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COVID-19 and Government Aid: An Economy on Life Support?

An exploratory study of the effects of deferred tax payments in Norway during COVID-19

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NORWEGIAN SCHOOL OF ECONOMICS

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Our time at NHH has been filled with fond memories, and we look forward to coming back in the future.

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Abstract

The number of bankruptcies in the Norwegian economy dropped substantially during the COVID-19 pandemic. We investigate to what extent the arrangement for deferred payments of tax and duty claims contributed to keeping non-viable firms artificially alive during 2020 and 2021.

First, we provide evidence that firms defined as non-viable prior to the pandemic were more likely to apply for and be granted tax deferrals than their healthier counterparts. This finding alone would imply that such firms might have exploited the arrangement to stay alive. Further, we estimate the effect of being granted tax deferrals on the probability of going bankrupt in 2020 or 2021. In 2020, we find that the firms granted tax deferrals were significantly less likely to go bankrupt than what would have been the case in the absence of support. However, we do not find statistically significant results when the same relationship is estimated in 2021. In sum, this implies that the arrangement may have kept non-viable firms artificially alive, albeit for a limited period of time.

Keywords – COVID-19, Government support schemes, Zombie firms, Corporate solvency, Bankruptcy Prediction

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1 Introduction

The number of bankruptcies in Norway decreased by 10% in 2020 and another 24% in 2021 (SSB, 2022a). This development occurred despite the severe economic consequences of the COVID-19 pandemic. In an efficient economy, bankruptcies play an important part in the reallocation of capital to more productive businesses (McGowan et al., 2017). If the reduction in bankruptcies is based on the prolonged life of non-viable firms, the long-term consequences may be that the economy's adaptability is impeded. This raises an interesting question of whether the extraordinary government support measures have been given to non-viable firms, and accordingly, have kept firms "artificially" alive. We investigate whether this holds true for Norway, with a specific focus on the arrangement for deferred payment of taxes and duties.

In our analysis, we use firm-level data on Norwegian firms to explore the potential misallocation of deferred payments to non-viable firms and its effect on bankruptcies during the pandemic. These relationships are analysed through three main steps.

In the first part (1), we define and identify firms that were deemed non-viable prior to the pandemic. To do so, we distinguish between *unwanted* firms in the economy (so-called zombie firms) and *distressed* firms (with a high probability of going bankrupt). Thereafter (2), we use a logistic regression model to estimate if these firms were more likely to apply for, and be granted, deferred payments of taxes and duties than their healthier counterparts. Lastly (3), we employ a matched sample of the firms that were granted deferrals to estimate the effect of the arrangement on the probability of going bankrupt. The use of a matched sample allows a comparison of what would have happened in a counterfactual setting where tax deferrals were not granted at all. In combination, these parts provide valuable insights into the potential role of the arrangement in keeping non-viable firms artificially alive during the pandemic.

We find that the firms deemed non-viable prior to the pandemic were significantly more likely to be granted tax deferrals. This finding alone provides indicative evidence that non-viable firms received life support which may have prolonged their existence. However, the final estimation of the effect of tax deferrals on the probability of going bankrupt reveals some important nuances. We find that tax deferrals in 2020 significantly reduced the probability of going bankrupt the same year. On the other hand, when estimating the effects on the probability of bankruptcy in 2021, the result is no longer statistically significant. Our findings thereby indicate that the arrangement may have contributed to keeping non-viable firms alive during the pandemic, but the effect is reduced over time.

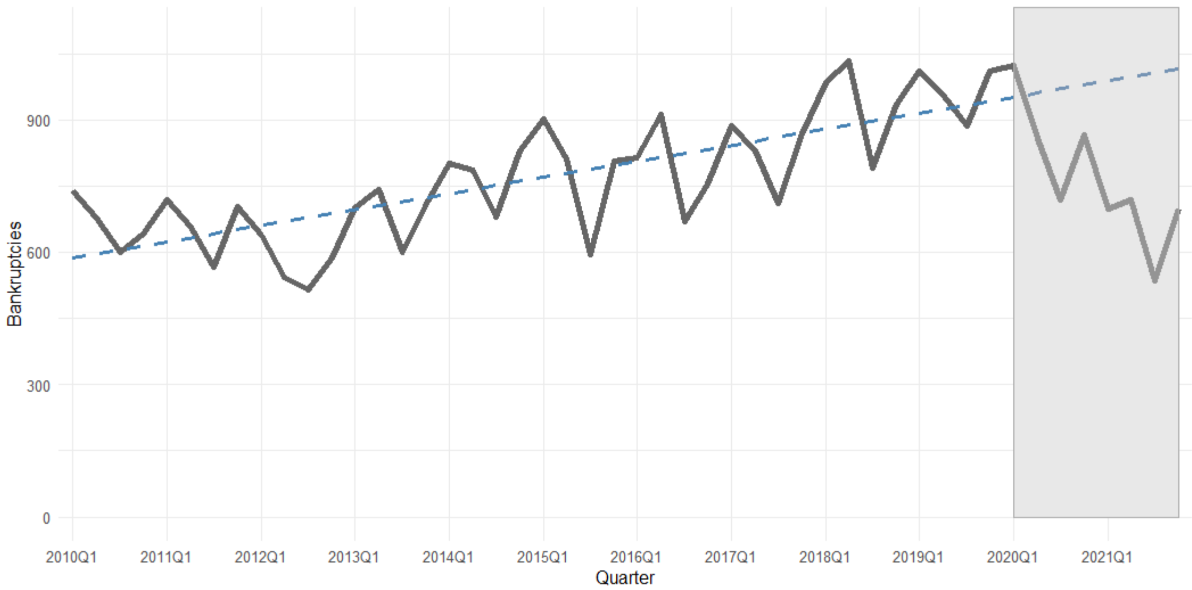
1.1 Background

Following nationwide lockdowns as a consequence of the spread of COVID-19, governments all around the world initiated unprecedented fiscal responses to alleviate the burdens on the real economy. The Norwegian government was no exception. The business compensation scheme ("Kompensasjonsordningen"), government-backed loan guarantees ("Lånegarantiordningen") and salary subsidies to reengage laid-off employees ("Lønnskompensasjon") are just a few examples of the extensive support schemes implemented (Regjeringen.no, 2022). The ultimate goal of the arrangements was to avoid mass bankruptcies and a sharp increase in unemployment. Simultaneously, there was growing concern about the longer-term effects of these measures and how they would affect the economic development once the crisis had passed.

Economic crises often present an opportunity to "cleanse" the economy. In Schumpeterian terms, creative destruction is the process of breaking down long-standing structures and replacing them with innovative ideas and methods. In times of crisis, this process is usually enhanced, and rapidly changing market conditions often imply a swift increase in insolvencies amongst weaker firms. This enables a reallocation of resources to other, more viable projects and firms. In Norway, bankruptcy statistics indicate that this "cleanse" has not occurred.

Figure 1.1 shows the quarterly development in declared bankruptcies in Norway. The number of bankruptcies during COVID (2020-2021) falls well below the linear trend extended from the years 2010-2019. Given the massive impact of COVID on the real economy, this dramatic decrease indicates that we may have missed the "cleansing opportunity" that the pandemic could have provided. On the other hand, the crisis - induced by rapidly increasing infection rates - was not caused by structural breaks within the economy. National governments were forced to impose lockdowns and thus viewed their role in the downturn as a strong argument to also alleviate some of the burden.

Figure 1.1: Quarterly bankruptcy statistics in Norway



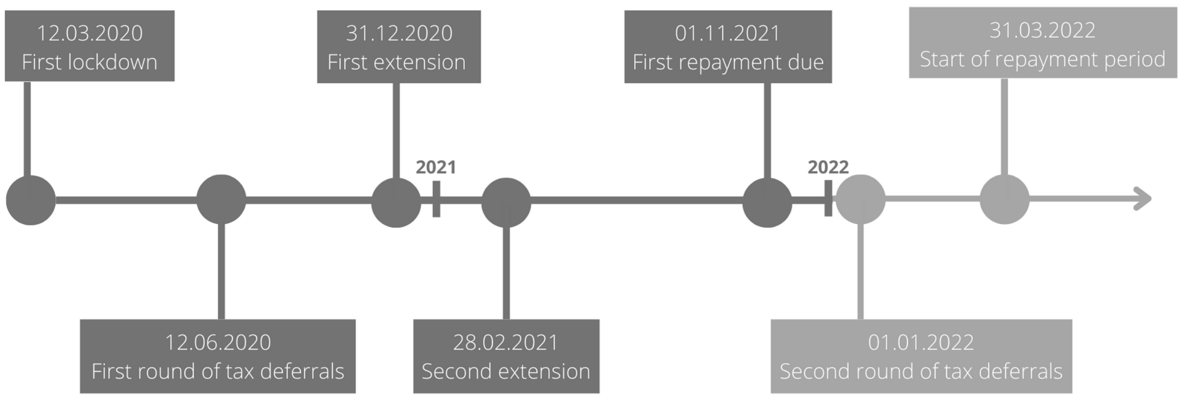
Note: The figure presents quarterly bankruptcy statistics in Norway. The dashed line shows the linear trend in bankruptcies from 2010 to 2019, and is extended through 2020 and 2021. Source: SSB (2022a).

The Arrangement for Deferred Payment of Taxes and Duties

The Norwegian Tax Administration has requested evaluations of the appropriateness and effectiveness of a variety of the government support schemes implemented during COVID. Of these schemes, this thesis aims to investigate the arrangement for deferred payment of taxes and duties (hereby often referred to as "tax deferrals"). Such an arrangement has existed for years (The Norwegian Tax Administration, 2022), but during the pandemic, all firms that experienced a COVID-related drop in revenues were eligible to apply. Given a general desire to roll out the arrangement as swiftly as possible, the only requirement for approval of tax deferrals was to self-report a reduction in revenue tied to the pandemic (The Lovdata Foundation, 2020). In normal times, the Tax Administration is widely regarded as the toughest creditor and is responsible for a large share of bankruptcy petitions (The Norwegian Tax Administration, 2021a). With the opportunity to defer payment of taxes and duties, we hypothesize that this arrangement may have played a crucial role in the observed reduction in bankruptcies.

Figure 1.2 depicts a timeline of the implementation of the arrangement. The first round of applications lasted from June 12, 2020 and lasted until December 31. Initially, the plan was for the arrangement to end at this point and that an instalment scheme would be imposed at the beginning of 2021. However, with continuously increasing infection rates and renewed lockdowns, the arrangement was first extended to February 28, 2021 and followed by another extension until June 30. The first instalments were then planned to take place from November 1, 2021, but after the second due date, the arrangement was yet again reimposed at the start of 2022. Our thesis specifically relates to the first three rounds of the arrangement, starting from June 2020 and ending in 2021. In sum, the arrangement (from 2020 to 2021) lead to deferrals of tax and duty claims amounting to NOK 4.6 billion (The Norwegian Tax Administration, 2021b). Of this, our sample includes approximately NOK 4 billion.

Figure 1.2: Timeline of the arrangement for tax deferrals



Note: The arrangement for tax deferrals was extended two times before the intended start of the repayment period. However, the arrangement was reinstated at the beginning of 2022 and the repayment period was thus delayed. Our data covers the deferrals granted from 12.06.2020 to 01.11.2021.

1.2 Hypotheses and outline

An investigation into whether the arrangement for tax deferrals significantly contributed to keeping firms *artificially* alive during COVID requires some clarifications. In order for a company to be held artificially alive, a measure of viability pre-COVID must be constructed. A firm should not be deemed to have been kept *artificially* alive if the sole reason for its potential bankruptcy would have been the government-imposed lockdowns. Therefore, the first part of this thesis aims to identify and assess the prevalence of non-viable firms prior to the pandemic.

To define non-viable firms, we offer two alternative definitions. The first is based on literature relating to so-called zombie firms. These firms are unproductive, unprofitable and hinder effective allocation of resources. The second definition is based on the predicted bankruptcy probabilities computed by our reproduction of the Norwegian Central Bank's bankruptcy prediction model, SEBRA. We deploy both these definitions since zombie firms, although *unwanted*, do not necessarily have a high probability of going bankrupt. On the other hand, the bankruptcy prediction model is very efficient at identifying those firms that were highly *distressed* prior to the pandemic.

Second, we aim to investigate if these non-viable firms were more likely to apply for – and be granted – deferred payment of taxes and duties. Deferring tax payments could provide vital liquidity to cover other debt obligations. There is reason to believe that weak and struggling firms would be more inclined to take advantage of this opportunity. Our hypothesis then subsequently becomes that non-viable firms, defined as *unwanted* and *distressed firms*, were in fact more likely to be granted this form of government support. The hypothesis that these firms were more likely to be granted tax deferrals will be tested through a logistic regression.

Third, for these non-viable firms to have been kept artificially alive, they must also have had a significantly lower probability of going bankrupt than those that did not receive deferrals. Given the Tax Administration's historical rates of bankruptcy petitions for firms that fail to repay government debts, we hypothesize that the companies that were granted tax deferrals have in fact been less likely to go bankrupt than other, similar firms. This hypothesis is tested through a logistic regression estimated on a matched sample of firms.

To answer our overarching research question, *"To what extent did the arrangement for deferred payment of taxes and duties keep non-viable companies artificially alive through the COVID-19 pandemic?"*, this thesis is organized as follows. First, related literature will be presented in chapter 2. In chapter 3, the data collected for the purpose of this thesis is presented and discussed. Thereafter, chapter 4 contains an initial descriptive analysis of the reduced bankruptcy rates, sector-specific impact of COVID and the distribution of tax deferrals. Following the descriptive analysis, chapter 5 provides the theoretical framework deployed in the subsequent empirical analysis in chapter 6. Lastly, the findings from both the descriptive and empirical analyses will be discussed in chapter 7 before the thesis is concluded.

2 Related Literature

In this section, we present and discuss the results from relevant literature related to misallocation of government support schemes, corporate solvency, and non-viable firms during the COVID-19 pandemic. Although different aspects of the pandemic have been extensively researched, limited research has been conducted on the arrangement of tax deferrals and the potential misallocation of support to non-viable firms. Also, at the time of writing, peer-reviewed empirical research from the aftermath of the pandemic is limited.

2.1 COVID-19 and Misallocation of Government Support

To prevent a massive cash crunch and sustain solvency at a pre-COVID level, several studies emphasized the importance of introducing efficient measures at the beginning of the pandemic (De Vito and Gómez, 2020; Mirza et al., 2020). Previous experience with lockdowns was limited, and decisions were made under great uncertainty. Thus, the need to assess if support measures were correctly targeted gradually increased. Amongst others, Cirera et al. (2021) found indicative evidence of mistargeted policies to firms that did not experience a negative COVID-related shock. They found the effect to be most prominent in low-income countries, with possible explanations being low implementation capacity and a lack of good governance.

Groenewegen et al. (2021) also studied the extent to which support measures were provided to firms affected by the pandemic, but also if these firms were expected to be viable in the future. Using logistic regression on firm-level data from the Netherlands in 2020, they found that state aid was given to firms that were hard-hit by COVID and that were, on average, most likely to be viable in the future. Future viability was defined based on management practices, such as the number of key performance indicators or targets the management uses.

In Norway, there is little publicly available research on this topic. Hjelseth et al. (2021a,b) published two staff memos for the central bank of Norway covering descriptive analyses of several government support measures in Norway. Hjelseth et al. (2021b) specifically focused on the arrangement for tax payment deferrals. They found indicative evidence that tax payment deferrals have been provided to more distressed firms, measured by low equity share in 2019 and poor credit rating. They did not find the same for other support measures such as the compensation scheme ("Kompensasjonsordningen").

We contribute to the literature regarding misallocation of support during the pandemic, through investigating if tax deferrals were granted to non-viable firms in Norway. The results found by Hjelseth et al. (2021b) are in line with our finding that a substantial amount of tax deferrals has been provided to distressed firms. We contribute to their research by statistically estimating if non-viable firms (defined as zombies or distressed) were more likely to apply for and be granted deferral of tax payments. Also, we study whether deferrals could have held these non-viable firms alive in 2020 and 2021.

