, such as firms, institutions, economies, and general society.

Furthermore, Sannes and Andersen (2016) claim that digitalization is the conversion from using IT as a support tool to IT being a part of the organizational DNA. As such, the firm designs its organization, practices, and business model to utilize today's and tomorrow's technology. Therefore, we understand digitalization as more than simply using IT tools and programs: it involves integrating these tools into business models and processes.

2.2.2 Digitalization: Advantages and Presence in Norway

The upsides of successful implementations of digital technologies are well documented in a wide range of industries and countries. Advantages digitally mature companies can enjoy are higher level of agility, better competitive performance and enhanced financial results (Kim et al., 2011; Mikalef & Pateli, 2017) and will be delved into in Section 3. Through our hypotheses, we expect these advantages to impact firms positively, also in the turbulent times of crisis.

Norway had a high degree of digital competence pre-pandemic (Innovasjon Norge, 2020). By the standard of the European Commission's Digital Economy and Society Index (DESI), Norway ranks as the top three overall, behind Finland and Sweden (European Commission, 2020). Moreover, Norway has a higher average score than the EU, 69.5 compared to 52.6 of 100 possible points. The DESI index is based on how well countries perform along five dimensions: *connectivity, human capital, use of internet services, integration of digital technology, and digital public services.*

Despite Norway's high DESI ranking, there is still a long way to go for Norwegian firms according to a report from EY (2018) commissioned by Microsoft. EY points out that even though around half of the Norwegian firms they surveyed have experimented with AI, only around a quarter have implemented it in their daily operations. Therefore, Norwegian firms who view themselves as more digitalized have not necessarily implemented breaking edge technology but rather made efficient use of well-established digital technologies in their workflow.

We expect survey respondents to have differing views on what digitalization is, ranging from mere *digitization* to a more comprehensive *digital transformation*. Parallel to this, we also expect respondents to view *digitalization* as a wide range of technologies, from broadly used ones such as Microsoft Excel, customer relationship manager systems to more breaking edge in the likes of artificial intelligence and machine learning. Nevertheless, due to the large number of survey respondents, we still expect these discrepancies to be evened out in the analysis.

3 Literature Review

In this section, we will review the relevant literature. As the COVID-19 pandemic is a recent event, literature covering effects of digitalization during the pandemic is still limited. Moreover, literature investigating how more and less digitalized companies have performed in response to other comparable crises is also scarce. Therefore, the reviewed literature will address digitalized businesses' performance in general, as this lays the foundation to why we believe that more digitalized companies ought to perform better under the COVID-19 pandemic than their less digitalized counterparts. The relevant literature highlights digital businesses' agility, competitive performance and financial performance.

Though there is a vast body of literature covering digitalization aspects in businesses, literature using the terminology "digitalization" is limited in scope. This is likely due to the lack of a common understanding of this very broad term. For this reason, the relevant research investigates more specific digital aspects of a firm, such as IT infrastructure capability, IT-enabled dynamic capabilities, IT leveraging competence, and big data analytic capabilities. We start this section by introducing the relevant literature before describing the literature's implication for our study.

3.1 Impact of Digitalization on Agility

Agility is important to survive in turbulent environments (Wilden et al., 2013). The COVID-19 pandemic is an example of a very turbulent environment. Therefore, the question of whether more digitalized firms are more agile than their counterparts, and thus more likely to survive in crises arises. The topic of agility is examined by Lu and Ramamurthy (2011) where they find that IT capabilities enhance both types of organizational agility in a firm. The first agility type is market capitalizing agility, which is defined as a firm's ability to closely follow changes in customer needs and quickly change their offering based on those changes. The second type is operational adjustment agility which is a firm's more comprehensive ability to quickly adapt to environmental changes by changing its internal processes and employee training to thrive in its competitive environment (Zhen et al., 2021).

Lu and Ramamurthy (2011) base their research on data from a survey sent to business and IT executives at medium-sized US companies in diverse industry groups. The authors use 128 matched-pair survey responses in their analysis, and a regression analysis with a multi-dimension construct to test their hypothesis. Furthermore, firm size, firm age, information system age and size, and industry are used as control variables. They find that the firm's age and information system age significantly impacted the firm's agility. As the study uses one-time sampled cross-sectional data, the authors do not find a causal relationship.

3.2 Impact of Digitalization on Competitive Performance

While Lu and Ramamurthy (2011) examine organizational agility as the end goal in their research, Mikalef and Pateli (2017) view it as a mediating step to go from IT-enabled capabilities to competitive performance. They find that IT-enabled capabilities facilitate the two types of agility in accordance with Lu and Ramamurthy's (2011) research.

IT capabilities are defined by Bharadwaj (2000) as firms' ability to utilize and organize their IT-based resources in combination with other capabilities and organizational resources.

Mikalef and Pateli (2017) also went further in their research by demonstrating that it is through this agility that firms can sustain enhanced competitive performance. Their view on how to best describe how IT capabilities lead to sustained competitive performance differs from the common resource-based view (RBV) present in similar research. The authors argue that a better way to understand the dynamics of IT capabilities in a firm is through the Reflective-Formative Measurement Model Type II coined by Chin (1998). This model helps explain that there are several ways for a firm to achieve the IT capabilities required to achieve sustained competitive performance.

The findings are based on a partial least squares structural equation modeling (PLS-SEM) analysis performed on survey data answered by managers at 274 international firms. All business sizes are represented, from micro to large, within a wide range of industries: high tech, consulting services, consumer goods, financials, industrials, telecommunications, basic materials, health care utilities, and oil and gas industries.

The authors find a significant total effect of IT-enabled dynamic capabilities on competitive performance. The effect remains significant but reduced when the mediators are accounted for. Thus, the main takeaway is that IT-enabled dynamic capabilities improve the firms' agility, which leads to competitive performance gains. Their findings can occur in all sorts of environments, ranging from relatively stable to highly uncertain.

Pavlou and Sawy (2006) also shed light on competitive performance by concluding that the effect of IT leveraging competence on competitive advantage is more pronounced in turbulent environments, specifically in the context of new product development (NPD). This effect is not direct but "fully mediated by both the dynamic capabilities and functional competencies" (Pavlou & Sawy, 2006, p. 198). IT leveraging competence is defined as "the ability to effectively use IT functionalities to support IT-related activities" (Pavlou & Sawy, 2006, p. 199).

Similar to Mikalef and Pateli's (2017) research, Pavlou and Sawy (2006) use PLS-SEM as their empirical approach on survey data from 180 NPD managers from a wide variety of industries. However, they did not test the longitudinal impact as the survey data was cross-sectional. Hence, as highlighted by the researchers, causality cannot be claimed. Two other drawbacks from their research are that they only focus on NPD managers, a relatively narrow view on IT capabilities, and their research dates from a time which is technologically different from today's world.

3.3 Impact of Digitalization on Financial Performance

The preceding reviewed literature indicated that more digitalized firms are more agile and enjoy competitive advantages over their less digitalized counterparts. The next step in this literature review is to determine whether these advantages will translate into improved financial performance. Kim et al. (2011) find that IT capabilities, mediated by Process-oriented dynamic capabilities (PDCs), affect financial performance while using SEM to identify causality. The researchers conduct a field survey in Korea and require a pair of respondents from each firm to receive reliable information about the firms' circumstances: one top leader from the IT department and one top leader from the business department.

The authors measure financial performance through survey questions amounting to a perceived financial performance over the last three years. Additionally, PDCs are defined as "a firm's ability to change (improve, adapt, or reconfigure) a business process better than the competition in terms of integrating activities, reducing cost, and capitalizing on business intelligence/learning" (Kim et al., 2011, p. 488). Their research includes two main sets of hypotheses. The first set suggests that PDCs are positively associated with financial performance and IT capabilities, more precisely, IT personnel expertise, IT infrastructure flexibility, and IT management capability. The other set of hypotheses is that a firm's IT personnel expertise, IT management capabilities, and infrastructure flexibility are positively associated.

Firm size and industry are used as control variables for firm performance, where only the latter control variable has a significant effect on the firm's performance (Kim et al., 2011). The authors test direct and indirect relationships between IT capabilities and firm performance. The results show no statistically significant relationships in the direct models, consistent with previous research claiming that direct relationships between IT capabilities and performance metrics can be problematic to identify due to a distance between cause and effect (Mikalef & Pateli, 2017).

However, in their indirect model, Kim et al. (2011) find significant positive relationships between IT capabilities and PDCs, and sequentially, a positive relationship between PDCs and financial results. Thus, the authors claim to identify the following route of causality: IT personnel expertise influences IT management capabilities, which in turn influences IT infrastructure flexibility, which affects PDCs.

3.4 Impact of Big Data Analytics on Firm Performance

Rialti et al. (2019) further confirm Kim et al.'s (2011) research by finding a significant positive relationship between a firm's performance and its big data analytics (BDA) capabilities. The latter is defined as the ability to utilize and organize BDA-based resources with other capabilities and resources. This confirmation is particularly valuable for our research as Rialti et al. (2019) expand the research on the topic to include European organizations, while Kim et al. (2011) studied Korean organizations.

Rialti et al.'s (2019) data consists of 259 survey answers from large European organizations' managers, and the findings should therefore be applicable to similarly-sized organizations. Analogous research is conducted by Ferraris et al. (2019), focusing on small and medium-sized Italian enterprises. Using knowledge management (KM) as a mediator between BDA capabilities and firm performance, they also find a significant and positive relationship between BDA capabilities and firm performance. Furthermore, they find that KM contributes to amplifying the effect of BDA capabilities in a firm.

3.5 Implications for our Study

As the reviewed literature reveals, firms with a higher level of digitalization, i.e., better IT capabilities and superior use of big data analytics, enjoy more agility in their organization, leading to increased competitive ability and financial results. Research has also shown that more agile firms are better suited to deal with turbulent environments.

Based on the reviewed research, we believe that more digitalized firms in Norway will, to a greater degree, readjust and seize opportunities and perform better in this crisis than their less digitalized counterparts. This expectation is based on two main reasons. First, they may have a more beneficial financial situation coming into the crisis, which means they are more likely to better weather through the pandemic. Second, more digitalized firms are likely to be more agile, which means that they may adapt faster and better to a new environment. However, we will not be able to separate these effects as our data is not sufficiently detailed.

The hypotheses of this thesis are a result of the reviewed literature and can be found in Section 1.2. Our paper contributes to the existing literature by exploring how more digitalized firms respond and perform in a unique and worldwide crisis. To the best of our knowledge, we are among the first to study the effects of digitalization in the context of the COVID-19 pandemic.

4 Data

To study our main hypothesis, we received access to two surveys from 2020 covering responses from Norwegian firms on how they have been affected by the crisis. We also extracted data from Proff, an online database for financial information on Norwegian firms. The Proff data contained detailed information about the businesses, and was consolidated with the survey data. This section is organized as follows: the two surveys will be described, before presenting the data from Proff and our control variables. Thereafter, we present descriptive data from our final data set.

4.1 The Surveys

Our primary data source consists of two cross-sectional surveys regarding companies' business environment and responses to the COVID-19 pandemic, one from May 2020 and the other from December 2020. The surveys covered businesses' responses to changes in the following areas: current operational status, strategy and competition, digitalization, employment and layoffs, HR and human capital, and government aid. The majority of the survey questions were based on a five-point Likert scale. The surveys were sent to two samples of business leaders. One sample of respondents came from Virke, an employers' organization for businesses in the trade and services industry. Kantar, a market analysis company, collected the other sample. The relevant questions from both surveys are in Appendix A5.

4.1.1 May 2020

The survey from May 2020 consists of businesses from the Kantar sample. Kantar sent the survey to a total of 20,116 businesses. During the survey period from May 14 until June 5, 2020, 2,046 businesses opened the survey, of which 1,878 answered, leading to a 9.3% response rate. The businesses received three email reminders. The complete list of firms to whom the survey was sent was not available to us, preventing a complete population description.

4.1.2 December 2020

The December survey was open from November 16 until December 9 and was sent to a total of 19,701 businesses. 8,737 members of Virke received the survey, in addition to 10,964 businesses from Kantar's database covering all private Norwegian firms. Respondents from Kantar received four email reminders to answer the survey, while respondents from Virke received three email reminders. After the survey closed, a total number of 1,418 businesses from Virke and 1,223 businesses from Kantar had answered at least one survey question. This represents a total response rate of 13.4%.

With our criteria of only keeping observations with answers to at least one of the five relevant questions to our analyses, the data consisted of 1,802 responses, 1,169 and 633 responses from Virke and Kantar, respectively. We removed observations for which we did not have sufficient data to compute a digitalized status or that did not have sufficient information from Proff to compute their earnings before interest and taxes (EBIT). Our final dataset consisted of 1,351 responses. As expected, the industries represented by Kantar and Virke are different as can be seen in Appendix A2.2. For instance, over a third of Virke respondents belong to the "Wholesale and retail trade; repair of motor vehicles and motorcycles" industry, while only 13.8% of Kantar's respondents belong to this group.