2.2 COVID-19 and Corporate Solvency

Many of the government support schemes were aimed at mitigating the impact of lockdowns on corporate solvency. Therefore, a need to assess the effect of these measures on the overall corporate solvency quickly emerged. Puhr et al. (2021) assessed several mitigating measures in Austria, including the arrangement for tax deferrals. They found in their study that deferral of short-term tax payments, i.e. social security contributions, decreased insolvency rates in 2020. However, they estimated that tax deferrals would increase insolvency rates when repayments were due in 2021. Intuitively this makes sense, as tax deferrals should not directly affect the financial statements positively, but rather provide short-term liquidity to survive until societies opens up and the revenue returns.

Although support measures were aimed at preventing a sharp increase in insolvencies, it was important that firms were not kept "artificially" alive through these policies. Dörr et al. (2022) studied the extent to which government support induced an insolvency gap in Germany and whether the gap could be characterized by firms that already struggled before the pandemic. They applied nearest neighbour matching (measured by the Mahalanobis distance metric) to compare the survival status of closely matched firms observed before the pandemic, with the survival status observed during the pandemic. Firms were matched based on size, industry, age and solvency information. They found that policy measures induced a backlog of insolvencies in Germany that was particularly pronounced among financially weak and small firms. The argued that this could have potential long term implications on economic recovery (Dörr et al., 2022).

Our study relates to the literature above in that we look at the relationship between the scheme for deferred tax payments and corporate solvency. Puhr et al. (2021) support our results in that payment deferrals are associated with lower probability of bankruptcy in the short term (2020), but not necessarily in the longer term (2021) when the deferrals fall due. Also, we adopt parts of the methodology from Dörr et al. (2022), as we apply a similar matching procedure to study if policy support can explain the decrease in bankruptcies during COVID. Similarly to their study, our results suggest that there exists an insolvency gap in the Norwegian economy. However, in contrast to their study, we investigate if the arrangement for payment deferrals specifically can help explain this gap.

2.3 COVID-19 and Non-Viable Firms

Our study also relates to literature focused on non-viable firms in the economy and during the COVID-19 pandemic. Especially, several studies have addressed the potential "zombification" of the economy during the pandemic (Favara et al., 2021). Zombie firms should naturally exit the market but are held alive due to poorly functioning markets (Caballero et al., 2008; Peek and Rosengren, 2005; Hoshi, 2006). The share of zombie firms tends to increase with government financial support to stimulate economic activity, e.g. expansionary monetary policy (through availability to cheap credit), subsides, financial support and taxes (Banerjee and Hofmann, 2018; Chang et al., 2021). Therefore, there is a growing concern that generous support during the pandemic has fueled an increase in such zombie firms (Favara et al., 2021).

In 2022, Favara et al. studied the extent of zombie lending in the U.S. economy. In 2021, the same authors conducted an analysis on the prevalence of zombie firms during the COVID-19 pandemic (Favara et al.). They found that the level of zombie firms has closely followed business cycles prior to the pandemic. Both after the 2000 dot-com bubble and the financial crisis in 2008, they found an increase in zombies in the subsequent years. However, during the pandemic, they found only a slight increase in the share of zombies from 2019 to 2020. The increase was not significantly higher than the average level from 2015 until 2019.

In contrast to the related research on zombie firms, the main aim of our study is not to estimate the exact level of zombie firms in the Norwegian economy. Our focus is on government support measures (and tax deferrals specifically) and how this may have affected the level of, and financial situation in, such firms.

3 Data

In the following, we present the data used in our study, provided by the Norwegian Tax Administration. As this thesis is an early investigation into the effects of COVID-19 and government support measures, we will present the available data and a detailed tracing of our construction of the final data sample. This will enable forthcoming research to retrace our steps and arrive at comparable data sets to be used for analyses. Following the data cleaning process, the final sample is presented and descriptive statistics will be provided. Lastly, the quality and limitations of the data is discussed.

3.1 Data

Our data is provided by The Norwegian Tax Administration, and contains firm-level information on Norwegian firms. The population is limited to private ("AS") and public ("ASA") limited liability companies that are VAT-registered with annual and bi-monthly statements. Since the data contains sensitive information, all organizational numbers are de-identified. All data was provided in separate tables from different sources and the following describes the relevant tables.

To obtain firm-level financial information, we use the Income Statement 2 ("Næringsoppgaven"). Income Statement 2 contains income statements and balance sheets for all the companies in our sample and forms the basis for all accounting variables used. All Limited liability companies are obliged to report their income, expenses and balances as part of the Income Statement 2 to the Norwegian Tax Administration (Skatteetaten, 2022). In theory, this data should equal information from firms' annual reports.

Information on COVID-related deferred payments of tax and duty claims has also been provided. The data contains information on which firms have been granted deferred payments of VAT and other taxes, and the respective amounts. As displayed in section 1.1, the arrangement was introduced in June 2020, and was supposed to end in December the same year. However, it was extended twice to June 30, 2021. This means that our data includes all granted deferrals of claims due between June 2020 to June 2021[1].

[1] A new arrangement was introduced in January 2022. Our data only covers the first arrangement, which lasted from 2020 to 2021.

Lastly, we also have access to data on bankruptcies, dissolutions and other changes in firms' statuses between 2010 and 2021. The official date of the change in status is included for each firm. Although the data contains different changes in status, our primary focus will be on the registered bankruptcies in the sample.

3.2 Data Treatment and Final Sample

After combining relevant variables from the different data sources, the initial sample consists of 297,143 unique firms from 2010 until 2021 across 2,767,999 observations. The data from 2021 is however limited to data regarding changes in company status and the arrangement for tax deferral during COVID-19. Since we want to analyze firm-level accounting data that is only reported annually, data originally provided more granularly is summed on an annual basis where relevant.

We exclude all financial firms (two digit NACE-codes 64-66) from the data and later analysis. Furthermore, we exclude firms that operate in sectors associated with public services. This includes NACE-codes 35, 36-39, 84, 85 and 86-88[2]. We argue these firms fundamentally differ from other private firms and are less relevant in light of the COVID-19 pandemic and government support. Therefore, the exclusion of these firms reduces the risk of distortions in the analysis. This removes 97,477 observations.

Upon inspection, we find that many companies continue to exist in the unit registry, even after a change in status (such as bankruptcy, dissolution etc.). These are observations of firms that are inactive. We therefore remove all firms after they have had a change in status, except for firms that were the acquiring company in a merger. This removes 522,756 observations.

Since the effects of COVID varied greatly between industries, we also remove all observations that lack a two-digit NACE code. The removal of missing NACE codes enables the use of industry groups as control variables in our estimations. This removes 32,087 observations.

Further, to ensure acceptable data quality, we test balance sheet equality. Total assets

[2]These NACE-codes represent the following sectors Electricity, Gas, Steam and Air Conditioning Supply (35), Water Supply; Sewerage, Waste Management and Remediation Activities (36-39), Public Administration and Defense (84), Education (85), and Human Health and Social Work Activities (86-88).

should equal the sum of equity and debt for all firms for all years. We allow for a deviation of positive or negative 5%, but remove any deviation above this threshold. Also, we remove any observations with total capital less than NOK 200,000. We do this to remove issues related to weak data quality for the smallest firms. A threshold of 200,000 is in line with Eklund et al. (2001) that is followed later in the analysis. This removes 220,670 observations.

In order to get comparable accounting figures Year-over-Year, the Income Statements are adjusted for inflation[3]. This enables comparisons of real values, rather than nominal. Using real values prevents distortions in the analysis due to general inflation over the years 2010-2020.

Since financial reports from 2021 will be made available in October 2022, we do not have access to income statements from 2021 at the time of writing. The only reported data that we have access to for 2021 is bankruptcy filings and granted tax deferrals. All other sources run from 2010 to 2020. To enable an analysis of slightly longer-term effects of the arrangement for tax deferrals on the survival of firms, we synthetically extend generic company variables (founding date, industry code and region) from 2020 to 2021. This entails that we assume companies have not switched NACE-code or primary region between 2020 and 2021. The limitations and implications for our analysis are discussed in section 3.3 and section 6.

Finally, we group industries into eight slightly less granular sectors. The sectors that are grouped are considered to be less interesting with respect to COVID-effects. The groups also ensure a sufficient amount of observations per industry per year and thus reduces biases in the deployed statistical models. The full overview of the remaining sectors can be found in table 3.1.

[3] Accounting figures were adjusted for inflation by the annual average Consumer Price Index through $\frac{\text{Nominal value}_t}{\text{Index value}_t} \times Index_{2021}$ (SSB, 2022c).

Table 3.1: Overview of grouped industries after filtering and grouping

Our sectors	2-digit NACE	Included sectors
Accommodation and Food Service	55-56	Accommodation and food service
Arts, Entertainment and Recreation	90-93	Arts, Entertainment and recreation
Construction	41-43	Construction
Domestic trade	45-47	Wholesale and retail trade; repair of motor vehicles and motorcycles
Manufacturing	10-33	Manufacturing
Service activities	69-75	Professional, scientific, and technical activities
	77-82	Administrative and support service activities
	94-96	Other service activities
Transportation and storage	49-52	Transportation and storage
Other sectors	01-03	Agriculture, forestry and fishing
	05-09	Mining and quarrying
	58-63	Information and communication
	68	Real estate activities

After the completion of the data treatment process, we are left with a sample of 283,684 unique firms from 2010 until 2021 over 1,895,009 number of observations. The final sample contains generic firm-specific variables such as age, number of employees and industry affiliation, as well as accounting figures from the Income Statement 2, granted tax deferrals during COVID-19 and relevant changes in firm statuses.

3.3 Data Quality and Limitations

Given that the data used in this thesis has been collected and provided by the Norwegian Tax Administration, there is no reason to believe that the overall quality of the data should be weak. All limited liability companies are obliged to report to the tax authorities, and any intentional data manipulation of data is considered to be illegal. However, there are several limitations of the data in the context of our analysis.

First, as firms approach bankruptcy, data quality appears to drop substantially. Specifically, most companies file their last financial report one, two, or three years before they are declared bankrupt in our sample. This limitation has the largest effect on our bankruptcy predictions and will be expanded on further in section 5.1.2.

Second, since our data is provided by the Norwegian Tax Administration, all company IDs have been de-identfied due to their sensitivity. This entails that we can not combine our data with firm-specific details from other sources. Therefore, our analysis is solely based on information readily available from the Tax Administration. When following methodology deployed in related research, we have had to rely on the most suitable proxies obtainable. Whenever relevant, this is commented clearly in the forthcoming analysis.

Third, given that the reduction in bankruptcies during COVID is the primary motivation for our thesis, it is vital that the bankruptcy registrations in our filtered sample resemble the overall development in Norway. Appendix A1.1 offers a graph of bankruptcy registrations from Statistics Norway (SSB, 2022a) compared to bankruptcies in our filtered sample. Overall, the YoY developments are very similar and the computed correlation is at 98.5%. Therefore, we conclude that our sample captures almost all of the general development in bankruptcy rates in the years 2010-2021.

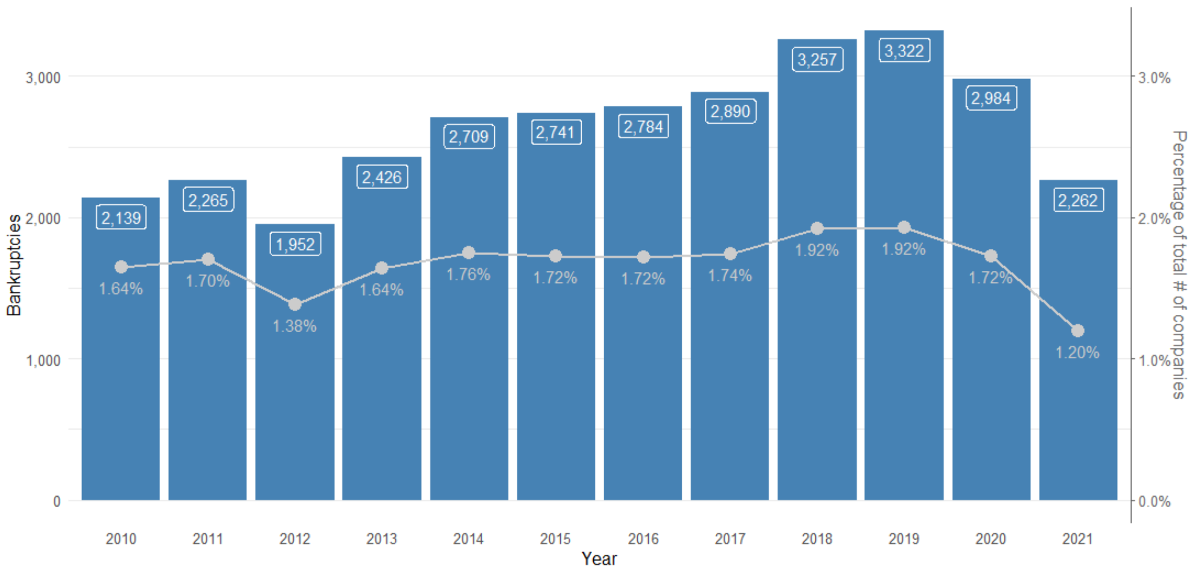
Lastly, as previously described, we extend generic company information from 2020 to 2021. The main limitation of this approach is that we only roll over firms that existed in 2020. This entails that companies *founded* in 2021 are not included in the analysis. The extension of age, sector and region is unlikely to introduce any major deficiency in the overall quality of this data as a company's sector and region is unlikely to change from one year to another.

4 Descriptive Analysis

This thesis relates to bankruptcies, COVID-effects and the arrangement for tax deferrals in Norway. In order to understand how the arrangement for tax deferrals potentially has kept business artificially alive, it is fundamental to gain an overview of all these aspects and how they interrelate. Therefore, we start by looking into the development in bankruptcies over time, examine the heterogeneity across sectors and provide an overview of the distribution of granted tax deferrals in our sample.

Bankruptcies

Figure 4.1: Bankruptcies over time

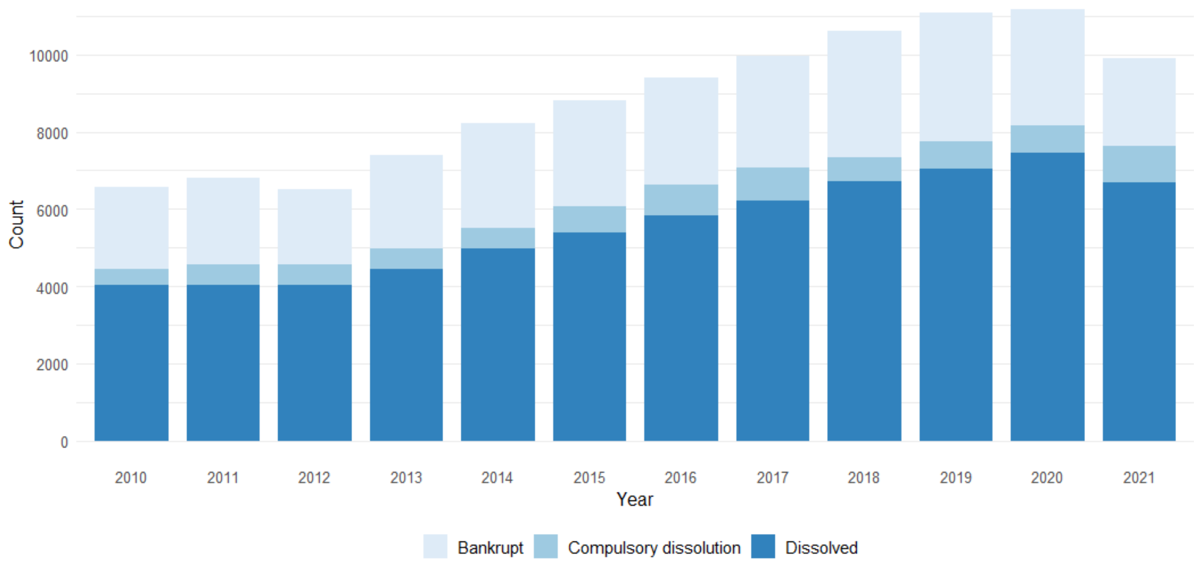


Note: The figure presents the absolute number of bankruptcies per year (LHS) and the bankruptcy rates per year (RHS) in our sample. Note that the share of bankruptcies in 2021 should be interpreted with caution as we do not have complete information about companies established in this year. The magnitude of the reduction is however in line with Statistics Norway, SSB (2022a). See Appendix A1 for a comparison.

Figure 4.1 shows the development in bankruptcies in our sample. Given the exclusion of certain sectors and observations with weak data quality, the absolute number of bankruptcies is lower in our sample than in official statistics. However, Appendix A1.1 shows that the development is quite similar for all years with a correlation of 98.5%. As can be seen, the number of bankruptcies in absolute terms steadily increased from 2010 to 2019 in the Norwegian economy (with the exception of 2012). Although the drop in bankruptcies in 2020 looks substantial, the actual bankruptcy rate is at about the same level as in the years 2014 to 2017. In 2021 however, there is a dramatic decrease to the lowest bankruptcy share in our sample.

Looking beyond bankruptcy statistics, figure 4.2 shows that the total number of companies that either went bankrupt or were voluntarily or compulsorily dissolved actually increased in 2020. Although there is still evidence of a significant reduction of dissolutions in 2021, the YoY-change is less dramatic than for bankruptcies alone. This is quite surprising as most Norwegian newspaper reports have commented on the dramatic drop in bankruptcy rates during COVID. This may indicate that even though there has been a decrease in declared bankruptcies, non-viable firms may still have exited the economy at similar rates to pre-COVID. Although this is an interest finding, our thesis relates to bankruptcy rates. Therefore, further analysis of this phenomenon is considered to be outside of the scope of this thesis.

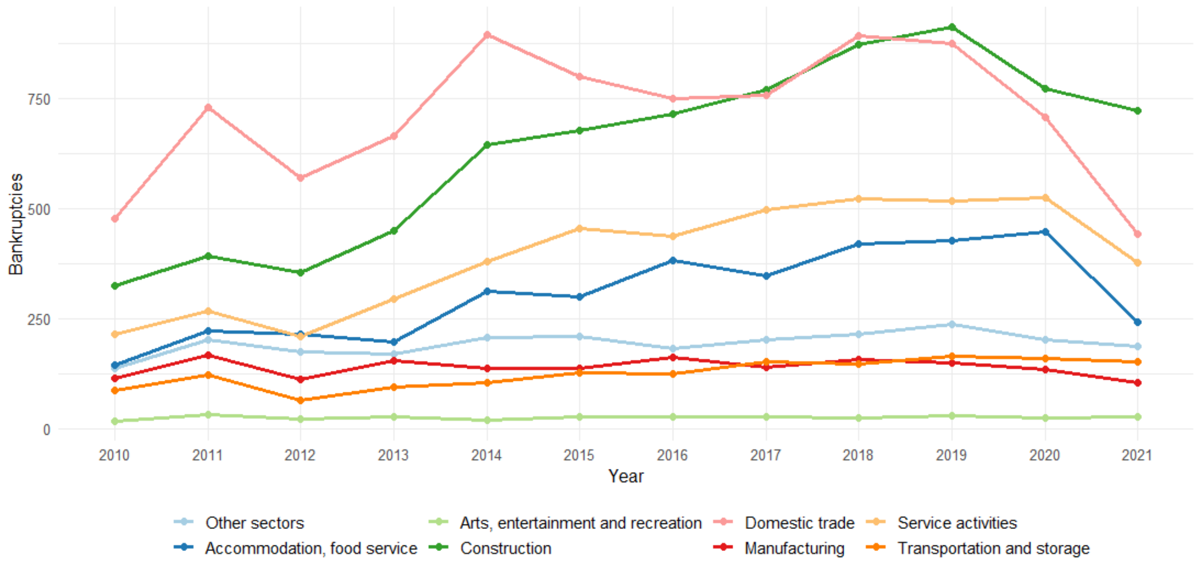
Figure 4.2: Total number of company status changes per year



Note: The figure presents the aggregate changes in firm statuses per year for our sample over time.

As an addition to the total number of bankruptcies in the Norwegian economy, figure 4.3 shows the annual number of bankruptcies across the main sectors defined in this thesis. Both Domestic trade and Construction are amongst the largest sectors in Norway and are also clearly ahead in the number of bankruptcies per year. These sectors also experienced the largest reduction in bankruptcies from 2019 to 2020. From 2020 to 2021, Accommodation and food service and Service activities also experienced similar reductions.

Figure 4.3: Bankruptcies per sector



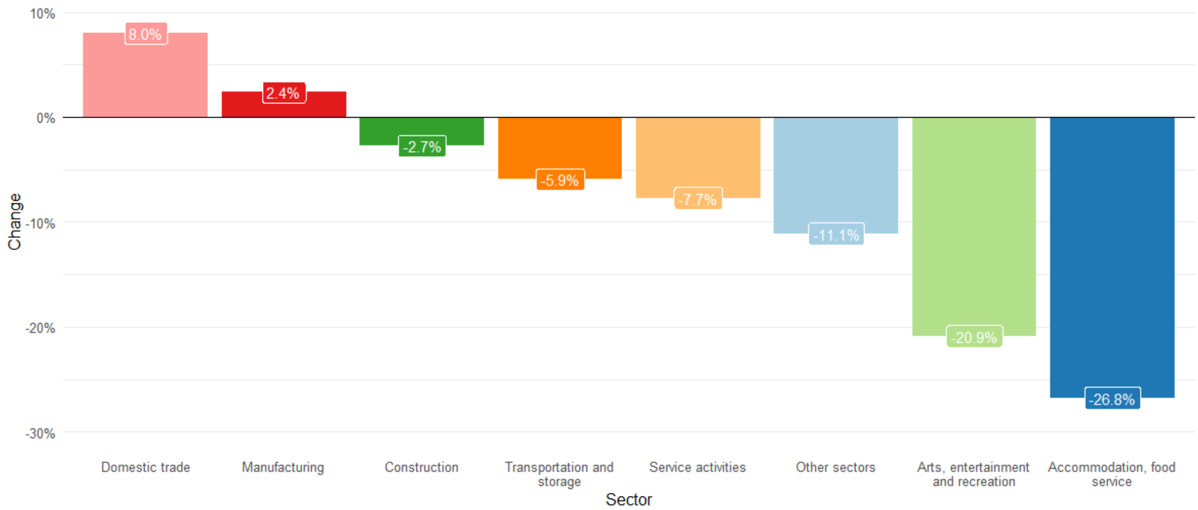
Note: The figure presents yearly number of bankruptcies per sector in our sample. From 2019 to 2020, Domestic Trade and Construction experienced the largest reductions in bankruptcies, while Accommodation and food service and Service activities had similar reductions from 2020 to 2021.

Another interesting finding is that the reduction in bankruptcies is clearly largest for the sectors that tend to cover a substantial share of the bankruptcies in "normal" years. The potential reasons behind this development may be manifold, but in the following, we investigate how these sectors fared during the first year of the pandemic and to what extent they were granted tax deferrals.

COVID-impact

Combining figure 4.3 and 4.4, Domestic Trade and Construction had the largest decrease in bankruptcies and were also the only two sectors that experienced an increase in sector-average turnover from 2019 to 2020. From 2020 to 2021, both Accommodation and food service and Service activities experienced similar reductions in bankruptcy rates. Interestingly, Accommodation and food service was also the sector most severely affected by COVID in terms of reduced revenue. The dramatic reduction in bankruptcies in 2021 may therefore be the result of a sharp bounce-back for this sector or may be indicative evidence of excessive government support.

Figure 4.4: Change in sector-average turnover from 2019 to 2020



Note: The figure presents the sample average change in turnover within each sector from 2019 to 2020.

Tax Deferrals

Concluding the descriptive analysis, table 4.1 shows the distribution of granted deferrals of taxes for 2020 and 2021 combined. In share of the total amount of deferred taxes, 71.2% of the deferrals were handed to companies in Service activities, Domestic trade and Construction. These sectors were also three of the four sectors that experienced the largest decrease in bankruptcies between 2019 and 2021. Thereby, there appears to be a strong relationship between tax deferrals granted during COVID-19 and the sector-specific development in bankruptcies. In contrast, the relationship is weaker between deferrals and a sector's average reduction in turnover. This could either be evidence of a skewed distribution of government support or of significant differences within sectors.

Table 4.1: Descriptive statistics - Tax deferrals

Sector	Amount (in 1000s)	N	Mean amount	SD Amount	Share of total amount
Service activities	1,100,899	1,181	932	5,026	27.4%
Domestic trade	880,867	1,323	666	2,978	21.9%
Construction	879,865	1,062	828	4,325	21.9%
Manufacturing	372,987	349	1,069	2,943	9.3%
Accommodation, food service	303,991	797	381	2,052	7.6%
Transportation and storage	251,935	234	1,077	3,854	6.3%
Other sectors	215,465	567	380	881	5.4%
Arts, entertainment and recreation	15,175	47	323	566	0.4%
Total	4,021,184	5,560	723	3,598	100%

Note: The number of granted deferrals is based on the number of granted deferrals in both 2020 and 2021.

Overall, the initial investigation of the relationships between COVID-19 effects, bankruptcies and the arrangement for tax deferrals shows great heterogeneity between sectors. Table 4.2 summarises the findings and also adds the share of companies within each sector that were granted tax deferrals in either 2020 or 2021. Although most sectors experienced a drop in revenues (measured by the sector mean), the bankruptcy rates dropped simultaneously. Also, there appears to be a relationship between granted tax deferrals and changes in bankruptcy rates, but there is no clear relationship between the timing of the granted deferrals and changes in bankruptcy rates. This shows that the effects of COVID-19 and government support schemes in Norway were manifold, and that there are several effects pulling in different directions at once.

Table 4.2: Summary of descriptive analysis

Sector	Bankruptcy change (%, 19/20)	Bankruptcy change (%, 20/21)	Revenue change (%, 19/20)	Tax deferrals (share of tot. amount)	Tax deferrals (share 20)	Tax deferrals (share 21)
Accommodation, Food Service	21 (4.9%)	-207 (-46.2%)	-26.8%	7.6%	4.7%	4.4%
Arts, entertainment	-6 (-20%)	3 (12.5%)	-20.9%	0.4%	0.8%	0.8%
Construction	-141 (-15.5%)	-50 (-6.5%)	-2.7%	21.9%	1.5%	1.9%
Domestic trade	-167 (-19.1%)	-264 (-37.3%)	8.0%	21.9%	1.5%	2.3%
Manufacturing	-15 (-10%)	-31 (-23%)	2.4%	9.3%	1.6%	2.0%
Service Activities	6 (1.1%)	-146 (-27%)	-7.7%	27.4%	1.3%	1.5%
Transportation and storage	-6 (-3.6%)	-8 (-5%)	-5.9%	6.3%	1.4%	1.7%
Other sectors	-34 (-14.4%)	-16 (-7%)	-11.1%	5.4%	0.6%	0.7%

Note: The table summarizes the findings of the descriptive analysis. Columns 2 and 3 show the change in bankruptcies from 2019-2020 and from 2020-2021 (%). The fourth column shows the change in mean revenue within the relevant sector from 2019-2020. The three rightmost columns provide statistics on tax deferrals in terms of the share of the total amount of granted deferrals (4) and in terms of the share of companies per sector that were granted deferrals (5-6).

5 Empirical Framework

In this section we present the methodology applied in the three-part empirical analysis. First, we define and identify non-viable firms for the forthcoming analysis. Second, we present the theory behind the logistic regression methodology used to estimate if non-viable firms were more likely to be granted tax payment deferrals. Third, we present the theory behind the matching procedure applied in an attempt to estimate the effect of tax deferrals on the probability of going bankrupt during COVID-19. Consequently, the three parts combined aim to answer our research question, *"To what extent did the arrangement for deferred payment of taxes and duties keep non-viable companies artificially alive through the COVID-19 pandemic?"*.

5.1 Method: Identifying Non-Viable Firms

To study whether non-viable firms have been held artificially alive through the COVID-19 pandemic, non-viable firms must first be defined. There are several possible approaches to define such firms. We distinguish between *distressed* firms (that have a high probability of going bankrupt), and *unwanted* firms in the economy (so-called zombie firms). While *distressed* firms are predicted to file for bankruptcy, *unwanted* zombie firms are unproductive firms that stay "artificially" alive in the economy over time (McGowan et al., 2017). These two definitions thus work in tandem to explore the evolution of both *unwanted* and *distressed* firms during the pandemic.

5.1.1 Zombie Firms

Zombie firms are often considered to be highly leveraged and unprofitable over time (Storz et al., 2017; Favara et al., 2022). There is no formal definition of zombie firms, but the literature proposes a range of different criteria to identify them (table A2.1 in appendix A2 presents the most prominent definitions). In this study, we follow the zombie definition proposed by Storz et al. (2017), combined with the definition proposed by Favara et al. (2022).

We define zombies as a firm which has (i) debt servicing capacity[4] less than 3.8%, (ii) negative return on assets and (iii) negative real sales growth for (iv) two consecutive years. Table 5.1 presents our measure compared to Storz et al. (2017) and Favara et al. (2022).

Table 5.1: Criteria for zombie firms

Source	**Definition of Zombie Firm (Criteria)**
Our definition	(i) Debt servicing capacity ($\frac{EBIDTA}{Total\ debt}$) $< 3.8\%$, (ii) negative return on assets ($\frac{Earnings}{Total\ assets}$), and (iii) negative real sales growth for (iv) at least two consecutive years.
Storz et al. (2017)	(i) Debt servicing capacity ($\frac{EBIDTA}{Financial\ debt}$) $< 5\%$, (ii) negative return on assets ($\frac{Earnings}{Total\ assets}$), and (iii) negative net investments for (iv) at least two consecutive years.
Favara et al. (2022)	(i) Interest Coverage Ratio < 1, (ii) leverage $>$ sample annual median, and (iii) negative real sales growth for (iv) three consecutive years

Our definition mainly follows the zombie definition proposed by Storz et al. (2017), and criteria (i), (ii), and (iv) are based on their definition. However, due to data availability, we have substituted their criterion of negative net investments, with criterion (iii) (negative sales growth) from the definition of Favara et al. (2022). The goal of both these criteria is to identify firms with limited expected future growth, and should to a large extent capture the same firms. Overall, both Storz et al. (2017) and Favara et al. (2022) try to identify firms that have low profitability, high leverage and low growth prospects over time. We argue that our set of criteria achieve the same goals as both.

In Storz et al. (2017), the debt servicing capacity threshold is set to below 5%. This threshold was chosen as it approximately was the median interest rate on outstanding debt in their sample. We set the threshold to 3.8%, based on the average interest rate on total outstanding loans to non-financial firms issued by Norwegian banks for the period 2011 to 2020 (SSB, 2022b). We do not have access to firms' interest costs, and argue 3.8% is the best estimate of our sample median interest rate on outstanding debt from

[4]Debt servicing capacity (i) is measured as $\frac{EBITDA}{Total\ debt}$, while return on assets is measured as $\frac{Earnings}{Total\ assets}$.

2011 to 2020 (first and last year we used to compute debt servicing capacities). With this assumption, the median firm in our sample will have an interest coverage ratio of 1, in line with Storz et al. (2017).

The rationale behind our chosen definition is both data availability and relevancy in the context of our analysis. Although the definition proposed by McGowan et al. (2018) (interest coverage ratio < 1 for three years and older than 10 years) has been more broadly applied in recent years, our data does not enable a computation of interest coverage ratios. Therefore, we instead combine Storz et al. (2017) with Favara et al. (2022) to arrive at a set of criteria that captures the relevant aspects of zombie firms. Additionally, Storz et al. (2017) argue that the criterion of interest coverage, which is applied in several zombie definitions, mistakenly classifies firms with highly subsidized credit as healthy firms. They argue that using debt servicing capacity (i) avoids this issue[5].

In the empirical analysis in section 6.1.1 we present the prevalence of zombie firms in Norway using our criteria, and evaluate its robustness.

5.1.2 Distressed Firms

We offer an alternative definition of non-viable firms to also identify firms with a high probability of going bankrupt. Using a customized version of the SEBRA model of the Norwegian central bank, we compute individual bankruptcy probabilities for all observations in our sample. These probabilities are later used directly or indirectly (as credit ratings) to measure the viability of a firm in a given year based on its financial state. The following presents a brief overview of the SEBRA model that our model is built on and the theory behind it. Thereafter, our customized model specification is described.