Possible Causes of Low and Uneven Response Rate

There are several reasons why the response rate is as low as 13.4%. Baruch and Holtom (2008) found that having leaders as respondents may give fewer responses than research that approach non-leaders to gather data, with an expected response rate of 35-40%. Still, our observed response rate of 13.4% seems considerably below the normal for such respondents. Another possible factor causing the low response rate is the expected time to complete the survey, approximately 15 minutes. Several of the respondents which completed the survey complained of its length and word-of-mouth may have deterred others from completing it.

The distribution between surveys sent and answered by the two groups changes drastically. Originally, Virke received 44.4% of the surveys, whereas businesses from the Kantar sample received 55.7% of the surveys. In our final sample, businesses from Virke represent 64.9%

while businesses from Kantar represent 35.1% due to substantially different response rates. 16.2% of the Virke firms answered while only 9.9% of the Kantar firms answered.

The businesses in the Virke and Kantar samples are likely to have a diverging level of motivation for answering the survey. Virke members pay a yearly fee to be part of the employer organization and might therefore be more incentivized to answer the survey, specially if they expect their contribution to create valuable insights. In contrast, Kantar is a marketing firm and their survey receivers are likely to feel less obligated to answer.

We attempt to correct for the specific group of firms Virke represents and the low and uneven response rates by adding weights to the two samples. Weighting data is a complex issue, and if it is not necessary, using WLS might give less precise estimates (Solon et al., 2013). However, we found that adding weights had little impact on our results.

4.1.3 May 2020 and December 2020

In addition to using the December survey for analyses, we wanted to use both May and December surveys in order to seek causal relationships in a DiD analysis. Therefore, we created a new dataset by matching answers from the two surveys by the firms' unique organizational number. We were able to identify 185 businesses that had answered the relevant questions regarding permanent and temporary layoffs at both times.

4.2 The Variables

4.2.1 Independent Variables

Independent Variable of Interest - Digitalization Score

Our main variable of interest is the degree of digitalization. There is no publicly available measure of digitalization or comparable digital scores on the business level in Norway. Hence, we created a weighted score ranging from one to five based on the firms' answers to the following survey statements. The answer options were "strongly disagree", "disagree", "neither agree nor disagree", "agree", "strongly agree".

1. *Digitalization plays a central role in our strategy* (50% weight)

2. *We were far along the path in digitalizing our internal work processes* (30% weight)

3. *We were far along the path of digitalizing our process of collecting and processing customer information* (20% weight)

These questions were chosen based on how different sources describe aspects of digitalization, such as digital maturity and technology capabilities. In particular, the strategy question was chosen and given the highest weight as having a clear digital strategy plays a central part in digital maturity (Kane et al., 2015), and the winners of digitalization closely tie their corporate and digital strategies (Bughin et al., 2017). Moreover, firm characteristics such as its organization and culture, customer experience (Deloitte, 2018), and internal processes (BCG, n.d.; Grebe et al., 2017) are highlighted as central in defining each firm's digitalization level. Hence, aspects such as strategy, customer relations, and processes may be considered central parts of a business's digitalization, and are reflected in our digitalization score. We used the weighted score to split the companies into a "more digitalized" category (1) and a "less digitalized" category (0) based on the median of 3.5.

Control Variables

Other factors than digitalization are likely to influence how well businesses performed during the pandemic and should thus be included in the regression as control variables. Including controls takes us one step closer to a *ceteris paribus* comparison between the two groups, as "failure to include enough controls or the right controls still leaves us with selection bias" (Angrist & Pischke, 2014, p. 69).

The control variables represent other characteristics of the businesses that may affect their performance during the pandemic. To create these variables, we contacted Proff to access their data about Norwegian companies. From their data, we extracted NACE-code, number of employees, incorporation date, turnover, earnings before interests and tax (EBIT), and legal business structure. This data was matched with the existing survey data by the organizational numbers.

We chose the following control variables as inputs to our Random Forest (RF) model: *EBIT*, *firm size*, *firm age*, *industry* (NACE-code), *county*, and *legal structure*. *EBIT* is based on the average EBIT of firms for 2017, 2018, and 2019. The number of employees measures firm size. Firm size is relevant as larger firms are less likely to be negatively affected by recessions when compared to small and medium-sized firms (Lai et al., 2016).

In comparison to large firms, small firms have "limited financial resources, narrow customer base and product lines across which to spread risk and less bargaining power with a variety of external actors, e.g., customers, suppliers and finance providers" (Cowling et al., 2012 & Smallbone et al., 2012, as cited in Lai et al., 2016, p. 117). Thus, we believe that larger firms may be better equipped to face economic challenges brought on by the COVID-19 pandemic. We categorized *firm size* along three levels: small (1-20 employees), medium (21-100 employees), and large (over 100 employees) in concurrence with the Confederation of Norwegian Enterprises' classification (Næringslivets Hovedorganisasjon [NHO], n.d.).

We based *firm age* on the company's incorporation date. We believe that this variable could have different effects on how well businesses performed as, on the one hand, being older and more established may make the business more resilient. On the other hand, a well-established firm may also be less adaptive to changes. For instance, Ebersberger and Kuckertz (2021) find that innovative start-ups have a faster innovation response time than more established firms. This could imply that young firms adapt better to the challenges brought on by the pandemic.

Finally, *industry*, *county*, and *legal structure* are categorical variables used in our regressions. Industry membership is essential as the pandemic hit some industries harder than others (Finans Norge, 2020; Nordby, 2021). The same argument applies to different areas within Norway, as counties and municipalities are unevenly affected (Johansen et al., 2021). We also believe a business' legal structure could explain how well the firms have performed.

4.2.2 Dependent Variables

As we base our analysis on the survey data, we used questions regarding the following areas to form our dependent variables: *R&D*, *investments*, *temporary and permanent layoffs*, and *government aid*. We also created a second variable for *temporary and permanent layoffs* which used both surveys to allow for the DiD analyses.

R&D

For *R&D*, our sub-hypothesis is that more digitalized businesses are more likely to develop new processes, products, logistics, or distribution. We chose the three questions below to make an index that separates the business which have developed to a greater extent and their counterparts. The answer options were "no", "yes – to a small extent", "yes – to some extent", and "yes – to a large extent".

Has the company as a result of COVID-19:

1. *Developed new products and/or services?*
2. *Developed new or improved processes that differ significantly from previous processes?*
3. *Developed new or significantly changed logistics, delivery or distribution of products and / or services?*

The distribution of the answers to all three questions are comparable, with approximately 50% of the firms answering "no" to each of the questions. The complete distribution is displayed in Appendix A1.1. We averaged over the three questions to aggregate them and created a dummy variable splitting the firms along the median. The firms with less R&D amounted to 41.8%, while the firms with a greater extent of R&D amounted to 57.8%. This difference is due to the choice of placing firms at the median score in the group with the greater extent of R&D. 0.4% of the firms in our filtered data did not answer this question.

Investments

For investments, our sub-hypothesis is that more digitalized businesses are more likely to continue planned investments or even increase investments to seize opportunities created by the pandemic. We used the five sub-questions shown below to form the scores. The answer options were "large reduction", "small reduction", "unchanged", "small increase", and "large increase".

How do you think the company's investments will change compared to the period before the COVID-19 crisis started?

1. *Investments in physical capital (machinery, equipment, real estate, etc.)*
2. *Investments in competence and learning*
3. *Investments in marketing and branding*
4. *Investments in innovation, research and development*

5. *Investments in organizational development and improvement projects*

We found the overall average score for the five questions for each firm and created a dummy variable based on those. We grouped "unchanged", "small increase" and "large increase" together, and "small reduction" and "large reduction" together. 78.2% belongs to the former group, while 21.8% belong to the latter. Across all questions, over 50% of the firms indicate that they plan to keep investments unchanged. Those numbers are visualized in Appendix A1.2.

Layoffs

Next, we created a dummy variable based on survey questions on temporary and permanent layoffs, hereafter referred to as *layoffs*. Firms that have either temporarily or permanently laid-off employees are grouped, and firms that have done neither are also grouped. We hypothesize that more digitalized firms, to a lesser degree, lay off their employees compared to their less digitalized counterparts. The data reveals only a small difference between the two groups. 52.8% of less digitalized firms have laid off employees, while 50.1% of more digitalized have done so. Overall, 43.9% of the firms have not laid off any employees, 51.5% of the firms have either laid off employees permanently or temporarily, and 4.6% either answered that they did not know or have not answered the survey question. Detailed visualization of the survey answers can found in Appendix A1.3.

Government Aid

Five questions regarding different types of government aid were chosen to create its variable. The types of government aid are "direct aid", "loan schemes (including low-interest loan schemes)", "guarantor schemes", "postponement of payments" or "reduced administrative burdens". The respondents could answer "yes", "no", or "don't know" when asked if they had made use of government aid. We hypothesize that more digitalized businesses use government aid to a lower degree than less digitalized businesses. An index for answering was created with a dummy value of 1 if the firm has used at least one type of aid. 47.5% of the firms have not made use of any government aid, 44.1% of the firms have made use of at least one type of government aid, and 8.3% either answered that they did not know or have not answered the survey question. Detailed visualization of the survey answers can be found in Appendix A1.4.

4.2.3 Descriptive Statistics

The respondents represent a wide range of industries. The industry "Wholesale and retail trade; repair of motor vehicles and motorcycles" is by far the most represented with over 28% of the firms belonging to this group. The next three most represented industries, amounting to 31.7% of the firms, are "Professional, scientific and technical activities", "Administrative and support service activities", and "Construction". A complete overview of each industry's frequency in the data can be found in Appendix A2.1.

The firm sizes present in our dataset are representative of the nationwide size distribution. 72.1% are small, 19.4% are medium-sized, and 5.4% are large. 3.0% are of unknown size as Proff did not have the number of employees for those firms. A visualization of this data can be found in Appendix A2.3.

The Norwegian counties' distribution follows the lines of the respective counties' sizes, with Viken, Oslo, and Vestland as the most represented counties. At the same time, the represented legal structures are overwhelmingly limited companies (AS) at 91.2%, while only two firms are listed companies (ASA). The counties' distribution can be visualized in Appendix A2.4 and the legal structures' distribution can be visualized in Appendix A2.5.

The visualization of the categorical data indicates that some category levels contain very few observations. This can be an issue as many levels with few observations tend to lead to sparse individual features, thus adding many low-signal regressors (Johannemann et al., 2020). To limit the number of infrequent levels in the variables *county*, *legal structure*, and *industry*, we pool together the levels with less than 1% of the total observations and group them into their respective "Other" categories.

In addition to the categorical variables, we also have two numeric variables: the average EBIT from 2017 to 2019 and the firms' age. The average firm EBIT from 2017 to 2019 is 8.9 million NOK with a standard deviation of 105.8 million NOK, while the minimum is -137.8 million NOK and the maximum is 3.4 billion NOK. As expected, there is a large spread in values as many industries and firm sizes are represented in the data. The mean firm age is 22 years with a standard deviation of 18, implying a good spread of firm ages. The full summary statistics for *firm age* and *EBIT* can be found in Appendix Table A2.1.

We also found that more digitalized firms outperformed their less digitalized counterparts with an EBIT median of 0.55 million NOK versus 0.34 million NOK. This difference is in line with our expectations based on the literature review - more digitalized firms seem to financially outperform less digitalized ones.

The large spread in values in the EBIT-variable could skew the analysis and impede the models. We chose not to remove the outliers in our analysis as we could end up selecting out a specific group of firms, namely very large firms. Rather, we created a categorical variable for EBIT. Eight categories are defined in the following intervals: above 100 million NOK, above 10 million NOK, above 1 million NOK, above 0 NOK, above -1 million NOK, above -10 million NOK, above -100 million NOK and above -1 billion NOK. This choice did not significantly impact the models' results, but gave more interpretable coefficients for the EBIT variable.

5 Estimation Methods & Models

As stated, our thesis aims to examine whether more digitalized businesses in Norway have performed better in response to the COVID-19 pandemic than their counterparts. To investigate what kind of traits led companies to perform better, we use the variable importance measure of the Random Forest models. Most of the data was collected during December 2020, well into the pandemic. Thus, the main part of our analyses consist of standard WLS regressions on cross-sectional data. We use the matched dataset with the firms having answered both the May and December survey to perform a DiD estimation on layoffs.

We present our Random Forest model before delving into our regular WLS regressions, followed by our difference-in-differences model.