Over the years, the selection of bankruptcy prediction models has increased substantially, both in terms of available algorithms and suitable explanatory variables. Beaver (1966) was the first to prove that financial ratios exhibit predictive ability on the probability of firm failure. Following these findings, renowned statistical models such as Altman's Z-score (Altman, 1968) and Ohlson's O-score (Ohlson, 1980) were developed. To ensure

[5]The literature on zombie firms often defines zombies as firms that receive subsidized credit (Caballero et al., 2008). Our definition rather aims to capture firms that are *unwanted* in the sense that they are unprofitable and with poor growth prospects and thus cause inefficiencies and misallocation of resources in the economy through their existence.

that our model is robust to Norwegian data and as precise as possible, we have opted to follow the SEBRA model of the Norwegian central bank (Eklund et al., 2001).

SEBRA

The original SEBRA model was first described in 1999 (Sæther and Larsen) and made use of Norges Bank's accounting database to classify companies into different bankruptcy risk groups. In 2001, the SEBRA model was expanded through a quantitative supplement (Eklund et al.). Instead of classifying firms into risk groups, they increased the number of explanatory variables to develop a statistical analysis using a Generalized Additive Model (GAM). In 2007, the model was assessed and revised to improve its predictive ability (Bernhardsen and Larsen). The main benefit of the statistical GAM model is that the model specification allows it to discover hidden non-linear relationships in the data. Also, it provides both individual company-specific bankruptcy probabilities as well as an overall aggregated bankruptcy risk in the sample.

GAM

SEBRA is modelled as a Generalized Additive Model (GAM), a semi-parametric model first proposed by Trevor Hastie and Robert Tibshirani (2017). GAM models are an extension of Generalized Linear Models (GLMs) which in turn extend linear regression models (LMs). Whilst LMs only allow for linear relationships, GLMs open for modelling non-linear relationships, such as through logistic regressions. GAMs expand on this by allowing for non-linear effects, while also allowing flexible relationships between an independent variable and the dependent variable for different intervals of the independent variable. To exemplify, our model allows different intervals of a company's size to interact differently with the dependent variable (bankruptcy) and this relationship forms a smoothed line.

Our model

Bankruptcy prediction models can be broadly categorized as either accounting-based or market-based (Agarwal and Taffler, 2008). Market values are only available for publicly traded firms, and our data (as well as the Norwegian economy in general) contains a vast majority of non-public firms. Therefore, our model is built using accounting ratios rather than market-based figures.

The dependent variable in the model is defined as the "last submitted financial report prior to declaration of bankruptcy within two years". In other words, if a company was declared bankrupt in 2015, but delivered their last financial statement in 2013, 2013 will be set as the bankruptcy year for that specific company. This definition is in line with the SEBRA-model(Bernhardsen, 2001)[6] and has some clear advantages.

Firstly, by setting the bankruptcy year to the last year a company filed their financial report, we are able to capture a much larger number of bankruptcies. Only a very limited part of the sample are declared bankrupt the same year that they deliver their last financial report. At the same time, the reporting quality drastically decreases when a company is closing in on bankruptcy declaration. The chosen dependent variable also entails that we cannot estimate bankruptcies before 2012 as our bankruptcy registrations in 2010 and 2011 are likely to exist without related financial statements.

The independent variables specified in our model can be found in table 5.2. When selecting these independent variables, we tentatively follow the variables used in SEBRA. A bankruptcy prediction model should include variables to account for age, size, financial strength, liquidity and profitability (Bernhardsen, 2001). In our model, these aspects are captured through the inclusion of the variables listed in table 5.2.

Table 5.2: Independent variables in our bankruptcy prediction model

Age	$Age\ dummies : age\_1, age\_2 \ldots age\_8$
Size	$ln(total\ assets)$
Liquidity	$\frac{Short\ term\ debt}{Total\ assets}$
Solidity	$\frac{Equity}{Total\ assets}$
Profitability	$\frac{Net\ income}{Total\ assets}$
Working capital	$\frac{Current\ assets\ Short\ term\ debt}{Total\ assets}$
Sector mean solidity	$S_i = \frac{\sum_{i=1}^{n} Solidity}{n}$
Sector mean profitability	$S_i = \frac{\sum_{i=1}^{n} Profitability}{n}$
Sector standard deviation profitability	$S_i = \sigma Profitability_i$
Unpaid taxes	$\frac{Taxes\ due}{Total\ assets}$
Unpaid VAT	$\frac{VAT\ due}{Total\ assets}$

[6]SEBRA uses "last financial report prior to declaration of bankruptcy within *three* years". We reduce the time frame to *two* years to allow for predicting bankruptcies in 2020 and 2021 from 2019-data. The main consequence is that we lose some bankruptcies in the data set. However, this time frame is consistent across all our measures and therefore robust.

Validation and testing

When building a bankruptcy prediction model, it is vital to evaluate the model on data the model has not been trained on. A full overview of our validation process can be found in Appendix A3, but the main results are reported below.

To validate our model, we have used both out-of-time and out-of-sample validation. These validation methods achieve an Area Under the Receiving Operating Curve (AUC) of 0.860 and 0.872, respectively. An AUC of 0.5 would indicate that the model performs no better than a random classifier, while an AUC of 1 would only occur for a perfect model (Mandrekar, 2010). Our AUCs mean that our model is able to separate bankruptcies from non-bankruptcies in 86%-87.2% of the cases on unseen data. In section 6.1.2, we will also compare the predicted bankruptcy probabilities to the actual bankruptcy rates across different risk groups.

In section 6.1.2, our customized SEBRA model is deployed to classify firms based on their predicted viability and identify the firms that were non-viable before the pandemic struck.

5.2 Method: The likelihood of Receiving Tax Deferrals

After the identification of firms deemed non-viable before the pandemic, we deploy a logistic regression model to investigate if non-viable firms were more likely to apply for and be granted tax deferrals than their healthier counterparts.

5.2.1 Logistic Regression

Logistic regression is applied in section 6.2 to estimate the effect of being non-viable pre-crisis on the probability of receiving tax deferrals during the COVID-19 pandemic. The goal is to examine whether non-viable firms were more likely to be granted deferred payments than viable firms. In the following, we will motivate the use of logistic regression in the context of our analysis and present the econometric principles underlying the model.

Model specification

We will apply a logistic model (logit model), which is often used to model the probability of a binary outcome (Stock and Watson, 2015). There are several underlying assumptions behind logistic models. Firstly, the sample should contain a sufficiently large number of independent observations. We have more than 144,000 independent observations in 2019. Secondly, there should be no multicollinearity among the independent variables. We test for this in the analysis with variable inflation factor (VIF) and find that our models do not violate this assumption. Thirdly, the sample should have no large outliers. We winsorize the top 1% of the relevant variables such that these are set to the 99th percentile.

Variable selection

The dependent variable used in our models will take a value of 1 if a firm was granted deferred tax payment in either 2020 or 2021, and 0 otherwise. Thus, the model seeks to explain the determinants of receiving tax deferrals during COVID-19. The independent variable in our models is non-viability, and thus, our models seek to explain if there exist a relationship between non-viable firms and being granted tax deferrals. Non-viable firms are defined as either zombie firms or firms that have a high probability of going bankrupt within two years, and these are two independent variables for two separate logistic models. The zombie variable is defined as either 1/0 while the variable for the bankruptcy probabilities is and ordinal variable providing different levels of viability pre-pandemic.

In addition, age, sector, size, number of employees and the percentage change in revenue from 2019-2020 will be included as control variables to limit the influence of confounding variables. Controlling for industry is especially important in the context of this analysis, because there is substantial heterogeneity across industries with respect to COVID-related effects, shown in the descriptive analysis in section 4[7]. We also control for age, size and number of employees in an attempt to control for other observable characteristics.

There are some limitations with our models. Most importantly, they might suffer from bias due to omitted variables. There are unobservable variables that could influence the probability of receiving tax deferrals, e.g. heterogeneity within sectors with respect to losses due to COVID-19. Such effects are partly accounted for through controlling for sectors and revenue change, but we might not capture other respective firm-specific details in terms of COVID-effects. As a result, our estimates might be biased, and we cannot make causal inference. In contrast to the following section (section 5.3, we are

[7]Controlling for industries could have been handled by including interaction terms in the model. However, we are not interested in interpreting the role of tax deferrals within each industry.

here less concerned with causality. We do not aim to uncover the exact effect of whether being non-viable pre-COVID causally lead to receiving tax deferral, but rather whether non-viable firms were more likely to receive support than other companies in the economy. In the broader picture, it is interesting to explore whether non-viable firms received tax deferrals.

5.3 Method: Effect of Tax Deferrals on the Probability of Bankruptcy

The preceding steps in the analysis aim to investigate whether non-viable firms pre-COVID were more likely to apply for, and be granted, tax deferrals during the first year and a half of the pandemic. In an attempt to uncover what part this played in the observed reduction in bankruptcy rates, we perform a matched logistic regression. By matching firms that were granted tax deferrals (treatment group) with similar firms that did not (control group), we aim to investigate the role of tax deferrals in reducing bankruptcy rates and thus contributing to keeping non-viable businesses artificially alive during COVID.

5.3.1 Matching

Matching is a method often applied in research to improve balance, minimize model dependence and reduce the risk of potential biases (Ho et al., 2007). In our research, we define the companies that received tax deferrals as "treated" and search for firms that were as similar as possible on observable characteristics prior to the pandemic. In theory, well-matched samples of treated and control groups should reduce bias due to the covariates and thus aim to estimate causal effects (Stuart, 2010). By studying whether the "treated" group were more likely to go bankrupt in 2020/2021 than the counterfactual "control" group, we aim to adjust for biases due to dissimilarities between the two groups.

The construction of the matched sample is based on observable firm characteristics in 2019[8]. For each treated firm, we search for firms operating in the same industry, are of similar age and size (in terms of the number of employees and the natural logarithm

[8] We only match on observables in 2019 to ensure that no COVID-related aspects, except for treatment (tax deferral), are captured in the matching procedure. Given the sudden nature of the pandemic, there is no reason to suspect that the measured variables are related to the unexpected events in 2020.

of total assets) and with similar bankruptcy probabilities prior to the pandemic. This matching process closely resembles the one used by Dörr et al. (2022) to estimate the COVID-induced insolvency gap in Germany.

The goal of matching on industry and size is to reduce biases stemming from large industry-specific heterogeneity across firms of different industries and sizes, and also to account for differences in COVID-related impact. By incorporating predicted bankruptcy probabilities before 2020, we also make sure that differences in financial states prior to the pandemic are accounted for. Matching on these variables reduces the risk of confounding variables affecting the estimate of whether tax deferrals have contributed to keeping businesses alive. Thus, the matching process reduces the biases we can control for. However, there are some issues related to the timing of the analysis. This will be further expanded on in the empirical analysis, section 6.3.

The matching methodology consists of three main parts (Ho et al., 2011). First, a matching method must be chosen. Depending on the research question, one can opt for either propensity score matching or distance-based matching. Propensity score matching matches companies with similar probabilities of being treated, while distance-based matching disregards the probability of being treated and rather focuses on matching companies based on their absolute similarity.

Secondly, within both matching methods there are several specifications on how exactly the matching procedure should be conducted. Given the aim of achieving a sample of similar firms in both the "treated" and "control" group, the balance (i.e. the similarity between the two groups) must be assessed. The ultimate goal is to reduce systematic differences between the groups as much as possible. King and Nielsen (2019) argue that propensity score matching, although popular, is not a suitable method for matching as a preprocessing step. In our analysis, we therefore opt for nearest neighbour[9] distance-based matching with Mahalanobis distance. This is in line with King and Nielsen and works to ensure that our treatment and control firms are as similar as possible on the set of observable characteristics.

The final step of the analysis is to estimate the treatment effect on the outcome variable

[9]There exists several matching algorithms. We tested several of these and found nearest neighbour to produce the closest matches.

of interest (i.e. what is the effect of receiving tax deferrals on bankruptcy rates). There are different estimands available. In our analysis, we focus on the ATT – the average effect on the treated. In doing so, we aim to uncover how the change in bankruptcy rates amongst the treated companies compares to the counterfactual setting where these firms were in fact not treated. This hypothetical potential outcome setting is the main reason to employ matching as a preprocessing step in the first place.

6 Empirical Analysis

As described in chapter 5 - empirical framework - the empirical analysis is split into three parts based on our problem statement. In the first part, we study the prevalence of non-viable firms in Norway before and after the COVID-19 outbreak. Further, in the second part, we apply logistic regression to estimate the likelihood of receiving tax deferrals dependent on being non-viable. The goal of these two parts is to study whether tax deferrals during COVID-19 were granted to firms that were non-viable before the outbreak of the pandemic. In the third part, we seek to estimate the effect of receiving tax deferrals on the probability of going bankrupt. The combination of these three parts aims to answer our research question of whether the arrangement for tax deferrals has contributed to keeping non-viable firms "artificially" alive through the COVID-19 pandemic.

6.1 Non-Viable Firms During COVID-19

6.1.1 Zombie Firms

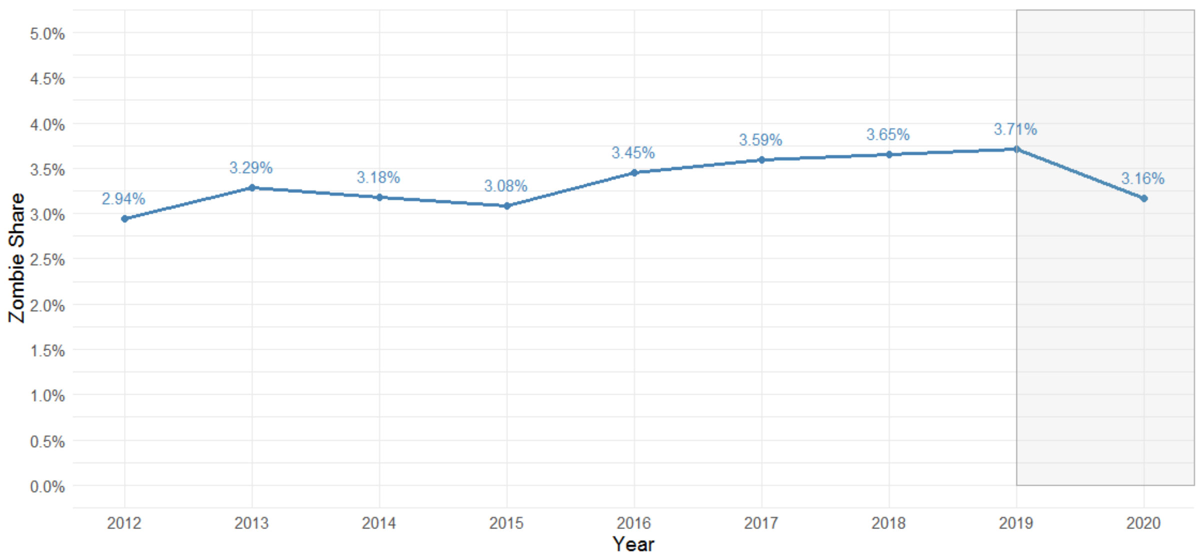
Zombie firms are economically non-viable firms that are held "artificially" alive by tapping banks and capital markets (Caballero et al., 2008; McGowan et al., 2018). Fueled by access to cheap credit, their prevalence in the economy tends to increase in times of distress and uncertainty (Peek and Rosengren, 2005; Favara et al., 2022). If such firms are held alive in the economy for longer periods of time, it could have large negative economic consequences. Through their existence, capital is tied up in unproductive firms and consequently prevents efficient capital reallocation (McGowan et al., 2017). In the following we examine the prevalence of such firms in Norway, including the first year of the pandemic.

Prevalence of Zombie Firms

We classify zombies as firms with (i) debt servicing capacity less than 3.8%, (ii) negative return on assets, and (iii) negative real sales growth for (iv) two consecutive years (see section 5.1.1 for the justification of these criteria). Using this definition, the prevalence of zombie firms in Norway from 2012 to 2020[10] is presented in figure 6.1.

[10]The time series runs from 2012 since we use "two consecutive years" in our zombie definition. Since

Figure 6.1: Prevalence of zombie firms in Norway



This figure presents the share of zombie firms in our sample, calculated as firms having (i) $\frac{EBITDA}{Total\,debt} < 3.8\%$, (ii) $\frac{Earnings}{Total\,assets} < 0$, and (iii) negative real sales growth for (iv) two consecutive years. We study non-financial public and private limited companies with total assets above NOK 200,000.

We estimate the zombie share in the Norwegian economy to vary between 2.9% to 3.7% over the estimation period, and with a slight increase from 2015 to 2019. Interestingly, we see a decrease in the relative share of zombies from 2019 to 2020, despite the economic severity of the COVID-19 recession. Seen in isolation, this is a positive development, implying a relative decrease in the number of weak firms in the Norwegian economy. However, there might be several reasons for this development.

Robustness tests in appendix A4 show that measurement error in the zombie definition is unlikely to be the main reason. On the other hand, our definition of zombies is mechanically tied to accounting figures. A decrease in zombie share from 2019 to 2020 is therefore likely a result of overall improvements in financial states for Norwegian firms during the first year of the pandemic (2020). In the following, the potential drivers of the reduction is discussed.

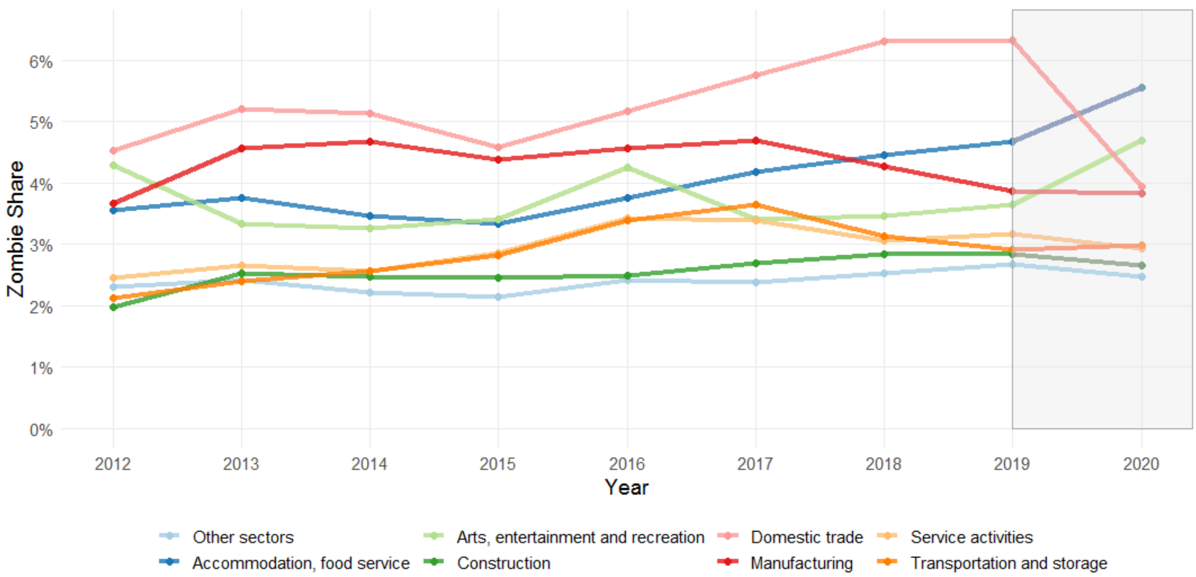
Drivers of the zombie share decrease

There might be several reasons why the relative number of zombie firms has decreased from 2019 to 2020. Figure 6.2 shows the development in zombie share across industries. In general, the decrease in zombie firms from 2019 to 2020 seems to be mostly driven by

our data runs from 2010 onward, 2012 is the first year where we can classify zombies.

the retail sector, while accommodation/food services and arts/entertainment have seen an increase in the number of zombies.

Figure 6.2: Zombie prevalence per sector



The figure presents the prevalence of zombie firms in Norway for different industries. Zombies are defined as i) $\frac{EBITDA}{Total\,debt} < 3.8\%$, (ii) $\frac{Earnings}{Total\,assets} < 0$, and (iii) negative sales growth for (iv) two consecutive years.

An increase for accommodation/food services and arts/entertainment is perhaps as expected, as these sectors have been severely hit by the pandemic and experienced large losses in turnover (seen in figure 4.4 in section 4). The decrease observed in domestic trade could potentially also be explained by a substantial increase in average turnover from 2019 to 2020. Interestingly, this sector has also received a significant share (21.9% in our sample) of the total amount of granted tax deferrals. However, it is difficult to see a direct connection between getting payment deferrals and the number of zombie firms in isolation. Other support schemes may for example directly impact a company's reported revenue (such as the compensation scheme), while granted tax deferrals will only be accounted for in the balance sheet as an increase in debt obligations.

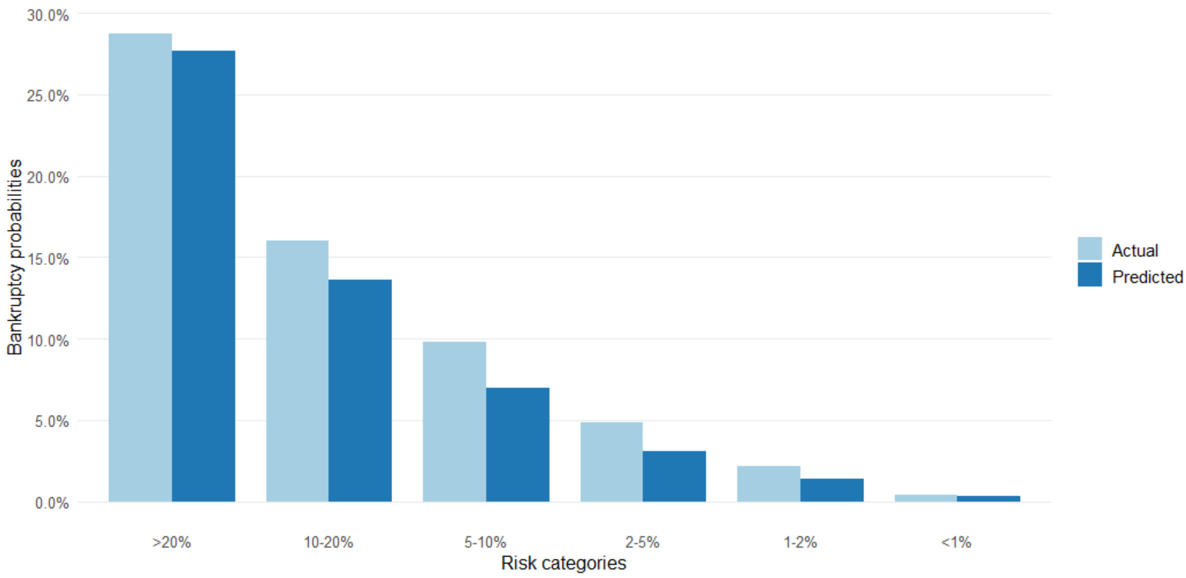
However, tax payment deferrals could have indirect effects on the financial state of zombie firms. Deferred payment of taxes could potentially provide weak firms the time to raise cheap capital or benefit from other support schemes. In this case, tax deferrals could indirectly lead to zombie firms surviving in the economy. This could also have longer term effects, as capital could be tied up in non-viable firms which in turn could weaken the adaptability of the economy. If this is the case, we would expect the number of zombie firms to increase in the years following our estimation period.

6.1.2 Distressed Firms

Our alternative measure of non-viable firms is firms with a high probability of filing for bankruptcy in the near future. We apply the SEBRA model proposed in section 5.1.2, and estimate probabilities of filing for bankruptcy within two years.

To evaluate the accuracy of the model before the pandemic, we check the predicted bankruptcy probabilities against the actual bankruptcy frequencies in the estimation period 2012-2017 (predicted bankruptcy declarations from 2013 to 2019)[11]. In table 6.1, the estimated bankruptcy probabilities are split into five different risk categories: 100-20%, 20-10%, 10-5%, 5-2%, 2-1% and 1-0%. In each of these categories, the difference between the average *actual* and *predicted* bankruptcy rates in the years prior to the pandemic is shown.

Table 6.1: Comparison of actual and predicted bankruptcy rates in bankruptcy risk groups - Before Covid-19



Risk categories	>20%	10-20%	5-10%	2-5%	1-2%	<1%
Actual	28.72%	16.04%	9.81%	4.84%	2.17%	0.42%
Predicted	27.69%	13.64%	6.99%	3.11%	1.40%	0.32%

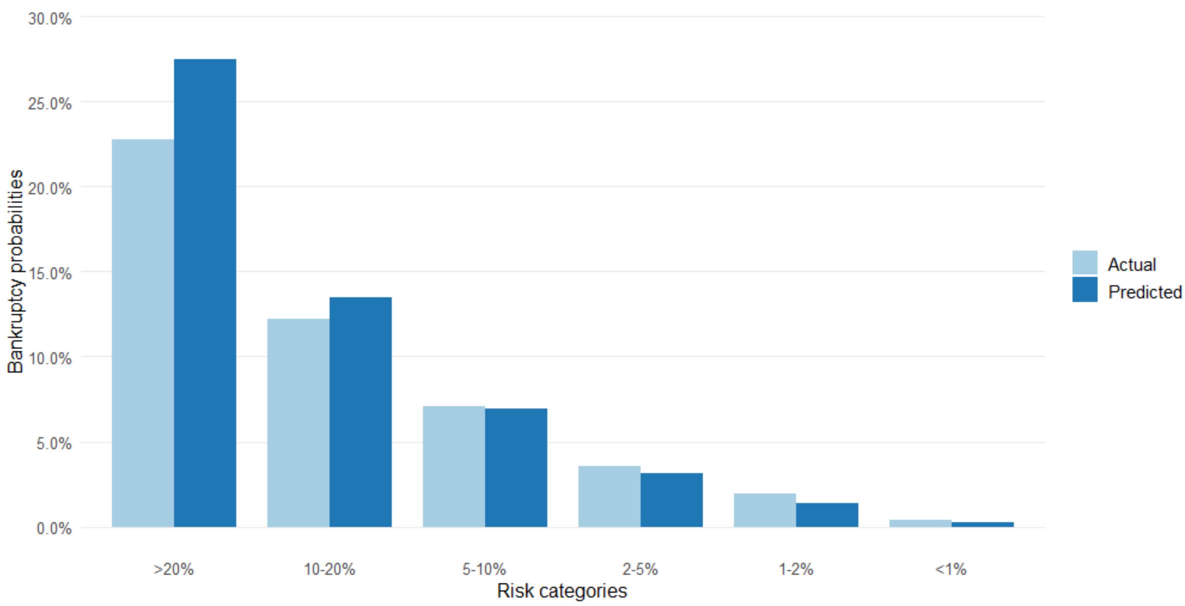
The risk categories relate to the predicted bankruptcy probabilities. In line with Eklund et al. (2001), we define predicted bankruptcies using: "last submitted financial report prior to declaration of bankruptcy within two years". The actual bankruptcies are calculated based on the date of bankruptcy declaration. These definitions allow comparisons over years and are therefore the most suitable to our application. See Appendix A3.2 for an expanded version of the table including the yearly actual bankruptcy rates.

[11]The full regression output and validation process can be found in Appendix A3.

The model slightly underestimates the bankruptcy rates across all risk groups. On the other hand, it seems to perform fairly well and the deviations are similar to the deviations in the original SEBRA model (Bernhardsen, 2001). We deem this, combined with a relatively high AUC-score of 87.2%[12], as sufficient evidence that our model has strong predictive power on the expected bankruptcy rates in the two years following a given year's financial statements.

As a first look into how the model predictions compare the actual development in bankruptcies during the first two years of the pandemic, we deploy the same methodology as in the previous paragraph on data from 2019-2021. The model is refitted on financial statements from 2019, meaning that the results presented in 6.2 shows the model's estimated bankruptcy probabilities compared to the actual bankruptcy rates in 2020 and 2021.

Table 6.2: Comparison of actual and predicted bankruptcy rates in bankruptcy risk groups - 2020 & 2021



Risk categories	>20%	10-20%	5-10%	2-5%	1-2%	<1%
Actual	22.76%	12.24%	7.10%	3.59%	1.95%	0.38%
Predicted	27.45%	13.49%	6.97%	3.11%	1.41%	0.26%

Note: The table displays the difference between actual and predicted bankruptcy rates within different risk groups. The actual rates are computed by actual bankruptcies in 2020/2021, while the predicted rates predict bankruptcies in 2020/2021 based on financial statements from 2019.

The figure above provides indicative evidence that there exists an insolvency gap in the

[12]See Appendix A3 for a full overview of the validation process.

Norwegian economy. Compared to the results in table 6.1, the model predicts a higher bankruptcy rate in the two highest risk categories (">20%" and "10-20%") than the actual rates in 2020 and 2021. In the groups "5-10%", "2-5%" and "1-2%" the actual rates are higher than in the predicted rates, but the gaps are substantially smaller than in table 6.1. Additionally, the actual bankruptcy rates are lower in every risk group compared to the rates in years 2012-2017. Later in the analysis, the potential role of tax deferrals in creating this insolvency gap will be investigated further.

Unlike the zombie definition, which is an absolute measure of viability (either zombie or non-zombie), we here classify companies into groups of viability. The companies assumed to be *least* viable before the pandemic are the firms in risk category ">20%", while the assumed *most* viable firms are the ones in category "<1%". The table below, table 6.3 provides the share of firms in each category.

Table 6.3: Share of companies per risk category - 2019

Risk categories	>20%	10-20%	5-10%	2-5%	1-2%	<1%
Share of sample	0.3%	1.4%	3.0%	7.0%	9.3%	79.0%

In the following analysis, we will investigate if the firms in the higher bankruptcy risk categories, along with our previously identified zombie firms, were more likely to receive tax deferrals during the pandemic than their healthier counterparts.

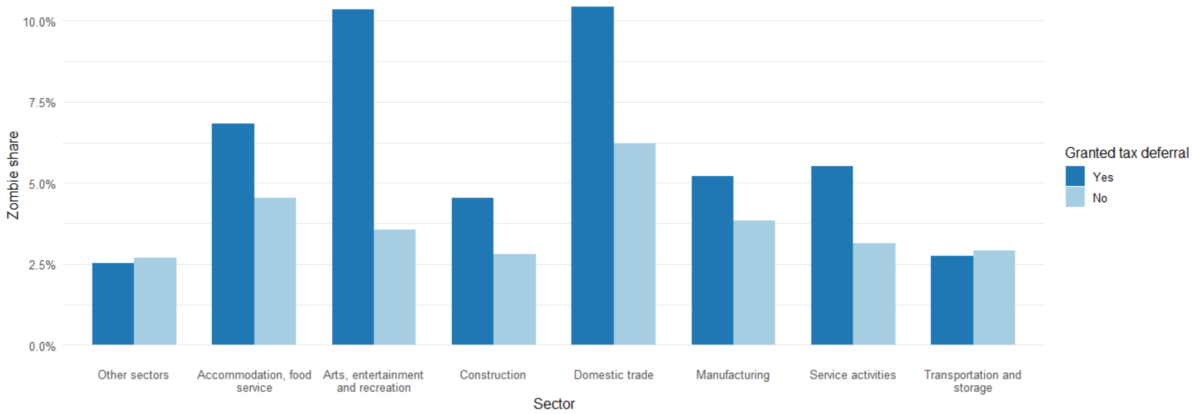
6.2 Estimating the Likelihood of Receiving Tax Deferrals

So far in this thesis, we have identified and estimated the prevalence of non-viable firms in the Norwegian economy. In this section, we study to what extent non-viable firms have been granted tax payment deferrals. We will first study zombie firms, and then firms with high probability of going bankrupt. Lastly, we draw the lines between the two analyses.

Zombie Firms

Figure 6.3 shows the relative share of firms categorized as zombie firms vs. non-zombie firms in 2019 that were granted tax deferrals in 2020 or 2021. In most sectors, the zombie share is higher amongst those that were granted tax deferrals than amongst those who did not. This suggests that non-viable firms in the period before the COVID-19 outbreak have been granted tax payment deferrals to a greater extent than viable firms.