5.1 Random Forest Model

As the first step in our analysis, we use machine learning, specifically the Random Forest (RF) algorithm. The reason behind our choice is to help us distinguish the meaningful variables in understanding the relationship between the dependent and control variables. We use seven control variables, and several of them are categorical with numerous levels, hence the need for uncluttering our regressions by removing less meaningful variables. Therefore, we use the algorithm to avoid bad controls and overcontrolling our models.

The RF algorithm is a supervised learning algorithm that uses the output of many individual decision trees, called ensemble learning, to perform predictions on classification or regression problems (Breiman, 2001). In addition to prediction, the model can also indicate which variables are the most valuable in the analysis. This method is widely acknowledged as robust as it generally performs well against comparable methods and is much less prone to overfitting[1] the data it is being trained on than decision trees (Hastie et al., 2017). The main difference between the RF method and decision trees is that the former splits at each node with the best split amongst a subset of randomly selected

[1]Overfitting in machine learning denotes an issue when an algorithm creates a model with strong performance on the training data but significantly weaker performance when applied to a new dataset. This issue occurs when the model finds patterns in the noise of the data, hence retaining the peculiarities of the data rather than more generally applicable rules (Dietterich, 1995).

variables, while the latter finds the best split amongst all available variables (Liaw & Wiener, 2002).

For our analysis, we choose to use an RF model as it performs well and manages to separate significant variables from less significant ones even among a large number of variables (Hastie et al., 2017). Additionally, the algorithm makes no formal distribution assumption, and since it is non-parametric, it can handle skewed and multi-modal in addition to both ordinal and non-ordinal categorical data (Richmond, 2016).

The RF algorithm is used in a wide range of applications and is popular due to its performance, even with few adjustments to its algorithm (Hastie et al., 2017). The RF algorithm is viewed as a black box algorithm because it is difficult to interpret its inner workings due to the large number of trees being used (Probst & Boulesteix, 2018). However, some adjustments, also called hyperparameter tuning, can be changed based on the data being analyzed to improve the model. The three main hyperparameters are the number of trees in the ensemble, the number of variables available for splitting at each tree node (*mtry*), and the node size, i.e., the minimum number of data points for a split to be made. The node size will implicitly define the depth of the decision tree.

In our classification problems, we attempt to predict what firms answered to specific survey questions on a discrete scale based on several discrete variables describing the firms such as *industry*, *firm size*, and *legal structure*. We have therefore chosen to set a fixed large number of trees according to best practice described by Probst and Boulesteix (2018), set the node size to one as is standard in classification problems, and iterated through six different values for *mtry* ranging from three to seven. For each classification, we will find the *mtry* value which maximizes the accuracy of the RF model.

Another important parameter in an RF model is defining what method should be used when splitting variables at each node. Several different methods are available for categorical variables, such as entropy, Chi-square, and Gini-splitting. Research has found that no method is evidently superior (Raileanu & Stoffel, 2004). Therefore, we opt for the commonly used Gini-splitting method. It is defined in Equation 5.1 (James et al., 2013).

$$G = \sum\nolimits_{k=1}^{K} \hat{p}_{mk}(1 - \hat{p}_{mk}) \tag{5.1}$$

It is the measure of total variance across K classes. $\hat{p}_{mk}$ is the proportion of observations in the m^{th} node for class k in the training dataset. We can observe that when $\hat{p}_{mk}$ approaches zero or one, the Gini index will tend towards zero. This is why small values of the Gini index indicate that a large proportion of the observations at that node belong to the same class, which is called a highly pure node (James et al., 2013).

Even though RF models tend to be robust against overfitting, using cross-validation to partition the data is common to reduce the chances of an uneven split of the data. Our analysis uses 10-fold cross-validation to reduce the likelihood of an uneven split. This method involves splitting the data into 10 equal partitions and running each RF model 10 times, each time with a different test and training data split (James et al., 2013). This process is repeated three times, meaning that the data is split along three different lines and that each model is run 30 times in total.

The analysis has a retrospective perspective as we do not seek to predict future behavior. For this reason, our desired output is to find strong candidate predictors on how firms have answered the different relevant questions in the survey. This is where the variable importance comes in. It is calculated through the mean decrease of Gini importance. Every time a tree is split, the improvement of adding the predictor is logged and is then averaged over all trees. Since a lower Gini index is synonymous with higher purity, the larger the mean decrease, the more important that variable is for the model (Archer & Kimes, 2008). We then use the most important variables as predictors in regression models, which will be discussed in the next sub-section. A visualization of the variable importance plot for the analysis on *R&D* can be found in Appendix A3.1.

We choose to use the variable importance data to decide which variables should be included in the regressions. The variable *firm age* is the only continuous variable in our regression, and when included in the RF model, the model consistently flagged it as the most important variable. This issue is particular to tree-based models with many categorical variables because of the large increase in the dimensionality of the feature representation caused by having categorical variables with many levels (Dingwall & Potts, 2016). This also means that a single level of a categorical variable must have a very high predictive power to be chosen as a split early in the tree, which can reduce the model's predictive power. Therefore, we choose to remove the *firm age* variable from the Random

Forest model and manually test it by including it in all regressions.

5.2 Regular WLS Regressions on the Impact of Digitalization on Firm Performance

Each of our regressions have limited dependent variables: dummies representing survey answers that either take on the value 1 or 0 to represent particular outcomes. Therefore, the dependent variables are binary. In such regressions, non-linear models like logit or probit may be well suited (Wooldridge, 2019).

However, as most of our independent variables are coded as dummies, our models are fully saturated. According to Angrist and Pischke (2009), saturated models "are inherently linear" (p. 37). With binary dummies as dependent variables, this means that we obtain linear probability models (LPM). We estimate robust standard errors in the models as the LPM residuals are heteroscedastic. As we have applied different weights to the samples from Virke and Kantar, we use weighted least squares regressions (WLS).

5.2.1 Models

The top three variables highlighted by the RF algorithm for each dependent variable were chosen for the regressions. In addition, regardless of the outcomes of RF, the variables *EBIT*, *firm size*, *industry* and *county* were added to each regression. These variables were found to be correlated with digital status in preliminary regressions where *digital status* was defined as the dependent variable. Excluding them from the model would therefore cause bias. The following model is estimated for the regression on R&D:

$$\begin{aligned} Y_{R\&Di} &= \alpha + \beta DigitalStatus_i + \gamma EBIT_i \\ &\quad + \sigma FirmSize_i + \delta Industry_i + \pi County_i + \epsilon_i \end{aligned} \tag{5.2}$$

Where $Y_{R\&Di}$ indicates whether firm i has developed new processes, products, logistics, or distribution as a response to the pandemic. For the last three regressions, we estimated the following models:

$$
\begin{aligned}
Y_i = \alpha + \beta DigitalStatus_i + \gamma EBIT_i + \sigma FirmSize_i \\
+ \delta Industry_i + \pi County_i + \mu LegalStructure_i + \epsilon_i
\end{aligned}
\tag{5.3}
$$

Where Y_i represents whether the firm has changed pre-COVID-19 investment plans, laid off employees, or used government aid as a response to the pandemic.

Given that these are linear probability models, the predicted value of the dependent variable is the predicted probability that $Y_i = 1$. Consequently, the coefficients of the independent variables reveal the change in the probability for the particular outcome $Y_i = 1$.

All variables in the models are coded as dummy variables. $DigitalStatus_i$ is the independent variable of interest, given value 1 if the firm is more digitalized, 0 otherwise. The variables $EBIT_i$, $FirmSize_i$, $Industry_i$, $County_i$, and $LegalStructure_i$ are all categorical variables with several levels. $EBIT_i$ indicates which EBIT-group the firm belongs to. $FirmSize_i$ reveals the size of the firm, $Industry_i$ indicates which industry the firm operates in, and $County_i$ represents the Norwegian county the business belongs to. $LegalStructure_i$ reveals what type of organization it is.

As *firm age* had no significance in our regression models, we chose to exclude it in our regressions.

5.2.2 Zero Conditional Mean Assumption

There are several assumptions that must hold in our regressions. In this section, the zero conditional mean assumption is discussed as it is important for a causal interpretation and likely violated in our models.

Given the data and relatively simple regression setups, we cannot control for everything that affects the outcome variables and the independent variable of interest. This causes problems such as reverse causality, selection, and omitted variable bias (OVB). Therefore, the digital score variable will be over- or underestimated.

For instance, important variables omitted from our models could be "the average age of the board" or having a chief digital officer (CDO), as these could influence firms' level of digitalization. Younger board members may bring expertise in technology, and may help lead firms through digital transformations (Brown et al., 2019; Sarrazin & Willmott, 2016). A CDO has the responsibility of a firm's digital transformation and focus on digital strategy (Kunisch et al., in press). As such, having a CDO would likely be correlated with *digital status*. Concludingly, as the zero conditional mean assumption is likely violated, we can only interpret the results correlationally and not causally.

5.3 Difference-in-Differences Strategy on Layoffs

5.3.1 Theoretical Background

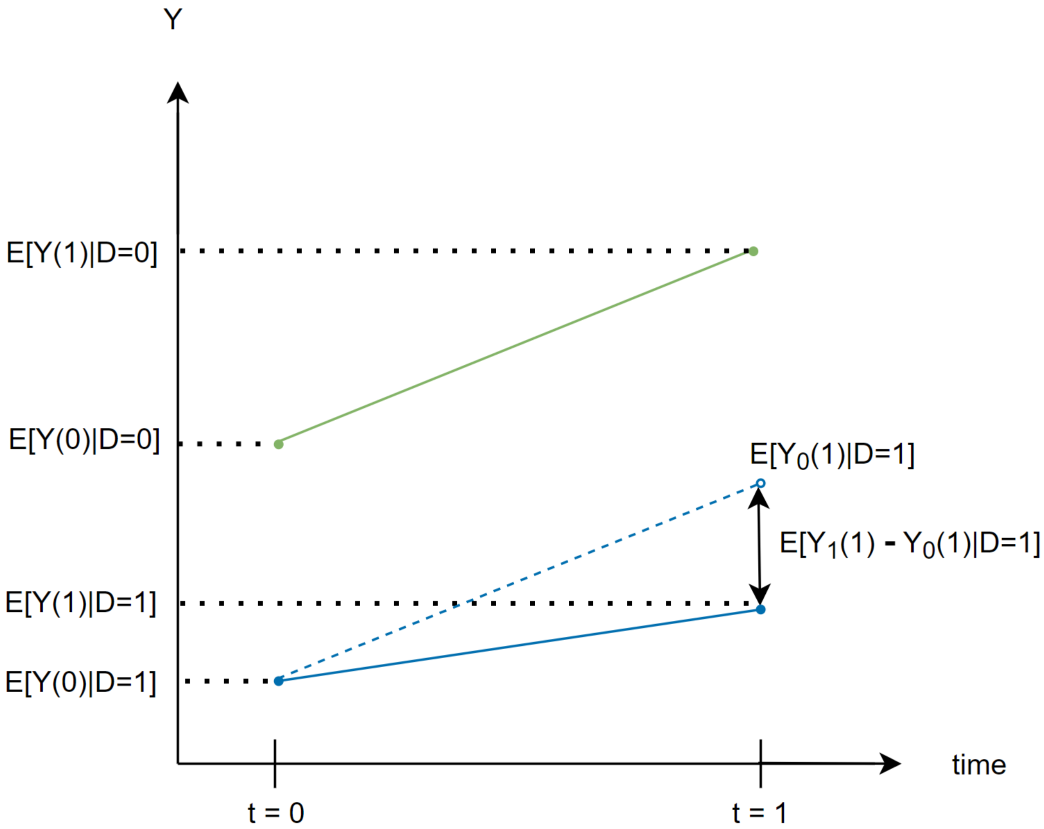
In addition to the regressions run solely on data from the December survey, we conduct DiD estimations in an attempt to identify the causal effect of digitalization on layoffs. We hypothesize that more digitalized businesses lay off employees to a lesser degree than their less digitalized counterparts during the first nine months of the pandemic. The best setup to test such a hypothesis is to compare the pandemic responses for a particular set of businesses in the same context, only differing in their level of digitalization.

In Figure 5.1, Y_{1i} symbolizes more digitalized firms, while Y_{0i} symbolizes their less digitalized counterparts. The causal effect of being more digitalized for each individual firm i would then be defined as $Y_{1i} - Y_{0i}$ (Angrist & Pischke, 2009). However, this effect is never observable as we, for a given firm, cannot observe its counterfactual situation, only its actual situation. To solve this problem, we exploit the law of averages. We can assemble a group of less digitalized businesses which, on average, mirror the selection of more digitalized businesses. Therefore, we can conclude that the change in outcomes is, on average, the causal effect of digitalization on layoffs due to the pandemic.

The crucial assumption for a DiD estimation is that, in absence of digitalization, the change would be the same for the two groups. This is referred to as the common trend assumption (Angrist & Pischke, 2009). The assumption is strong, but important. If it holds, a deviation in trends may identify a causal interpretation. To illustrate, we present the simplest setup of DiD in Figure 5.1.