Figure 6.3: Zombie share amongst firms that were, and were not, granted tax deferrals



Note: The figure shows the relative share of zombie firms within the group that were granted tax payment deferrals and the group that did not. The figure represents firm categorized as zombies in 2019. In every sector apart from Other Sectors and Transportation and Storage, the share of zombies amongst those that were granted tax deferrals is higher than amongst those who were not.

To empirically test if zombie firms were more likely have been granted tax deferrals, we perform a logistic regression. As the dependent variable, we introduce a dummy for tax payment deferrals (taking a value of 1 if a firm has received deferrals either in 2020 or 2021, and 0 otherwise). The main independent variable is a dummy for zombie firm (taking a value of 1 if a firm is categorized as zombie in 2019, and 0 otherwise). Also, we include control variables for industry, age, number of employees, size (ln of total assets) and revenue change (in %) from 2019 to 2020[13].

Table 6.4 shows the regression output of our specified model. The two columns represent different specifications: (1) is modelled without any control variables, while (2) controls for age, number of employees, size (ln of total assets), industry affiliation and revenue change from 2019-2020. The effect of being categorized as zombie in 2019 on the probability to receive tax deferral in 2020 or 2021 is significant at a 1% significance level in both specifications. The explanatory power of the model is improving with more control variables. However, a pseudo R^2 of 4.8% suggests that receiving tax deferral is explained by several other factors. We will in the following study to what extent bankruptcy risk

[13]Revenue change is also used to define zombie firms. However, multicollinearity is not an issue in the regression model as the zombie variable represents zombies in 2019, while the revenue change variable is based on the change from 2019 to 2020.

could explain the probability to receive tax deferrals.

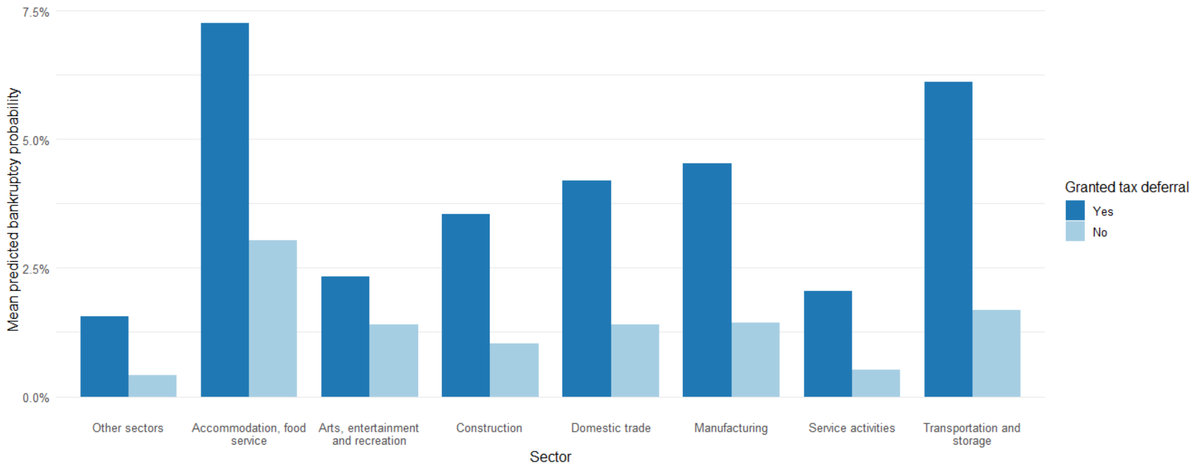
Table 6.4: Effect of being zombie in 2019 on the likelihood of being granted tax deferrals

	Dependent variable:	
	Tax deferral (1/0)	
	Without controls	With controls
	(1)	(2)
Zombie = 1	0.665***	0.654***
	$t = 9.156$	$t = 8.806$
Age		−0.028***
		$t = -13.537$
of employees		0.023***
		$t = 23.266$
Size		−0.151***
		$t = -10.621$
Revenue change 2019/2020		0.011
		$t = 0.498$
Constant	−3.779***	−2.076***
	$t = -208.323$	$t = -9.439$
Industry controls	NO	YES
Pseudo R^2	0.002	0.048
Observations	144,127	144,127
Log Likelihood	-15,761.340	-15,035.960
Akaike Inf. Crit.	31,526.680	30,097.910
Note:		*p<0.1; **p<0.05; ***p<0.01

Distressed firms

To further study the extent of which non-viable firms were granted payment deferrals, we are interested in whether firms with higher probabilities of bankruptcy were relatively more likely to receive support. Figure 6.4 shows the average bankruptcy probability before the COVID-19 outbreak for firms that were granted tax deferrals vs. those that were not granted deferrals across sectors. As can be seen, the average bankruptcy probability was higher for firms that were granted deferrals across all sectors.

Figure 6.4: Sector-average bankruptcy risk amongst firms that were, and were not, granted tax deferrals



Note: The figure shows the average predicted bankruptcy probability for firms that did, or did not, receive tax deferrals across all sectors. The predicted probabilities are based on financial statements in 2019 and thereby on bankruptcy probabilities in 2020/2021. The average bankruptcy probability is higher for the firms that were granted deferrals than those who did not. This is consistent across all sectors.

Table 6.5 shows the regression output for the effect of being in different bankruptcy probability intervals on the likelihood of receiving tax payment deferrals. Column 1 does not include any control variables, while column 2 includes controls for industry, age, number of employees, size and revenue change from 2019 to 2020 (in%). The pseudo R^2 is higher for column 2, which suggests the control variables improve the model. However, the two specifications estimate somewhat similar results, which suggests the estimates of bankruptcy probabilities do not vary much within the chosen controls.

The coefficients of bankruptcy probabilities are all significant at 1% level. Also, the likelihood of receiving tax payment deferrals increases for higher probability intervals, with the highest probability for firms having 20%-100% bankruptcy risk. This implies that firms with higher probability of filing for bankruptcy in the period before COVID-19 were significantly more likely to receive tax payment deferrals in 2020 and 2021. On the other hand, similar to the model for zombie firms, the explanatory power of the model (pseudo R^2) indicates that there is much unexplained variation. This means that although less viable firms were more likely to receive tax deferrals, there are other important factors that we are unable to control for. However, there is a significant positive correlation between having a higher bankruptcy risk score and applying for (and be granted) tax payment deferral.

Table 6.5: Effect of risk category affiliation on the likelihood of being granted tax deferrals

	Dependent variable:	
	Tax deferral (1/0)	
	Without controls	With controls
	(1)	(2)
P=1% - 2%	1.314***	1.270***
	$t = 25.941$	$t = 23.149$
P=2% - 5%	1.724***	1.713***
	$t = 34.731$	$t = 30.372$
P=5% - 10%	2.201***	2.207***
	$t = 37.236$	$t = 32.820$
P=10% - 20%	2.633***	2.606***
	$t = 37.881$	$t = 32.977$
P=20% - 100%	2.964***	2.884***
	$t = 24.809$	$t = 22.594$
Age		−0.004**
		$t = -2.273$
# of employees		0.014***
		$t = 12.488$
Size		0.068***
		$t = 4.516$
Revenue change (%) 2019/2020		−0.010
		$t = -0.493$
Constant	−4.434***	−6.002***
	$t = -160.953$	$t = -24.571$
Pseudo R^2	0.09	0.106
Industry controls	NO	YES
Observations	144,127	144,127
Log Likelihood	-14,378.450	-14,117.750
Akaike Inf. Crit.	28,768.900	28,269.510
Note:		*p<0.1; **p<0.05; ***p<0.01

To conclude, both zombie firms and highly distressed firms (before the pandemic) were significantly more likely to be granted tax payment deferrals. Appendix A5 also shows that both of these non-viable types of firms were granted more in tax deferrals than their respective prevalence in the economy could justify. In addition, one cold argue that these, ideally, should perhaps not have been granted deferred payments at all, as their potential prolonged existence could impede the overall adaptability of the economy.

Following the finding that non-viable firms appear to have been more likely to apply for and be granted tax deferrals, it is relevant to study if tax deferrals lead to lower risk of going bankrupt in 2020 and/or 2021. If so, this would suggest the arrangement of tax deferrals has held non-viable firms alive through the pandemic. Therefore, we will in the next section study the effect of tax payment deferrals on the probability of going bankrupt during COVID-19.

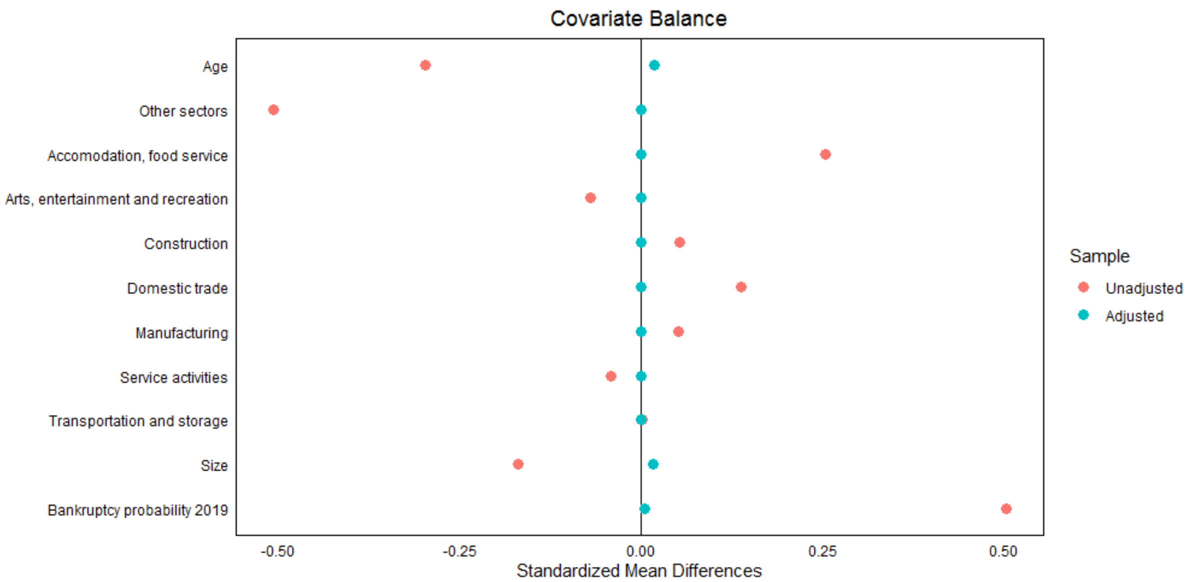
6.3 Estimating the Effect of Tax Deferrals on the Probability of Bankruptcy

Given that *unwanted* and *distressed* firms seem to have been more likely to apply for and be granted tax deferrals during the pandemic, a natural final step is to estimate the effect tax deferrals have had on the probability of going bankrupt. If we find that (1) receiving tax deferral is related to lower bankruptcy rates - combined with our finding that (2) non-viable firms were more likely to be granted tax deferrals than viable firms - then this is a strong indication that the arrangement for tax deferral has contributed to keeping weak firms alive. To explore this relationship, we deploy the matching methodology described in chapter 5.3 and a logistic regression model.

Matching is applied as a pre-processing step to enable an estimate of the effects of tax deferrals on the probability of bankruptcy. The matched sample allows us to compare the potential outcome for the firms that were granted deferrals, in the counterfactual setting where they were not. This entails that through comparing firms that were similar pre-COVID - and assumed to be similarly affected by lockdowns - we can simulate what would have happened in the absence of tax deferrals. Thereby, through a logistic regression, the coefficient on tax deferrals against bankruptcy declaration (1/0) should resemble the average effect tax deferrals had on the probability of going bankrupt amongst those firms that were granted deferrals. Matching also reduces the risk of confounding variables, model dependencies and potential biases (Ho et al., 2007).

The matching process is based on Mahalanobis distance, meaning that observations are matched on their absolute similarities, rather than on their probability of receiving tax deferrals (Ho et al., 2011). Since we deploy three different variations of the treatment variable (tax deferral in 2020, tax deferral in 2021 and tax deferral in either 2020 or 2021), the matching process has also been conducted three times. Figure 6.5 shows the improvement in balance after the matching procedure has been conducted on those firms that were granted tax deferrals in either 2020 or 2021. A full summary of the improvement in balance for all variations of the matched samples can be found in appendix A6. All firms that were granted tax deferrals have been matched with three other companies in their respective industry, at about the same size in terms of ln(assets) and number of employees, and with similar predicted probabilities of going bankrupt prior to the pandemic outbreak.

Figure 6.5: Data balance after matching firms granted tax deferrals in either 2020 or in 2021



Note: The difference between the "Adjusted" and "Unadjusted" points shows the improvement in balance after the matching process. Points closer to the vertical line show precise matches. All "treated" companies have been matched 3:1 with similar firms in 2019.

To estimate the effect of tax deferrals, we include the same independent variables as were used in the matching procedure, in addition to the treatment variable *tax deferral*.

To explore the effects over different time horizons, we deploy different combinations of dependent and treatment variables.

The first two models estimate the effect of being granted tax deferrals in 2020 on the probability of going bankrupt in 2020[14] (1) and 2021 (2). Model (3) gives the estimated effect of payment deferrals in 2021 on the probability of bankruptcy in 2021, while model (4) investigates the effects of receiving tax deferrals in either 2020 or 2021 on the probability of going bankrupt in 2021.

The estimated effects should be interpreted as the average effect of the treatment on the firms that were actually treated. Through estimating these effects on different timing combinations of receiving tax deferrals and bankruptcy declarations, the models should give the best possible picture of the effects of tax deferrals on bankruptcies to date.

Table 6.6 shows the summary of the matched logistic regression. The coefficient for tax deferral is the only coefficient that should be interpreted as the inclusion of the controls is merely a double safeguard against any remaining biases after the matching procedure.

[14] The dependent variable "Bankrupt in 2020" is based on bankruptcies after the initiation of the arrangement for tax deferrals. Therefore, only bankruptcies after 12.06.2020 are counted.

Table 6.6: Effect of tax deferrals on the likelihood of bankruptcy

	Dependent variable:			
	Bankrupt in 2020	Bankrupt in 2021		
	(1)	(2)	(3)	(4)
Tax deferral 2020	−3.620***	−0.185		
	t = −3.598	t = −1.202		
Tax deferral 2021			−0.237	
			t = −1.607	
Tax deferral 2020/2021				−0.201
				t = −1.540
Age	0.007	−0.012	−0.014	−0.014*
	t = 0.527	t = −1.288	t = −1.622	t = −1.756
Size	−0.305***	−0.113*	−0.081	−0.085
	t = −2.718	t = −1.699	t = −1.314	t = −1.525
Number of employees	0.018***	0.008*	0.008*	0.008**
	t = 2.838	t = 1.779	t = 1.928	t = 2.018
Predicted bankruptcy prob 2019	9.087***	7.884***	8.245***	8.626***
	t = 8.007	t = 9.961	t = 10.893	t = 12.976
Constant	−1.040	−3.248***	−3.746***	−3.724***
	t = −0.618	t = −3.114	t = −3.852	t = −4.216
Pseudo R^2	0.143	0.098	0.095	0.098
Industry controls	YES	YES	YES	YES
Observations	8,592	8,592	10,740	13,556
Log Likelihood	−486.007	−1,064.208	−1,216.678	−1,524.263
Akaike Inf. Crit.	998.014	2,154.417	2,459.357	3,074.526

Note: All control variables are based on firm characteristics in 2019. *p<0.1; **p<0.05; ***p<0.01

We estimate negative coefficients on tax deferral in all specifications. This means that our models estimate a negative effect of tax deferrals on the probability of going bankrupt. However, model (1) is the only specification that shows a statistically significant effect. This model also gives the largest negative effect, meaning that being granted tax deferrals in 2020 was strongly correlated with not going bankrupt in 2020. For the remaining models, the results are less certain. As we do not see a significant effect on the probability of going bankrupt in 2021, it seems that tax deferrals have not had a significant effect on keeping *unwanted* and *distressed* firms artificially alive beyond 2020.