The simplest DiD setup includes two groups, D = 1 for the treated group and D = 0 for the control group. There are two time periods, t = 0 for pre-treatment and t = 1 for post-treatment. The solid lines in the Figure 5.1 display actual outcomes. The green

Figure 5.1: Graphical Representation of the Simplest DiD Setup



line represents the control group (D = 0), whereas the blue lines represent the treatment group (D = 1). The dashed blue line illustrates the development of the treatment group in absence of treatment. The causal effect of treatment is identified as the difference between the two blue lines, as this is the deviation from the common trend between the two groups. We expect the effect to be negative in our setup, as we hypothesize that more digitalized firms lay off fewer employees than less digitalized firms in response to the pandemic.

Mathematically, the setup is described as:

$$\begin{aligned} E[Y_1(1) - Y_0(1)|D=1] = \{&E[Y(1)|D=1] - E[Y(1)|D=0]\} \\ &- \{E[Y(0)|D=1] - E[Y(0)|D=0]\} \end{aligned} \tag{5.4}$$

Where $E[Y(1)|D=1] - E[Y(1)|D=0]$ is the difference between the treatment and control group in the post-treatment period. Further, $E[Y(0)|D=1] - E[Y(0)|D=0]$ is the difference between the treatment and control group in the pre-treatment period.

Without the causal effect, $E[Y_1(1) - Y_0(1)|D = 1]$ should be zero, as the difference between the green and the dotted blue line in Figure 5.1 is always the same.

5.3.2 Models

The treatment group is more digitalized businesses, and the control group is less digitalized businesses. In our setup shown in Equation 5.5, the treatment group is exposed to the treatment in both periods, whereas the control group is not. We consider the COVID-19 pandemic a negative productivity shock to the economy. Since both surveys were collected after the pandemic hit the economy, we investigate how the more and less digitalized businesses perform during the COVID-19 pandemic. As such, the DiD estimations aim to isolate the effect of digitalization, and a deviation from common trend can be considered as a "digitalization premium". We estimate the following model:

$$\begin{aligned} Y_{it} = \alpha + \beta Treated_i + \gamma Post_t + \delta_{dd}(Treated_i \times Post_t) \\ + \theta County_i + \pi Industry_i + \sigma May28_t + \mu X_i + \epsilon_{it} \end{aligned} \tag{5.5}$$

Y_{it} is the dependent variable, demonstrating layoffs for firm i at time t. This outcome variable is a dummy, indicating self-reported answers to whether a firm has laid off employees. $Treated_i$ is 1 if the firm is more digitalized, 0 otherwise. This variable controls for fixed differences between the compared firms (Angrist & Pischke, 2014). $Post_t$ is also a dummy, and is 1 if the data comes from the December survey, 0 if the data stems from the May survey. This variable demonstrates that, regardless of group, conditions change over time for everyone. The interaction term $(Treated_i \times Post_t)$ is 1 if the observation is both a more digitalized firm and from the December survey. Thus, δ_{dd} is our main coefficient of interest, which reveals the causal effect.

The variables $County_i$ and $Industry_i$ are both categorical variables with several levels. $County_i$ is a dummy controlling for counties. This variable allows us to consider that the different areas in Norway are unequally exposed to the virus and lockdown at different times. $Industry_i$ is a dummy included to control for the fact that the pandemic hits the economy unevenly. For instance, business areas such as hairdressing and hotel operations are hit harder than auditing (Finans Norge, 2020; Nordby, 2021).

The Norwegian government announced a new extensive set of government aid on May 28. It introduced grants for firms per employee taken back to work for the period of July and August 2020 (Finansdepartementet & Nærings- og fiskeridepartementet, 2020). Thus, the aid may have influenced businesses' layoff decisions and should be considered in our estimation. For this reason, we create a dummy variable, $May28_t$, taking on the value of 1 if May-survey respondents answered on or after May 28, and 0 otherwise. As this change occurred during the May-survey collection time, and all December-survey answers were collected after this change, the December-survey answers receive a value of 0 for this variable.

X_i represents a vector of time-invariant individual level controls, namely *Firm Size*, *EBIT* and *Legal Structure*. The coefficient μ reveals the effect of these controls on the dependent variable. As *firm age* had no significance in the DiD regression models, we chose to exclude it in our regressions.

5.3.3 Common Trend Assumption

The common trend assumption, illustrated in Figure 5.1 is vital to identify the causal effect in a DiD estimation (Angrist & Pischke, 2014). It is common to illustrate the assumption by setting up timelines of the outcome before and during the relevant periods (Angrist & Pischke, 2009). However, in our case, data on layoffs is not publicly available at a firm level, only at higher levels such as counties and regions. Therefore, we cannot separate our treatment and control group in an investigation using timelines.

Accordingly, our argumentation of the common trend assumption is based on the nature of the COVID-19 pandemic shock. The pandemic can be considered a negative productivity shock to the economy. By controlling for *county* and *industry*, the effect of the shock should be similar for the two groups as we assume that common trends are displayed within each of these category levels. Industries have structural factors which make it easier or harder to digitize and adjust to the lockdown. Moreover, different parts of Norway are hit differently by the pandemic. We believe that the controls for industries and county pick up these effects.

Local regulations are often based on a municipal level, and neighbouring municipalities will sometimes choose to adapt the same level of regulation to best combat the virus. For instance, this was the case for the municipalities surrounding Oslo during an outbreak in the Norwegian capital where they were recommended by the Norwegian Directorate of Health to implement stricter regulations to slow the spread of the virus (Torgersen, 2020). Therefore, we expect the *county* variable to catch some of the trends stemming from diverging regulatory levels. Similarly, we expect the *industry* variable to catch trends stemming from the diverging impact of industry-wide regulations. E.g. a hairdresser and a grocery shop in the same county are likely to be impacted by local regulations differently because of the industry they belong to.

To summarize, firms' layoff trends should be common because the negative shock is assumed to hit similarly: given *county* and *industry* controls, infection control measures such as industry lockdowns should hit the firms equally, thus making the effect within each industry and county parallel.

Nevertheless, the assumption that the trend of layoffs would have been similar in the absence of digitalization is a strong one to make. It is possible that the common trend assumption does not hold. Regarding infection and lockdown, it is more likely that the trends are similar at a municipal level than at a county level. As such, not all firms within a county would be constrained in the same manner by infection control measures.

In addition, the two groups might not have common trend as firms who are more digitalized might not be counterfactuals to the less digitalized firms. For instance, more digitalized firms might be more efficient to begin with or have different management styles that may affect their ability to adapt to the pandemic.

6 Main Findings

In this section, we will present our findings on whether more digitalized businesses perform better during the pandemic than their less digitalized counterparts. First, we present the results from the regular WLS regressions before presenting the results from the DiD analyses. Second, we present our robustness analyses and give some remarks on the results.

6.1 Results

6.1.1 Regular WLS Regressions

R&D

We start by presenting the result from the regression on *R&D* based on the regression model in Equation 5.2. The estimated results are shown in column (1) in Table 6.1.

The reference group contains small, less digitalized firms, with a positive EBIT between 0 and 1 million NOK, belonging to the "Manufacturing" industry, located in Agder. From the regression table, we read that the effect of being more digitalized on *R&D* is significant at the 1% level. Specifically, being more digitalized increases a firm's probability of having developed new products, logistics, and distribution due to the pandemic by 8.5 percentage points.

Investments

Column (2) displays the result from estimating the model in Equation 5.3 presented in Table 6.1. The reference group is the same for the *R&D* regression in addition to its legal structure being a private limited company (AS). As revealed by Table 6.1, being more digitalized insignificantly increases the likelihood of investing by 2.2 percentage points.

Layoffs

The reference group is identical to the one for *investments*. As read from column (3) in Table 6.1 estimating the model in Equation 5.3, being more digitalized reduces the probability of *layoffs* by 3.0 percentage points. However, the effect is not significant.

Government Aid

Last, the result from the estimated model on *government aid* in Equation 5.3 is displayed in column (4) in Table 6.1. The reference group is the same as for the two preceding regressions. From the table, we read that being more digitalized increases the probability of using *government aid* by 3.8 percentage points. Nonetheless, the effect is insignificant.

Table 6.1: Regular WLS Regressions

	Dependent variable:			
	R&D	Investments	Layoffs	Government Aid
	(1)	(2)	(3)	(4)
Digital Status	0.085***	0.022	−0.030	0.038
	(0.030)	(0.026)	(0.031)	(0.032)
Observations	1,307	1,307	1,246	1,198
R^2	0.104	0.086	0.158	0.112
Adjusted R^2	0.081	0.060	0.133	0.085
EBIT	yes	yes	yes	yes
Firm Size	yes	yes	yes	yes
Industry	yes	yes	yes	yes
County	yes	yes	yes	yes
Legal Structure	no	yes	yes	yes

Notes: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parentheses.
The columns (1) to (4) display the regressions on *R&D*, *investments*, *layoffs* and *government aid*. The dependent variables are dummies, represented by the value 1 if the outcome has happened, 0 otherwise. There are five control variables, where the first is a categorical dummy that divides EBIT into eight sub-groups. The second variable is a dummy for firm size. The third and fourth variables are dummies controlling for industry and county. Last, a dummy for legal structure is added to all but the R&D regression. For column (1), the reference group is small, less digitalized firms, with a positive EBIT between 0 and 1 million NOK, belonging to the manufacturing industry, located in Agder. In addition, the other regressions also add legal structure of a private limited company (AS) to their reference groups.

6.1.2 DiD Estimations on Layoffs

Table 6.2 presents the findings from estimating the DiD models in Equation 5.5. The columns present different specifications of the regression model. The interaction term ($Treated_i \times Post_t$) measures the causal effect. Column (1) displays the result from the simplest DiD setup, and shows that being more digitalized leads to a 1.4 percentage point increase in the probability of having laid off employees permanently or temporarily. Column (2) also includes the control for May 28, which decreases the coefficient of the interaction term to 1.1 percentage points.

The coefficient of the interaction term varies slightly when adding more controls, but remains insignificant trough all specifications, as seen in Table 6.2. As such, we find no causal effect of being digitalized on the likelihood of laying off employees during the pandemic[2].

[2]The small sample size might be a reason for the large standard errors.

Table 6.2: DiD Regressions

	Dependent variable:						
	Layoffs						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Interaction term	0.014	0.011	0.012	0.009	0.004	0.028	0.025
	(0.119)	(0.120)	(0.121)	(0.113)	(0.111)	(0.117)	(0.116)
Observations	289	289	289	289	287	261	261
R^2	0.007	0.008	0.053	0.247	0.280	0.324	0.338
Adjusted R^2	−0.004	−0.006	0.005	0.166	0.195	0.218	0.218
May 28	no	yes	yes	yes	yes	yes	yes
County	no	no	yes	yes	yes	yes	yes
Industry	no	no	no	yes	yes	yes	yes
Firm Size	no	no	no	no	yes	yes	yes
EBIT	no	no	no	no	no	yes	yes
Legal Structure	no	no	no	no	no	no	yes

Notes: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.
The outcome variable is a dummy represented by a value of 1 if the firm has used *layoffs*, 0 if not. There are six control variables. The first takes the value 1 if the May-survey was answered on or after May 28. The second and third control variables are county and industry dummies. The fourth variable is a dummy for firm size. The fifth control variable is a dummy for EBIT, divided into eight sub-groups. The sixth control variable is a dummy for legal structure. Column (1) displays the result from running the simple DiD setup, whereas columns (2), (3), and (4) include model specifications where controls for answering after May 28, *county* and *industry* are added stepwise. Columns (5), (6), and (7) display the results when stepwise adding *firm size*, *EBIT*, and *legal structure*.

6.2 Robustness Analyses

This section presents our robustness analyses, which test whether our previous findings are sensitive to changes. We do this by making two separate alterations to our analyses. First, we relax the definition of a more digitalized firm to only include whether a firm has a strategy where digitalization plays a central role. Second, by standardizing the dependent variables of *R&D* and *investments*, and the independent variable *digital status* instead of using their binary values. Overall, our results from the robustness analyses are consistent with our main analysis although the magnitude and significance of our estimates differ somewhat.

6.2.1 Change in Definition of a Digital Firm

For our main analysis, we define the more digitalized businesses as those agreeing that digitalization plays a central role in their strategy, being far along the path of digitalizing internal work processes and collecting and processing customer information. Due to the expected important relationship between digital level and digital strategy (Bughin et al., 2017; Kane et al., 2015), we want to check if our results hold if we only focus the definition of digitalization on its strategy aspect.