Our findings of insignificant relationships for 2021 can make intuitive sense, as the first payment deferrals fell due at the end of 2021 (in November). In light of our finding that weaker companies were granted deferrals, it is reasonable to assume that a significant proportion of these were illiquid at the time of the first repayment. If companies did not make the first repayment, the Norwegian Tax Administration would immediately initiate a collection process. Consequently, one could expect that some of these firms would file for bankruptcy at the end of 2021. If so, this could explain the non-significant relationship between tax deferrals and bankruptcies in 2021. However, bankruptcy proceedings tend to take time. Therefore, it seems unlikely that the debt collection in November 2021 is the sole reason for the bankruptcies in 2021 among the companies that were granted tax deferrals.

Another more likely explanation is that the firms which would have struggled to repay the Tax Administration, also struggled to repay other creditors throughout the year. Thereby, there is reason to believe that either creditors, or the owners themselves, would file for bankruptcy before the Tax Administration. Our sample of firms only includes limited liability companies in which the owners are not personally accountable in the case of default on debt obligations. In our view, this is a more likely cause to explain that firms covered by the arrangement for tax deferrals have filed for bankruptcy in 2021.

One last alternative explanation is that the sum of all the other support measures - implemented simultaneously with the arrangement for tax deferrals - had a bigger effect on corporate solvency than tax deferrals alone. Appendix A7 shows that our bankruptcy prediction model estimates lower predicted bankruptcy rates when refitted on the Income Statements from 2020. Along with our finding that the zombie share fell in 2020 (see figure 6.1 and 6.2 in section 6.1.1), it seems likely that the support schemes with a more direct effect on the financial accounts of firms may explain more of the reduction in bankruptcy rates in the longer term.

An important caveat is the availability of data at this point in time. First of all, as discussed in section 5.1.2, statistics on declared bankruptcies often include a time lag from the *real* bankruptcy timing. This means that our sample of declared bankruptcies during COVID may suffer from spillover effects from previous years. In the instances where such spillover effects are present, the relevant firms will not have financial statements reported in 2019. Thereby, this weakness is partly accounted for through the matching process deployed in our analysis. Since the matching is performed on firm information from 2019, only firms that delivered an Income Statement in 2019 are eligible matching candidates. Therefore, the analysis should be based on companies that *de facto* went bankrupt in the relevant years.

Additionally, our sample does not contain complete registrations of all granted deferrals in the arrangement for tax deferrals. Through the exclusion of certain NACE-codes and filtering on total assets (to ensure data quality), we do not capture the full extent of the arrangement. Therefore, our results only apply our filtered sample of firms. However, our sample covers 90% (NOK 4 billion of a total of NOK 4.5 billion) of the deferred amounts in 2020/2021 and could thus be viewed as a representative sample.

Furthermore, the available data at this point in time only provides an opportunity to investigate short-term effects. In time, when deferred taxes are due and with updated data on firms' financial accounts and bankruptcy filings from the years post-pandemic, longer-term effects may be exposed. Since we find that non-viable firms were relatively more likely to apply for and be granted tax deferrals, it is not unlikely that these firms will struggle to fulfill their debt obligations to the tax authorities.

7 Discussion

This study contributes to the overall research on COVID-19, government support and corporate solvency. While there exists extensive research on the potential effects of government support, there is limited research on the topic of misallocation to non-viable firms. The literature is even more limited on the arrangement for tax deferrals, and especially in a Norwegian context. In general, this topic is highly complex as COVID-19 induced wide-spread effects, and several government support schemes were implemented simultaneously.

Although we control for confounding variables obtainable in our data, we cannot control for the net effects of all other support measures simultaneously introduced. The same applies to our ability to control for the full extent of the heterogeneity in COVID-related impacts. Thereby, our models are likely to be subject to omitted variable bias. We try to control for this through a matching procedure, but we cannot be sure that this sufficiently isolates the effect of tax deferrals on bankruptcies.

There is little doubt as to whether the full extent of the government support schemes have had a large combined effect on corporate solvency through the pandemic. We find that both the estimated zombie share and predicted bankruptcy probabilities (predicting bankruptcies in 2021/2022) are reduced in 2020. Deferred payment of taxes should not have any direct positive effect on the financial statements of firms. On the other hand, other "free money" schemes (eg. the compensation scheme) could help explain why the financial states appear to have been improved in 2020 despite the impact of lockdowns. However, given the fact that the Tax Administration is usually responsible for a large proportion of bankruptcy petitions (The Norwegian Tax Administration, 2021a), it seems likely that the lack of government debt collection is responsible for at least parts of the reduction of bankruptcies in Norway.

An important aspect when assessing the effects of the arrangement for tax deferrals is the economic significance of its potential misallocation. Excessive support to non-viable firms runs the risk of direct cost in terms of lost tax revenue in the short term. However, in the process of granting tax deferrals, it would have been difficult to differentiate between firms based on viability. Also, the potential costs of not granting payment deferrals could have been large-scale bankruptcies and high unemployment levels. Such a scenario is likely to have resulted in more severe economic consequences than lost tax revenue.

In sum, zombie firms and highly distressed firms (the two highest risk categories) received 5.6% and 5.9% of the total arrangement for tax deferrals, thus amounting to NOK 225 million and NOK 257 million, respectively in our sample. However, as the arrangement was extended further into 2022, the total amounts granted further increased from the NOK 4.5 billion granted by the end of 2021. Our sample only covers NOK 4.0 billion in deferred amounts and since our definition of non-viable firms only covers the businesses on the absolute lower-end of the spectrum of business viability, these estimates are therefore highly conservative.

Additionally, the sums equate to a larger share of the arrangement than the two groups' respective share in the economy (see appendix A5). The figures are also large enough to potentially have kept many non-productive firms alive and their prolonged existence in the economy may have caused inefficiencies and halted the reallocation of both financial and human capital that the pandemic could have induced. On the other hand, our results indicate that the arrangement overall did not keep the firms that were granted deferrals alive for a longer period of time, and thus the longer-term impact on the economy is likely to be limited.

7.1 Limitations and Further Research

In the process of writing this thesis, we have encountered several issues. The main limitation of our study relates to data availability and quality. Crucial to our problem statement is new and updated data regarding financial statements and bankruptcies during or even after the COVID-19 pandemic. At the time of writing, the last available complete set of financial statements is for 2020. Ideally, we would have assessed the financial situation of Norwegian firms in 2021, or even 2022, to get a more complete overview of the effects of COVID-19 and support measures on the prevalence of non-viable firms. Also, when data on the repayment (or lack thereof) of deferred tax debt is made available, it will be easier to estimate the actual consequences of the arrangement. Therefore, when more data becomes available in the coming years, more robust results can be estimated.

Lastly, estimating the causal effects of specific, COVID-related government policy measures is a complex exercise due to numerous effects all happening at once. Lockdowns, support measures and expansionary monetary policy are all examples of events that took place at the same time. Ideally, several of these events should be controlled for to isolate the causal effect of any given policy measure. For future research, the availability of more data would help reduce bias stemming from omitted variables.

8 Conclusion

This thesis has examined one of many government support schemes implemented to alleviate the burden of COVID-19 on Norwegian businesses. Our focus has been on the arrangement for deferred payment of taxes and duties and whether this arrangement contributed to keeping non-viable firms alive through the pandemic. Weak, unproductive, and unprofitable companies should naturally be outcompeted in an efficient economy. Keeping such firms *artificially* alive hinders effective reallocation of capital and thus, also impedes economic adaptability.

Our findings suggest that Norwegian businesses that were non-viable prior to the pandemic were more likely to apply for and be granted tax deferrals than their healthier counterparts. Although this *misallocation* ideally should not have occurred, it would be close to impossible to ex ante separate these firms. Moreover, we found evidence that the tax deferral arrangement significantly contributed to keeping businesses alive through the pandemic. However, this result only holds true through 2020. In sum, it seems like the arrangement for tax deferrals may have contributed to keeping firms artificially alive - albeit for a limited period of time. Whether this should be viewed as an argument against using tax deferrals as an economic policy tool in the future will be a matter of preference. Although businesses have been kept on temporary life support, the alternative could have been a lot worse.

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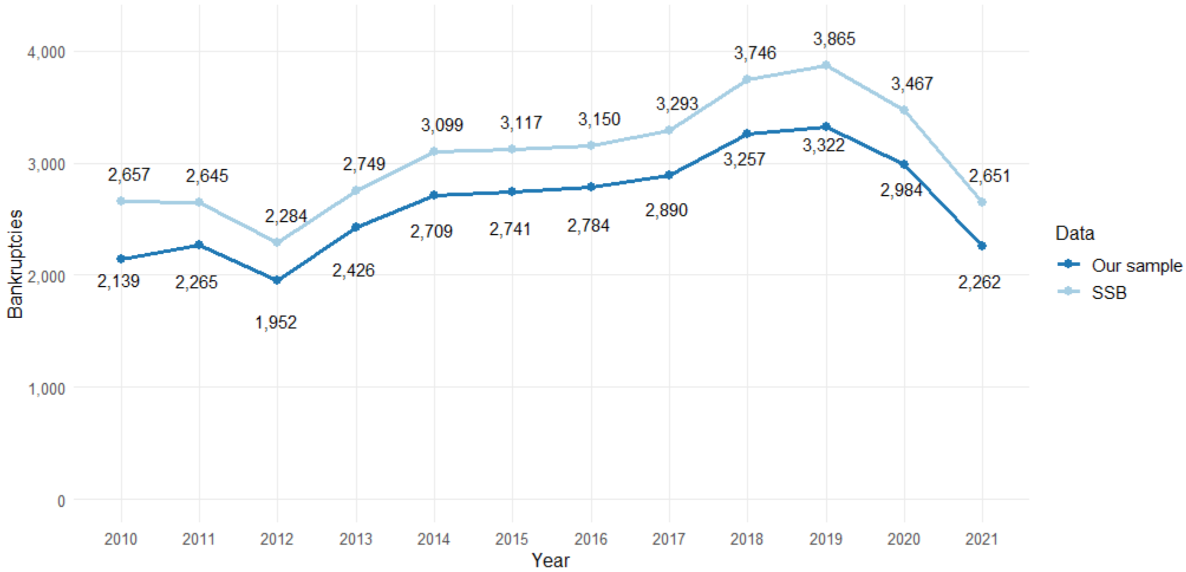
Appendix

A1 Bankruptcies in Sample vs. SSB

Figure A1.1: Bankruptcies over time for sample vs. SSB



Note: Although our sample contains fewer bankruptcies than in official statistics, the development is almost identical with a computed correlation of 98.5%.

A2 Overview of prominent zombie definitions

Table A2.1: Overview of Zombie Definitions

Source	Definition of Zombie Firm (Criteria)	Explanation
Caballero et al. (2008)	They seek to identify firms that receive subsidized credit by defining a lower bound interest rate, and define firms which pay interest below this bound as zombies.	Caballero et al. (2008) study the Japanese stagnation and forbearance lending to otherwise insolvent borrowers (zombies). Rather than to hard-write that zombie firms are unprofitable and unproductive, they want to test for it by defining zombies as firms receiving subsidized lending. They do this by defining a lower bound interest rate. However, to accurately calculate a lower bound one would need detailed firm-level information on debt distributions (McGowan et al., 2018).
McGowan et al. (2017, 2018)	(i) ICR <1 for three consecutive years, and (ii) age >10 years	McGowan et al. (2017) was the first to introduce a criterion of Interest Coverage Ratio in their zombie definition (ICR). They argue ICR is a comparable measure across countries (in contrast to Caballero et al. (2008)). They also argued that ICR accounts for other channels than subsidised credit through which zombies might be kept alive (e.g. poor insolvency regimes and government guarantees).
Storz et al. (2017)	(i) Debt servicing capacity ($\frac{EBIDTA}{Financial\ debt}$) $<5\%$ (ii) negative return on assets ($\frac{Earnings}{Total\ debt}$), and (iii) negative net investments for (iv) at least two consecutive years.	In combination, (ii) and (iii) ensure to only identify firms which are neither profitable, nor invest beyond the value of their depreciation. In particular, (iii) ensures to not mistakenly classify young, growing firms as zombie firms. Also, low debt servicing capacity (i), in contrast to interest coverage (as proposed by McGowan et al. (2017)), avoids classifying zombies that receive subsidized credit as healthy firms. (i) will in addition capture highly indebted firms. The debt servicing capacity threshold of 5% is set to the approximately median interest rate on outstanding debt in their sample.
Banerjee and Hofmann (2018)	(i) ICR <1 for three consecutive years, (ii) age >10 years, and (iii) tobins Q ($\frac{Assets\ market\ value}{replacement\ cost}$) $<$ sector median	Banerjee and Hofmann (2018) follow the definition proposed by McGowan et al. (2017), but introduce a new criteria of Tobins Q to avoid to mistakenly classify young, expanding firms as zombies. Other studies correct for this in the age criterion of 10 years. However, Banerjee and Hofmann (2018) argue that young firms do not necessarily invest heavily in growth.
Favara et al. (2022)	(i) ICR <1, (ii) leverage $>$ sample annual median, and (iii) negative real sales growth for (iv) three consecutive years	Low ICR (i) and high leverage (ii) help identify firms that cannot cover their debt-servicing costs. (iii) negative sales growth identifies firms with low growth prospects, as they argue sales growth is a good predictor of firms' future performance

A3 Bankruptcy Prediction Model - Validation and Testing

Table A3.1: Summary of GAM - Bankruptcy model

	Model	
Parametric terms		
	Coefficients	Standard errors
(Intercept)	-5.79^{***}	(0.04)
Age = 1	0.95^{***}	(0.03)
Age = 2	0.63^{***}	(0.04)
Age = 3	0.51^{***}	(0.05)
Age = 4	0.46^{***}	(0.05)
Age = 5	0.33^{***}	(0.06)
Age = 6	0.23^{***}	(0.07)
Age = 7	0.11	(0.07)
Age = 8	0.18^{*}	(0.07)
Non-parametric smoothed terms		
	EDF	Ref.DF
EDF: s(Liquidity)	8.74^{***}	(8.97)
EDF: s(Solidity)	8.97^{***}	(9.00)
EDF: s(Profitability)	8.94^{***}	(9.00)
EDF: s(Working capital)	8.56^{***}	(8.94)
EDF: s(Size)	8.48^{***}	(8.90)
EDF: s(Mean solidity)	8.91^{***}	(8.99)
EDF: s(Mean profitability)	8.97^{***}	(9.00)
EDF: s(SD profitability)	8.82^{***}	(8.99)
EDF: s(Unpaid VAT)	7.14^{***}	(8.05)
EDF: s(Unpaid employer's tax)	8.67^{***}	(8.96)
Num. obs.	603003	
AIC	66084.94	
Log Likelihood	-32947.26	
Deviance explained	0.21	
Adjusted R^2	0.06	

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Note: The table shows the summary of the fitted bankruptcy prediction GAM. For the non-parametric terms, EDF stands for estimated degrees of freedom. High EDF-values indicate highly complex functional forms and significance levels.

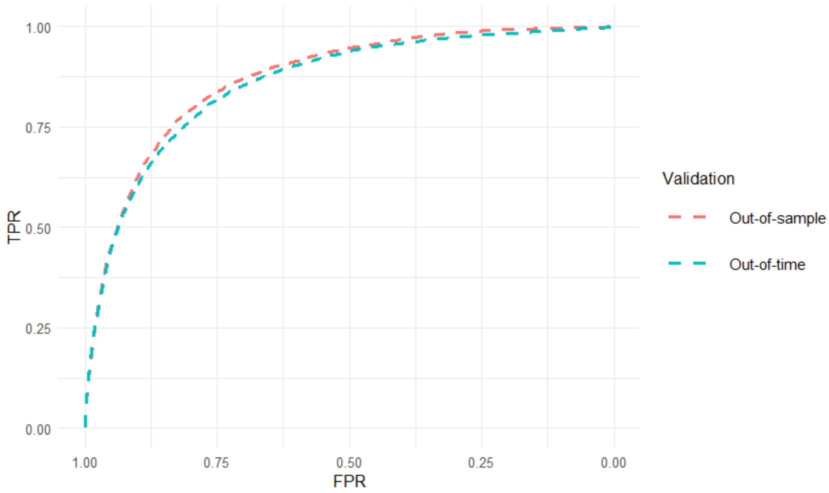
Validation and Testing

When developing a bankruptcy prediction model, it is important to obtain a sensible metric that is not a result of mere overfitting to the sample the model was trained on. Therefore, we have conducted a dual validation process, both out-of-sample and out-of-time. For the out-of-sample validation, the data was split into 70%/30% into a training and test set for the years 2012-2017. This entails that the model uses financial statements from 2012-2017 to predict filed bankruptcies in the years 2013-2019. The out-of-time validation is performed through training the model on data from 2012-2014 (predicting bankruptcies in 2013-2016) and tested on 2016-2017 (predicting bankruptcies in 2018-2019). Including several years in the training set also makes the model less susceptible to year-specific effects and smooths the results over cyclical effects. These effects could also have been handled by a panel data structure controlling for time fixed effects, but we choose to follow Bernhardsen (2001) in assuming that the observations are sufficiently independent and therefore enable a pooled regression.