With the amendment of the digital definition, more companies are categorized as more digitalized, from 54 to 61%. This relaxation may include businesses who were wrongly categorized as less digitalized firms in their survey answers. If this is true, our original definition is too strict, excluding more digitalized businesses from the treatment group. Therefore, the effect of the digital score coefficient could be larger than our previous estimates. Alternatively, the new definition could include firms who are not truly digitalized, and therefore may not have obtained the advantages from being digitalized. In this scenario, the effect of the digital score coefficient may be lower than our previous estimates.

By the new definition, we separate the treatment and control group by the median of 4. All firms scoring 4 or 5 rank as more digitalized, and the firms which score 3 or lower are less digitalized.

The results of the robustness analyses are shown in Appendix A4.1. For the regular

WLS regressions, the findings from the robustness analyses are mostly consistent with the results from our main analyses. The sizes of some coefficients change, but not drastically. Additionally, the signs of the coefficients remain identical. For all the regressions, conclusions remain the same.

For the regression on *R&D*, being more digitalized is still significant at the 1% significance level. However, using the new definition raises the coefficient for digitalization from 8.5 to 13.9 percentage points. This increase of 5.4 percentage point does seem to indicate a change in the categorization of digitalized firms, and hence, our previous definition might have excluded some firms that were actually digitalized. However, the change in coefficient does not seem to be large enough to indicate that the two definitions are drastically different.

Furthermore, for the regressions on *investments*, *layoffs*, and *government aid*, the results of the main analyses and robustness analyses are consistent. The coefficients of the digital status change somewhat, but remain insignificant.

In all specifications of the DiD analyses, the interaction term changes from positive to negative, and the magnitude increases. The conclusion is unchanged as the interaction term remains insignificant through all specifications.

6.2.2 Standardizing Dependent Variables

For our main analyses, we defined all dependent variables as binary. For this robustness analysis, we want to investigate whether our results hold if the dependent variables are defined on a more continuous scale. Two of the variables, *layoffs* and *government aid*, are inherently dichotomous as the possible answers are "yes", "no", and "don't know". Thus, these variables cannot be changed to continuous and will not be tested. This also implies that the DiD regression on *layoffs* cannot be included in this robustness analysis.

The variables measuring *R&D* and *investments* are on a four-point scale and a five-point Likert scale, respectively. We standardize these variables by subtracting their mean and dividing by their standard deviation (Kreyszig et al., 2011). In addition, we also standardize the binary variable digital status, which is originally a score average between one and five, to allow for better interpretability. The estimations of *digital status* on *R&D* and *investments* are illustrated in Appendix A4.2.

We find that a firm's digital status still has a significant impact at a 1% level on *R&D*. More interestingly, *digital status* now has a significant impact on *investments* at a 1% significance level. Since the variables are standardized, we can also interpret that digital status seems to have a larger impact on *R&D* than on *investments*. A change of one standard deviation in *digital status* leads to a 0.147 standard deviation change in *R&D*, and a 0.097 standard deviation change in *investments*. Based on this, we observe that our categorization of the *digital status* variable is somewhat sensitive to changes.

6.3 Remarks on the Results

We find some support for our main hypothesis stating that more digitalized firms outperform their counterparts in response to the pandemic. Only one out of four sub-hypotheses is supported. When regressing digitalization on *R&D*, we find that more digitalized businesses are 8.5 percentage points more likely to undertake R&D than their counterparts.

The conclusion of the analysis mainly remains the same when relaxing the definition of digitalized firms. However, the coefficient of *digital status* on *R&D* increases moderately. Also, when *R&D*, *investments* and *digital status* are standardized, *digital status* gains positive significance at the 1% level in the *investments* regression. Therefore, our findings are slightly sensitive to changes.

7 Discussion

This section will discuss the findings and possible weaknesses of our analyses. First, we present the implications of our thesis. Second, we put forth weaknesses to our dataset before discussing possible weaknesses to our study's internal validity, construct validity and external validity. We also discuss possible issues regarding sample bias and the common trend assumption. Third, we present possibilities for future research.

7.1 Implications of our Thesis

This thesis contributes both to the literature on digitalization and literature on consequences of the COVID-19 pandemic. Our research may have implications for businesses deciding to invest in digitalization and for society's general understanding of the effects of digitalization. Our results mainly apply to Norwegian private businesses in the trade and services industries, namely "Wholesale and retail trade; repair of motor vehicles and motorcycles", "Professional, scientific and technical activities" and "Administrative and support service activities".

Our first sub-hypothesis is supported, as we found that being more digitalized increases a firm's likelihood of developing new products, logistics and distribution as a response to the pandemic. This result coincides with the COVID-19-report of Steen et al. (2020), claiming that as a response to the pandemic, businesses with a high degree of digital competence would exploit their technologies to develop products and take advantage of new business opportunities. A possible explanation for this is that more digitalized firms are more aware of the opportunities enabled by R&D because, to become digitalized they are likely to have invested in a digital transformation process. Hence, when met with an unprecedented crisis, they will more easily turn to new and innovative ways of adapting their business to the new situation. Additionally, the more digitalized firms came into the pandemic with a higher average EBIT over the three preceding years, and may have had better financial abilities to invest in R&D.

However, we find no support for our three last hypotheses in our main analyses. Based on previous literature's findings, our operating presumption was that more digitalized businesses, to a lesser degree than their counterparts, laid off staff, or made use of government aid. The lack of significant relationships could be caused by way the pandemic has hit Norway. Lockdowns have been directed at geographical regions and specific industries, and may have impacted businesses regardless of their level of digitalization. For instance, a more digitalized hairdresser would likely face the same financial hardships as a less digitalized counterpart during a lockdown. In addition, since the government aid needed to be given on very short notice to prevent bankruptcies, it has not been possible to keep strict control of the actual eligibility of the firms. This may have led to skewed incentives for all firms, regardless of their level of digitalization, by trying to ensure that they received government aid.

We also believed that more digitalized firms would increase their investments due to the pandemic but we did not find empirical evidence supporting this. This finding is somewhat at odds with our significant findings on R&D. However, more focus on R&D could stem from a reorientation of resources which is less risky than investing with a new influx of resources in the turbulent environment of the pandemic.

In summary, our findings from regressing digitalization on *R&D* coincide with the expectations of digitalized firms. Being more digitalized may help firms respond, adapt and seize new opportunities that arise due to the pandemic. However, being more digitalized does not increase planned investment, help reduce layoffs or reduce the use of government aid.

7.2 Limitations

7.2.1 Limited Data Sets

The main part of our data is cross-sectional collected at a single point in time, and the main part of our analyses are regular WLS regressions. Therefore, these analyses only investigate correlations as several issues prohibit causal interpretation.

Even though both surveys covered the same topics, most questions were different. More extensive overlap between the surveys would have been preferable as we could, to a larger degree, have exploited data from different time points. This would further have enabled us to use a DiD strategy on several of the analyses, allowing for potential causal interpretations.

7.2.2 Internal Validity

Although we control for many different factors, we cannot rule out the existence of other factors influencing *digital status* and the dependent variables. As such, selection bias and omitted variables might affect our estimates.

Digitalized firms may have some common traits that make them choose to digitalize, which less digitalized firms may not possess. Even though the pandemic was unforeseeable to most, more digitalized firms could hold traits that would make them better prepared for its consequences. If this is true and not controlled for, there might be a systematic difference between the two groups that will bias our results.

Closely related to selection bias is OVB. It also leads the digital score coefficient to be under- or overestimated. Examples of possible variables missing from our analyses are "average age of the board" and a variable for having employed a CDO, as both could influence whether a firm has digitalized or not (Brown et al., 2019; Kunisch et al., in press; Sarrazin & Willmott, 2016). Digitalized firms could tend to have younger average boards, implying a negative relationship between average board age and digitalization level. If companies with a younger average board are also more likely to seize new market opportunities regardless of digitalization, the effect of omitting average board age on dependent variables such as *R&D* would also be negative. Therefore, the product of these two negative terms is positive, and the digital score variable would be overestimated in our *R&D* regression. The same argumentation could apply to having a CDO. As there are likely several omitted variables, we cannot state whether the digital score variable in total is under- or overestimated.

7.2.3 Construct Validity

Construct validity regards how well the concept we are looking at is represented and measured in our analyses (Taherdoost, 2016). That is, whether we are using "well-established definitions and measurements procedures for variables" (García-Pérez, 2012, p. 1).

There is reason to believe that we have an insufficient representation of digitalization. There is no shared firm-standard measure for the degree of digitalization in Norway.

Consequently, instead of basing the scores on a well-established measure, we base our variable on features of digitalization found in companies such as BCG and Deloitte's digitalization indexes. Even so, we could not embrace all aspects highlighted by these companies as the survey questions are limited in scope. Despite incorporating strategy and customer dimensions, our digital score does not embrace digitalization in business operations. Therefore, we have an imperfect measure of digitalization.

Additionally, our measurement procedure for digitalization might not be sufficient. The measurement is based on self-reported answers to the firms' digitalization rather than a comparable and standardized score. The respondents may have different understandings of the term "digitalization". Nevertheless, the surveys were sent to business leaders who are assumed to be well-informed regarding the businesses' degree of digitalization. We also expect that respondents have answered as correctly as possible, and that the large sample size evens out different understandings of digitalization, over- and underestimation and possible lack of rationality.

7.2.4 External Validity

External validity regards whether findings are applicable to other settings, times, measures and people (Steckler & McLeroy, 2008). Our results mainly focus on small and medium sized private firms within the industries "Wholesale and retail trade; repair of motor vehicles and motorcycles", "Professional, scientific and technical activities" and "Administrative and support service activities". Therefore, it is possible that our results applies only to this specific group of firms. Additionally, our results do not encompass public sector firms, as both Virke and Kantar sent the surveys to firms exclusively in the private sector.

The unique time and setting of the survey may not hold for other situations. The COVID-19 pandemic crisis differs from other previous worldwide economic crises as its health aspect brought a new level of uncertainty. Furthermore, lockdowns may have restricted authorities and firms from using usual remedies to increase economic activity.

To sum up, the external validity of our sample mainly applies to small and medium sized private firms within the industries "Wholesale and retail trade; repair of motor vehicles and motorcycles", "Professional, scientific and technical activities" and "Administrative and support service activities".

7.2.5 Sample Bias

Our study might face sample bias issues as the response rate is low, and the Virke and Kantar samples may be substantially different from each other.

Albeit higher response rates make it more likely that the sample is representative for the target population, a low response rate is not automatically a sign of bad data quality (Baruch & Holtom, 2008; Rindfuss et al., 2015). Consequently, a test for participation bias should be conducted. Unfortunately, this was prevented by the limited data. Without the test, we cannot be certain that the low response rate causes participation bias in our analyses.

The main problem is not the low response rate in itself, but arises if the non-responding firms share characteristics that separate them from the responding firms. This becomes an issue if we are not able to control for such differences. For instance, one could hypothesize that not responding to the survey indicates that the firm in question does not have sufficient capacity to allocate resources for this purpose. This could be an indication that the firm is faring poorly. Such self-selection would lead to badly performing firms being underrepresented in our data, and therefore skewing it. Additionally, the systematic differences between the Virke and Kantar samples that lead them to respond at different rates are likely problematic.

As there are several reasons why the firms from Virke and Kantar would or would not respond, we cannot conclude whether a possible sample bias would be positive or negative. The presence of sample bias may lead our sample to be non-random, and might therefore reduce the validity of our findings. As such, we must be careful in drawing conclusions based on our results. In the presence of sample bias, we cannot be certain that our findings are valid for our target population.

7.2.6 Common Trend Assumption

A DiD strategy opens for causal interpretation, yet, this highly depends on the strict common trend assumption. Control and treatment group trends have to follow the same pattern in the absence of treatment. Firm-level data is not publicly available on layoffs, which prevents us from visually inspecting and testing the common trend of the less and more digitalized firms. Without inspecting the trends, we argued that the layoff trends should be parallel by controlling for county and industry. The control for county makes it more likely that all firms within a given location face the same infection rates and therefore also the same restricting infection control measures. Given the industry controls, businesses within a given industry should face similar market changes due to the pandemic.

Nevertheless, this argumentation is based on an aggregated level and is not likely enough to make common trend hold. As discussed, it may be more likely that companies within the same municipalities face the same infection rates and control measures. Within a given county covering large areas, it is likely that separate population clusters have diverging infection rates levels. Therefore, the effect of belonging to a particular county for a given firm may be over- or underestimated, depending on the actual infection rate of a business' location.

Firms within the same industry may face different market reactions due to the pandemic. For instance, some firms operating within the retail industry, such as yarn stores, may have experienced increased demands despite the lockdowns, as people seek to find pastime activities while they must spend more time at home (Darrud, 2020; Hyldbakk, 2021).

Additionally, the common trend assumption will not be suited to identify causality, if the two groups are not proper counterfactuals. I.e., if the groups have different traits that systematically affect their ability to respond to the pandemic.

7.3 Further Research

This study has mainly looked at private businesses within the trade and services industries in Norway. Future research could provide new insights by focusing on other industries and using samples from other countries. It would also be interesting to investigate the effect digitalization has on the public sector and other industries less represented in our data.

The main parts of our analyses have used cross-sectional data collected at a single point in time. This limits the analysis to investigate how the firms perform at that specific time and only allows for a correlational analysis. Future research may use panel data to investigate the stability and effects of being digitalized over time, in addition to seek causality by using strategies such as DiD.

A retrospective analysis further into the future may also investigate how the firms performed during the entire period of the pandemic instead of its first nine months, allowing for more comprehensive data. To illustrate, we could not use firm EBIT from 2020 as this is not available until the middle of 2021.

8 Conclusion

The aim of our thesis has been to provide empirical evidence for our main hypothesis:

More digitalized firms perform better than less digitalized firms during the first nine months of the COVID-19 pandemic

The COVID-19 pandemic created a turbulent and demanding environment for many Norwegian firms. The main motivation for writing this thesis was to investigate whether the advantages of being more digitalized could serve as a buffer to economic hardships during the pandemic. We base our main and sub-hypotheses on studies mostly focusing on firm performance in normal times, not in the turbulent environment of a crisis. However, we still expect their findings, which exclusively find that digitalization has positive or insignificant effects on firm performance, to be upheld during the unstable times of a pandemic.

Through our analyses of 1,351 Norwegian firms, we find that being a more digitalized firm increases the likelihood of developing new products, logistics, and distribution by 8.5 percentage points due to the pandemic. However, a firm's digitalization level does not significantly affect its planned investments, its propensity to lay off employees, or its use of government aid due to the pandemic. Our findings are somewhat sensitive to changes, as the digital score coefficient turns from insignificant to highly significant when standardizing the digitalization score and investments variable in a robustness test. Due to the cross-sectional nature of our data, these findings are not causal but correlational.

Our findings remain insignificant after further analysis of layoffs at 185 firms using a DiD strategy. We analyze if firms' level of digitalization has influenced the likelihood of laying off employees between May and December 2020. The findings of both analyses mainly apply to private sector firms in the trade and services industries and must be interpreted with caution due to the limitations of our analyses.

Although we only find partial empirical evidence for our main hypothesis, we still conclude that our thesis adds to the existing literature documenting the benefits and the lack of significance of digitalization on aspects of firm performance. Further research could study the effects of digitalization after the pandemic's end to view the crisis in its entirety.

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Appendix

A1 Dependent Variables

Figure A1.1: Has the company as a result of COVID-19 developed...?

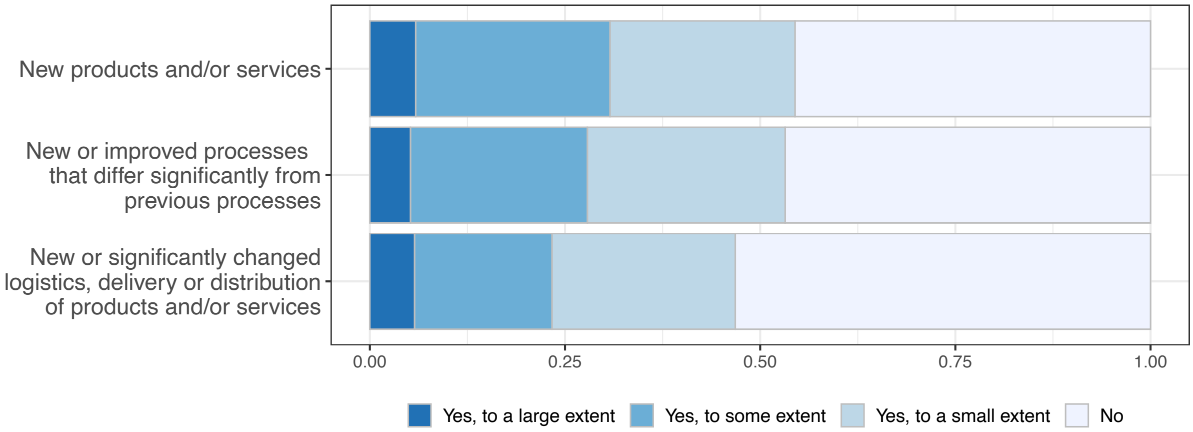


Figure A1.2: How do you think the company's investments will change compared to the period before the COVID-19 crisis started?

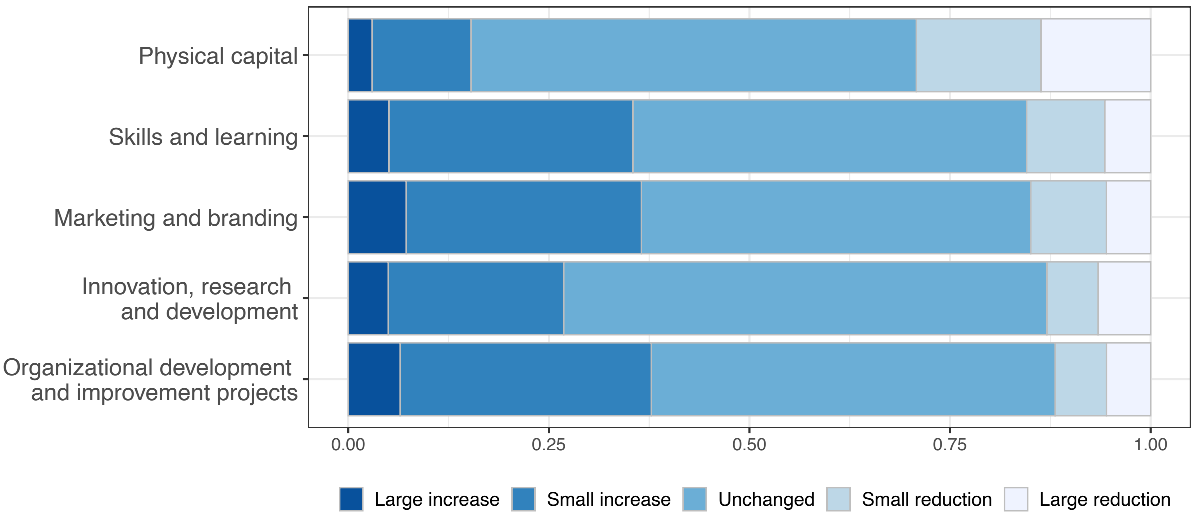


Figure A1.3: Have you permanently or temporarily laid off employees due to COVID-19?

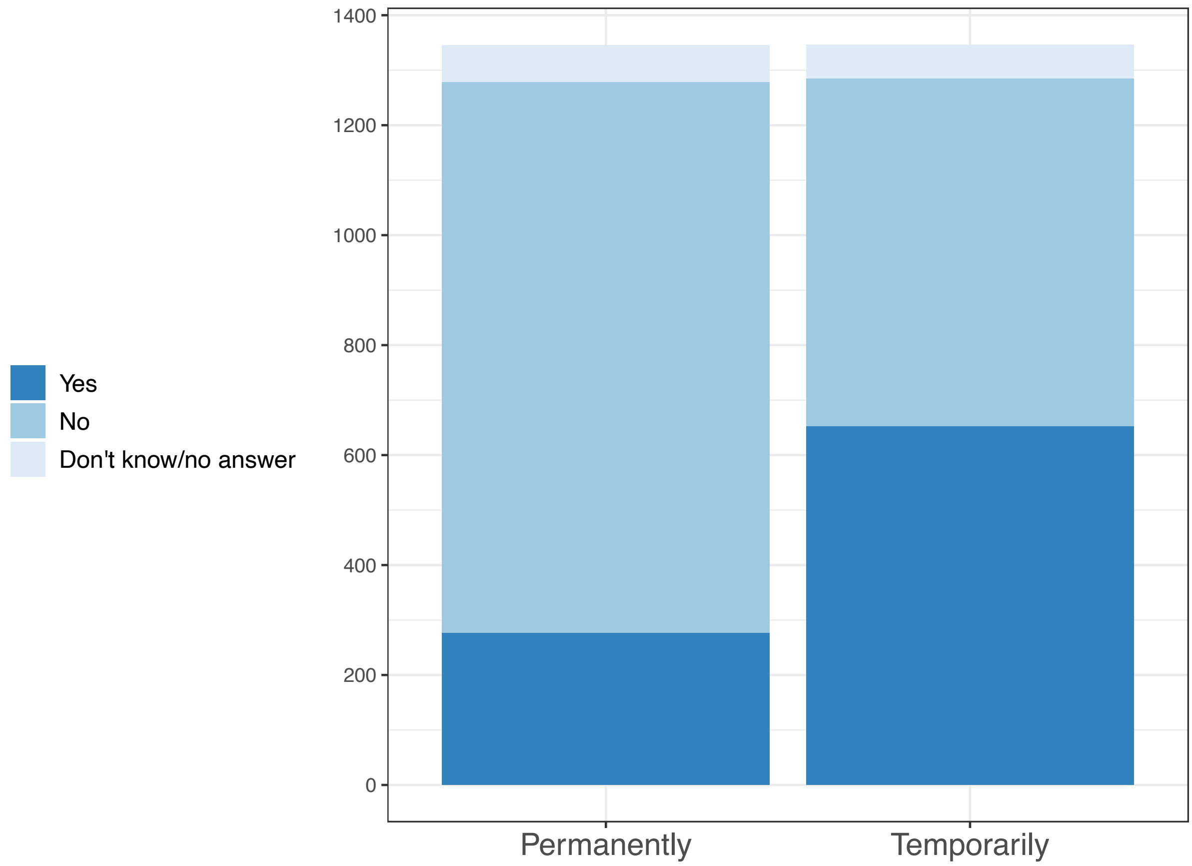
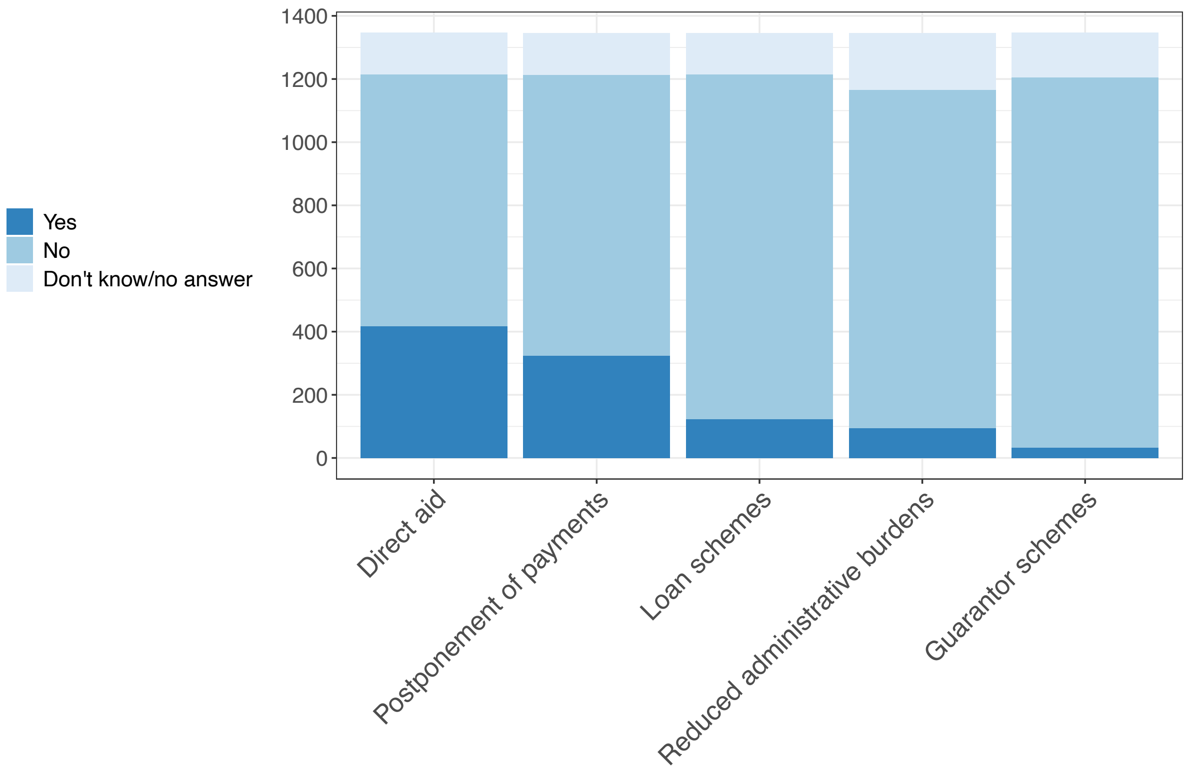


Figure A1.4: Has your firm made use of the following schemes?



A2 Descriptive Statistics on Firms

Table A2.1: Numeric Descriptive Variables in the Dataset

Variable name	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Std. Dev.
Firm age (years)	1	9	17	22	28	174	18
EBIT (2017-2019)(NOK)	-137 766 000	20 500	417 667	8 910 451	1 811 667	3 377 818 333	105 807 772

Figure A2.1: Count of the Industries Represented in the Survey Dataset with NACE Level Code 1

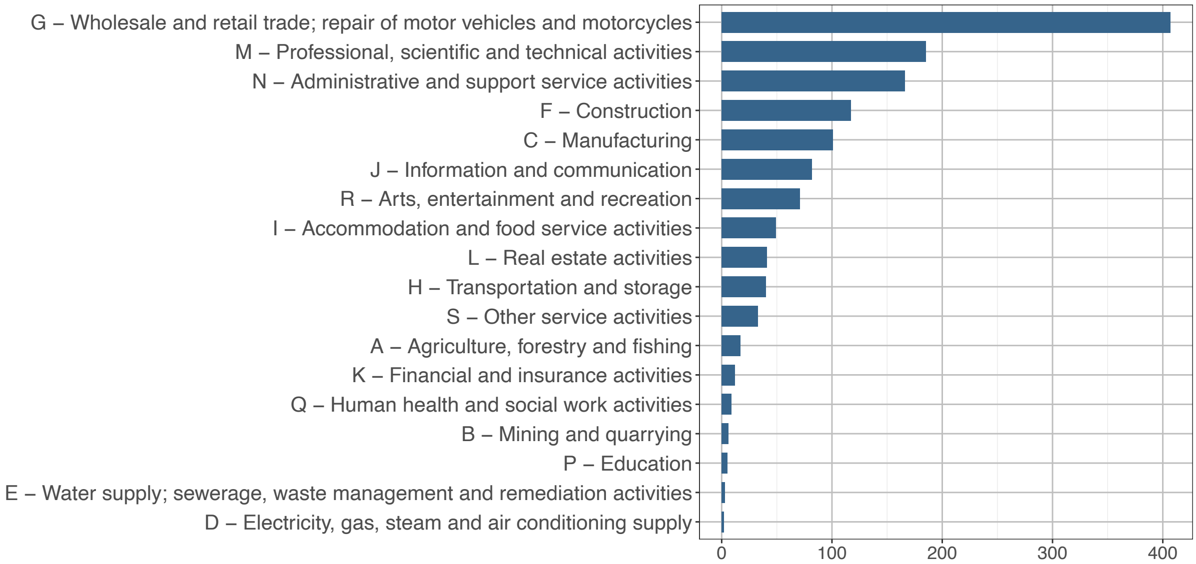


Figure A2.2: Industries Represented by Kantar and Virke Data

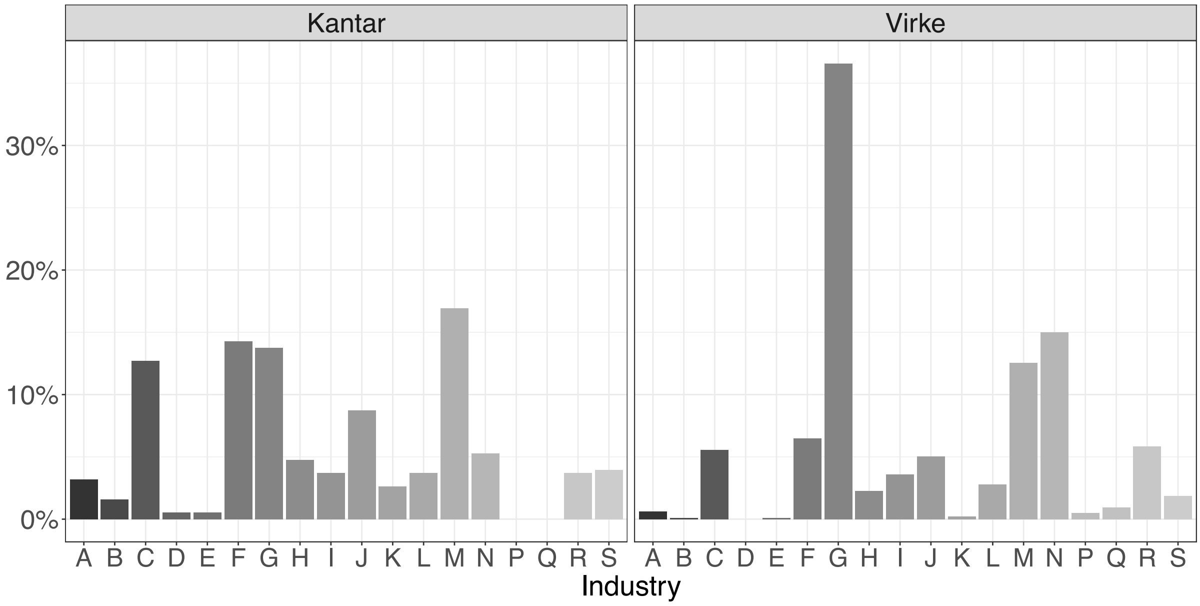


Figure A2.3: Count of the Firm Sizes Represented in the Survey Dataset

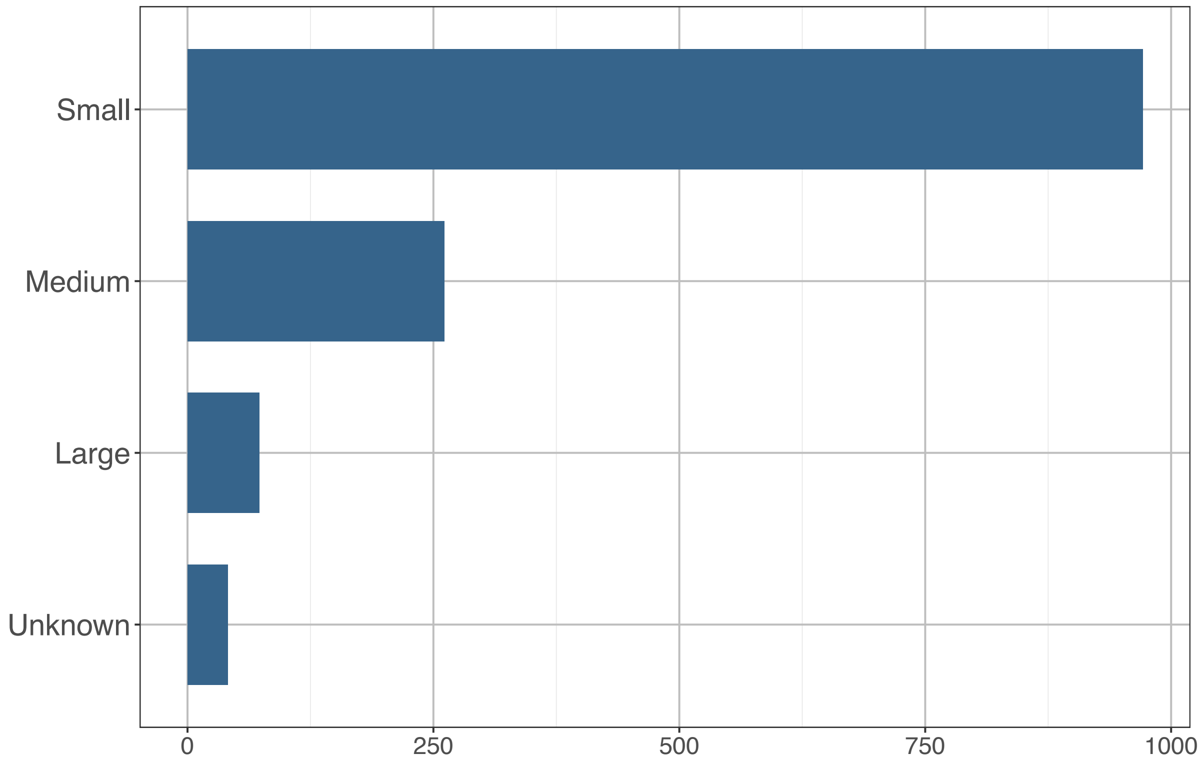


Figure A2.4: Count of Counties Represented in the Survey Dataset

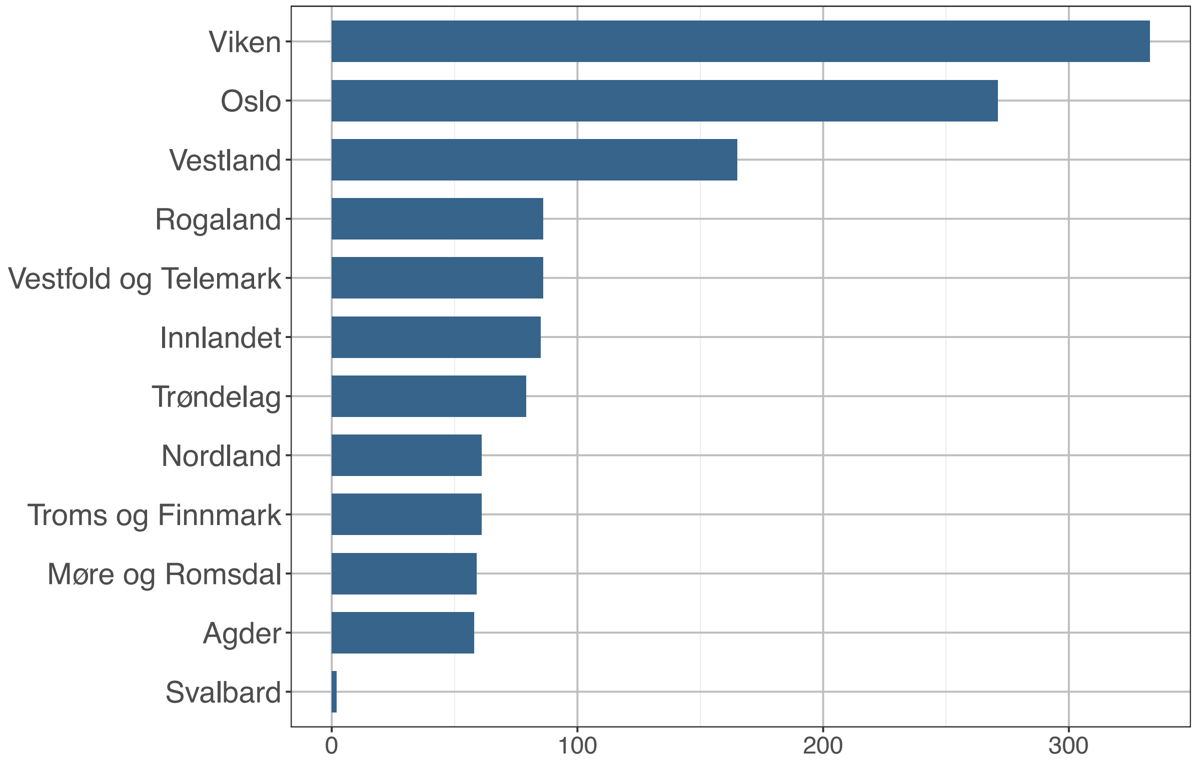
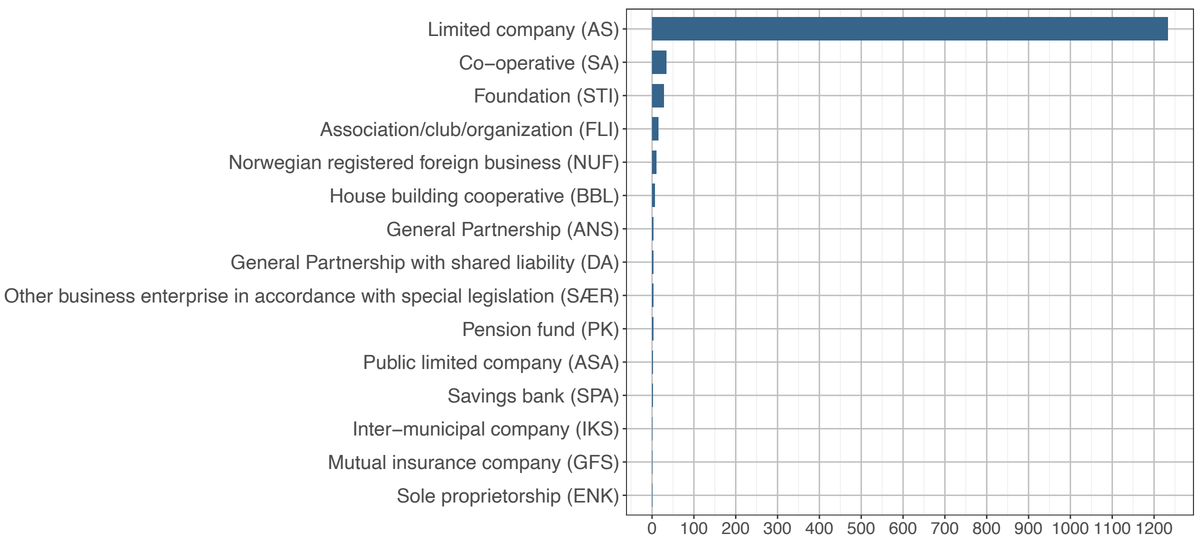
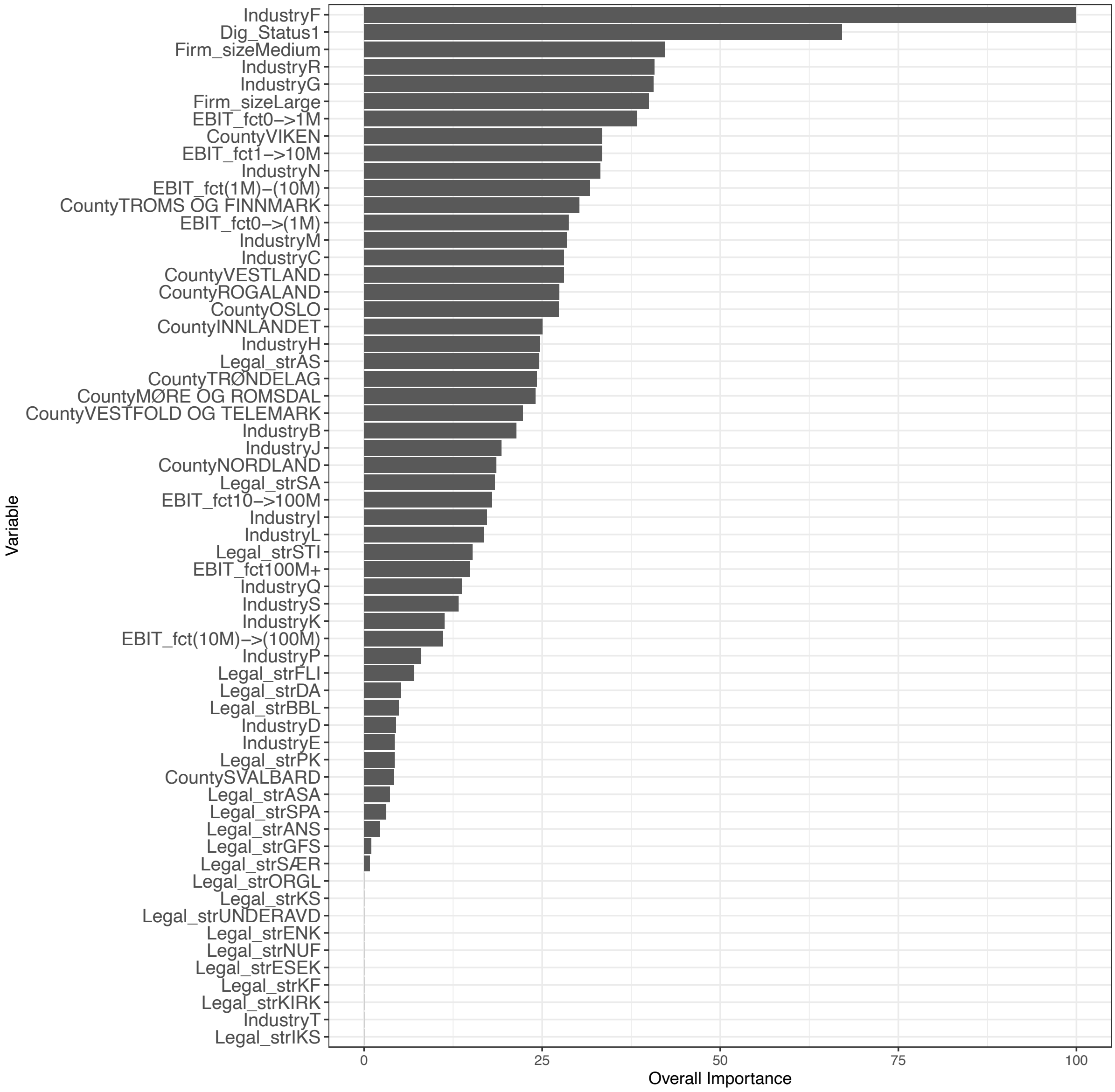


Figure A2.5: Count of Legal Structures Represented in the Survey Dataset with Norwegian Acronyms in Parentheses



A3 Random Forest

Figure A3.1: Variable Importance Plot (VIP) for Random Forest Classification of Survey Question on R&D



Note: the VIP shows that the three most important variables are Industry F: "Construction", Digital Status and Medium sized firms. The most important variable will always have an importance value of 100, and the remaining importance values are therefore relative to it.

A4 Robustness Analyses

A4.1 Change in Definition of a Digital Firm

Table A4.1: Regular WLS Regressions

	Dependent variable:			
	R&D	Investments	Layoffs	Government Aid
	(1)	(2)	(3)	(4)
Digital Status	0.139***	0.031	−0.015	0.052
	(0.030)	(0.026)	(0.031)	(0.032)
Observations	1,351	1,351	1,262	1,214
R^2	0.113	0.084	0.154	0.110
Adjusted R^2	0.091	0.059	0.129	0.083
EBIT	yes	yes	yes	yes
Firm size	yes	yes	yes	yes
Industry	yes	yes	yes	yes
County	yes	yes	yes	yes
Legal structure	no	yes	yes	yes

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parenthesis.
The columns (1) to (4) display the regressions on *R&D*, *investments*, *layoffs* and *government aid*. The dependent variables are dummies, represented by the value 1 if the outcome has happened, 0 otherwise. There are five control variables, where the first is a categorical dummy that divides EBIT into eight sub-groups. The second variable is a dummy for firm size. The third and fourth variables are dummies controlling for industry and county. Last, a dummy for legal structure is added to all but the *R&D* regression. For column (1), the reference group is small, less digitalized firms, with a positive EBIT between 0 and 1 million NOK, belonging to the manufacturing industry, located in Agder. In addition, the other regressions also adds having a legal structure of a private limited company (AS) to their reference groups.

Table A4.2: DiD Estimations

	Dependent variable:						
	Layoffs						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Interaction Term	−0.042	−0.046	−0.042	−0.043	−0.049	−0.029	−0.032
	(0.121)	(0.121)	(0.122)	(0.115)	(0.113)	(0.120)	(0.119)
Observations	292	292	292	292	290	264	264
R^2	0.001	0.003	0.049	0.242	0.273	0.314	0.331
Adjusted R^2	−0.009	−0.010	0.001	0.161	0.189	0.208	0.211
May 28	no	yes	yes	yes	yes	yes	yes
County	no	no	yes	yes	yes	yes	yes
Industry	no	no	no	yes	yes	yes	yes
Firm Size	no	no	no	no	yes	yes	yes
EBIT	no	no	no	no	no	yes	yes
Legal Structure	no	no	no	no	no	no	yes

Notes: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.
The outcome variable is a dummy represented by a value of 1 if the firm has used *layoffs*, 0 if not. There are six control variables. The first takes the value 1 if the May survey was answered on or after May 28. The second and third control variables are county and industry dummies. The fourth variable is a dummy for firm size. The fifth control variable is a dummy for EBIT, divided into eight sub-groups. Lastly, the sixth control variable is a dummy for legal structure. Column (1) displays the results from running the simple DiD setup, whereas columns (2), (3), and (4) include model specifications where controls for answering after May 28, and county and industry affiliation are added stepwise. Columns (5), (6), and (7) display the results when stepwise adding *firm size*, *EBIT*, and *legal structure*.

A4.2 Standardizing Dependent Variables

Table A4.3: Standardizing Dependent Variables R&D and Investments

	Dependent variable:	
	R&D	Investments
	(1)	(2)
Digital Status	0.147***	0.097***
	(0.060)	(0.066)
Observations	1,309	1,309
R^2	0.119	0.067
Adjusted R^2	0.096	0.039
EBIT	yes	yes
Firm Size	yes	yes
Industry	yes	yes
County	yes	yes
Legal Structure	no	yes

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parenthesis.
The columns (1) and (2) display the regressions on *R&D* and *investments*. Both dependent variables are standardized with a mean of 0 and a standard deviation of 1. This is also true for the independent variable *Digital Status*. There are five control variables, where the first is a categorical dummy that divides EBIT into eight sub-groups. The second variable is a dummy for firm size. The third and fourth variables are dummies controlling for *industry* and *county*. Lastly, a dummy for legal structure is added to the investments regression. For column (1), the reference group is small, less digitalized firms, with a positive EBIT between 0 and 1 million NOK, belonging to the manufacturing industry, located in Agder. In addition, column (2) also adds legal structure of a private limited company (AS) to the reference group. Since both dependent variables and the independent variable of interest are standardized, we can interpret the coefficients as follows: a change of one standard deviation in the independent variable leads to a change of $coefficient \times standard\,deviation$ in the dependent variable.

A5 Excerpt of Relevant Survey Questions

Figure A5.1: May 2020 Survey

Har dere permittert eller nedbemannet som følge av COVID-19?

- ◯ Ja
- ◯ Nei

Figure A5.2: December 2020 Survey (1)

Har bedriften **som følge av** COVID-19:

	Nei	Ja, men i liten grad	Ja, i noen grad	Ja, i stor grad
Utviklet nye produkter og/eller tjenester?	◯	◯	◯	◯
Utviklet nye eller forbedrede prosesser som adskiller seg vesentlig fra tidligere prosesser?	◯	◯	◯	◯
Rettet eksisterende produkter eller tjenester til nye kundegrupper eller segmenter?	◯	◯	◯	◯
Utviklet ny eller vesentlig endret logistikk, levering eller distribusjon av produkter og/eller tjenester?	◯	◯	◯	◯

Figure A5.3: December 2020 Survey (2)

Hvordan tror du bedriftens investeringer vil bli endret sammenlignet med perioden ***før*** COVID-19 krisen startet?

	Stor reduksjon	Liten reduksjon	Uendret	Liten øking	Stor økning
Investeringer i fysisk kapital (maskiner, utstyr, eiendom, osv)	○	○	○	○	○
Investeringer i kompetanse og læring	○	○	○	○	○
Investeringer i markedsføring og merkevarebygging	○	○	○	○	○
Investeringer i innovasjon, forskning og utvikling	○	○	○	○	○
Investeringer i organisasjonsutvikling og forbedringsprosjekter	○	○	○	○	○

Figure A5.4: December 2020 Survey (3)

Hvilken rolle spilte digitalisering i din bedrift ***før*** COVID-19 krisen startet?

	Helt uenig	Uenig	Hverken eller	Enig	Helt enig
Digital kompetanse ble betraktet som viktig	○	○	○	○	○
Digitalisering spilte en sentral rolle i vår bedrifts strategi	○	○	○	○	○
Digitalisering representerte en trussel for vår virksomhet	○	○	○	○	○
Digitalisering representerte en mulighet for vår virksomhet	○	○	○	○	○
Vi lå foran våre konkurrenter mht. digitalisering	○	○	○	○	○

Figure A5.5: December 2020 Survey (4)

Hvor digitalisert var bedriften ***før*** COVID-19 krisen startet?

	Helt uenig	Uenig	Hverken eller	Enig	Helt enig
Vi leverte digitale produkter/tjenester	○	○	○	○	○
Digitale salgskanaler var viktigere for oss enn fysiske salgskanaler	○	○	○	○	○
Digital distribusjon var viktigere for oss enn fysisk distribusjon	○	○	○	○	○
Vi var kommet langt i digitalisering av våre interne arbeidsprosesser	○	○	○	○	○
Vi var kommet langt i å digitalisere vår innhenting og bearbeiding av kundeinformasjon	○	○	○	○	○
Vi lå foran våre konkurrenter mht. å utnytte digital teknologi	○	○	○	○	○

Figure A5.6: December 2020 Survey (5)

Har dere permittert ansatte eller nedbemannet som følge av COVID-19?

	Ja	Nei	Vet ikke
Permittert ansatte	○	○	○
Nedbemannet	○	○	○

Figure A5.7: December 2020 Survey (6)

Regjeringen har innført en rekke tiltak rettet mot norsk næringsliv. En del av disse ordningene er rettet bredt mot alle bedriftene, mens andre er rettet mot spesifikke bransjer eller typer virksomhet (f.eks. grunderbedrifter).

Har din bedrift benyttet seg av følgende ordninger?

	Ja	Nei	Vet ikke
Direkte støtte	○	○	○
Låneordninger (inklusiv låneordninger med lav rente)	○	○	○
Garantordninger	○	○	○
Utsettelse av betalinger	○	○	○
Reduserte administrative byrder	○	○	○