To evaluate our model, we use Receiver Operating Characteristics and Area Under the Curve (ROC AUC) Mandrekar (2010). ROC is a curve which depicts the relationship between the false positives (type I error) and false negatives (type II error) of the model for all probability thresholds. AUC is then computed as the area under the curve (AUROC = Area under the receiver operating characteristic) and gives an overall evaluation of the model. An AUC of 0.5 implies that the model is no better than a random classifier, while an AUC of 1 implies a perfect model.

When validating our model both out-of-time and out-of-sample we find that both models perform equally well and the deviations are small (AUC of 0.860 and 872, respectively). Therefore, we deploy the out-of-sample-validated model on data from 2019 to encapsulate as many years as possible in the estimation.

Figure A3.1: ROC curves with the different validation methods



Validation method	Out-of-sample	Out-of-time
AUC	0.872	0.860

Table A3.2: Comparison of actual and predicted bankruptcy rates

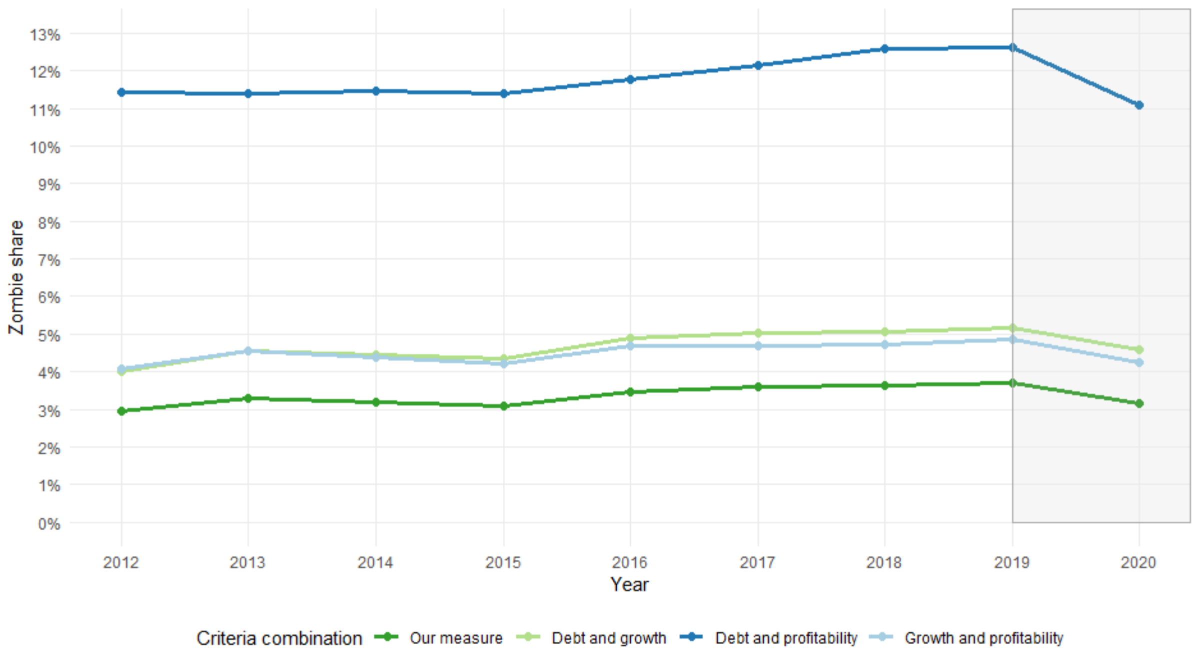
Year	>20%	10-20%	5-10%	2-5%	1-2%	<1%
2012	27.59%	16.24%	10.33%	4.99%	2.14%	0.42%
2013	28.47%	15.13%	9.35%	4.69%	2.09%	0.40%
2014	27.65%	14.67%	8.66%	4.26%	1.92%	0.39%
2015	27.60%	14.75%	9.54%	4.78%	2.16%	0.40%
2016	31.42%	17.94%	10.69%	4.97%	2.26%	0.45%
2017	29.52%	17.39%	10.33%	5.36%	2.45%	0.47%
Actual	28.72%	16.04%	9.81%	4.84%	2.17%	0.42%
Predicted	27.69%	13.64%	6.99%	3.11%	1.40%	0.32%

Note: The figure presents, for each bankruptcy risk group (>20%-<1%), actual bankruptcy rates within two years for each year from 2012 to 2017. The last two lines represent the actual average bankruptcy rates for each risk group from 2012 to 2017, compared to the average predicted bankruptcy rates (actual and predicted bankruptcy rates in 2013-2019, as we estimate bankruptcies within two years).

A4 Robustness Tests of Our Zombie Definition

To assess the robustness of our estimates of zombie firms, A4.1 presents different combinations of criteria and their effects on the level of zombie firms. The different combinations estimate a similar development in the relative zombie share over time. Especially interesting, all combinations of criteria estimate a decrease of zombie firms in the Norwegian economy from 2019 to 2020. This indicates that our estimates are quite robust to different criteria and also consistent over time.

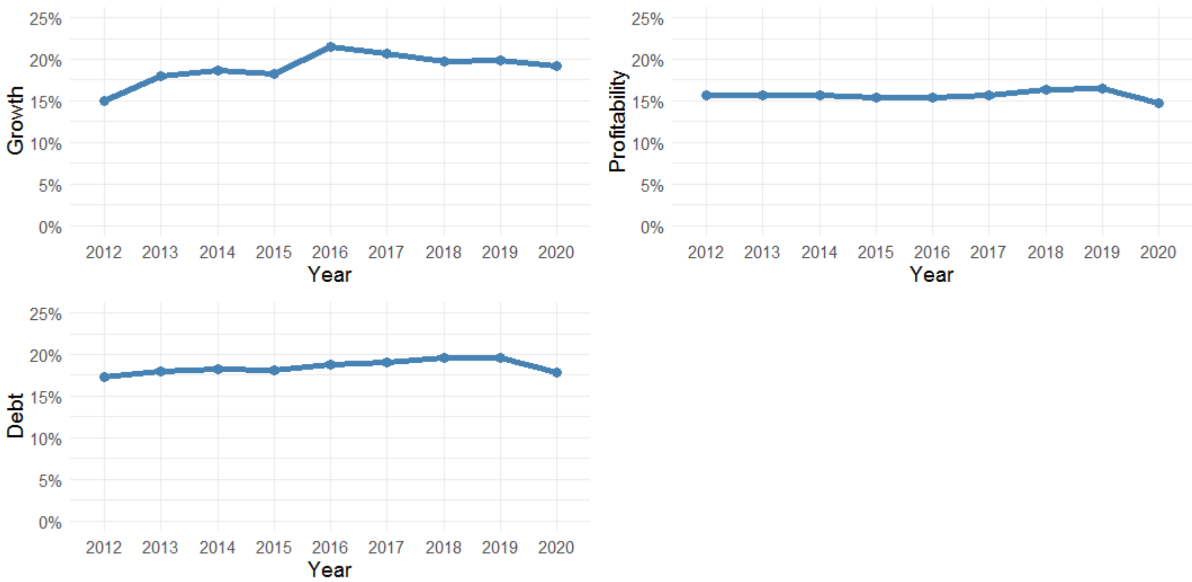
Figure A4.1: Zombie prevalence with different zombie criteria combinations



Note: This figure graphs the share of zombie firms in our sample from 2012 to 2020 using different combinations of criteria. The different combinations are:
Our measure = (i) $\frac{EBITDA}{Total\,debt} < 3.8\%$, (ii) $\frac{Earnings}{Total\,assets} < 0$, and (iii) negative real sales growth for (iv) two consecutive years.
Debt and growth = (i) $\frac{EBITDA}{Total\,debt} < 3.8\%$ and (iii) negative real sales growth for (iv) two consecutive years.
Debt and profitability = (i) $\frac{EBITDA}{Total\,debt} < 3.8\%$ and (ii) $\frac{Earnings}{Total\,assets} < 0$ for (iv) two consecutive years
Growth and profitability = (ii) $\frac{Earnings}{Total\,assets} < 0$ and (iii) negative real sales growth for (iv) two consecutive years.

Further, figure A4.2 presents the computed share of zombie firms for each of the criteria included in our zombie definition. Each criterion estimate a zombie share that is stable over time. Also, all criteria estimate a decrease from 2019 to 2020.

Figure A4.2: Zombie prevalence for each criteria in our definition

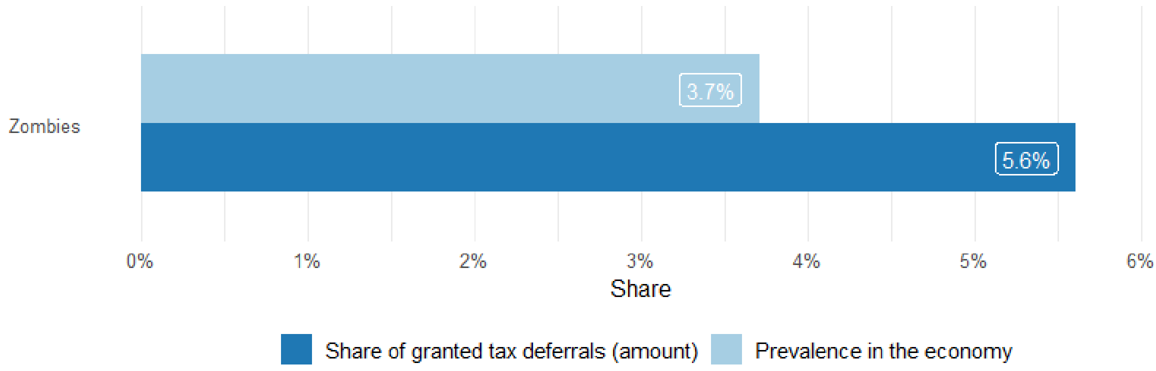


Note: This figure graphs the share of zombie firms in our sample from 2012 to 2020 using each criteria we have defined as relevant in section 6.1.1. The different criteria are:
Growth = negative real sales growth for two consecutive years.
Profitability = $\frac{Earnings}{Total\,assets} < 0$ for two consecutive years.
Debt = $\frac{EBITDA}{Total\,debt} < 3.8\%$ for two consecutive years.

To the best of our knowledge, the only existing literature that has studied the prevalence of zombie firms in Norway is Matre and Solli (2019). They found in their master's thesis a decrease in the relative zombie share from approximately 3% in 2012 to 2% in 2016. They used the definition of (McGowan et al., 2018), i.e. firms older than ten years with interest coverage ratio less than one for three consecutive years. Because we do not have access to firms' interest expense, we cannot cross-check our results by using the same definition. However, we estimate approximately the same level of zombie firms in Norway (2.9% in 2012 and 3.5% in 2016), which indicates that our calculated zombie share is robust to other zombie firm definitions and should resemble the "true" level in Norway.

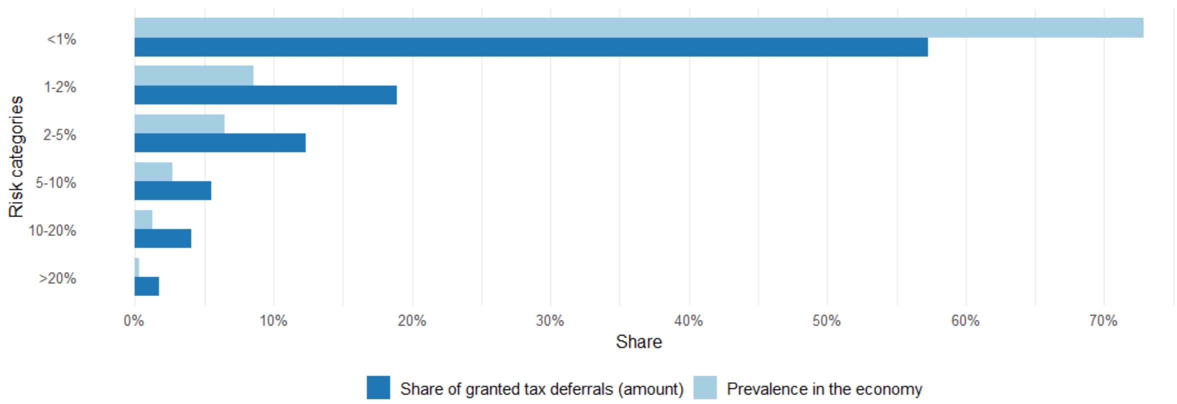
A5 Deferred Tax and Duty Payments Provided to Non-Viable Firms

Figure A5.1: Zombies: Share of granted tax deferrals (in amount) compared to their prevalence in the economy



Note: The zombie share was at 3.7% in 2019, while these firms were granted 5.7% of the overall amounts granted in deferred payments. This means that zombie shares were granted a disproportionately high amount compared to their prevalence in the economy. One could also argue that zombie firms ideally should not have been granted tax deferrals at all.

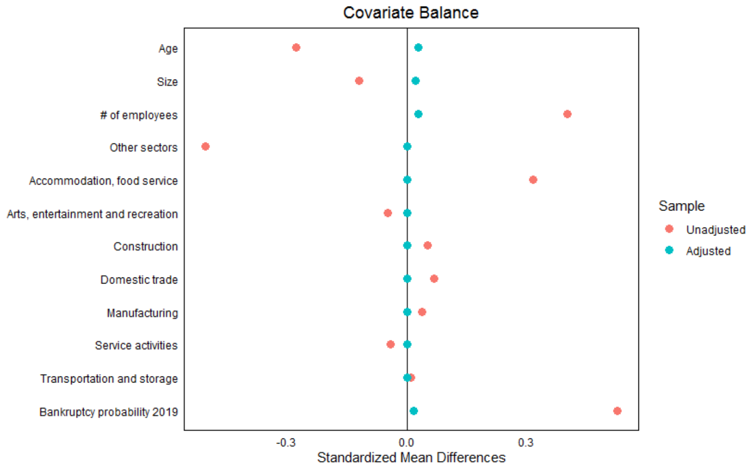
Figure A5.2: Distressed firms: Share of granted tax deferrals (in amount) compared to their prevalence in the economy



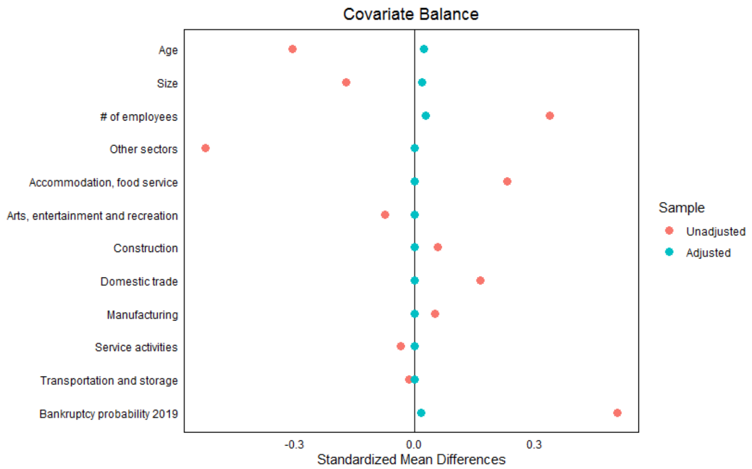
Note: Distressed firms, defined by a higher probability of bankruptcy, were granted higher amounts in deferred payments than their share of the economy would indicate. This relationship holds for all risk categories above the least risky category. The number of companies in the two highest risk groups equate to the number of companies that would go bankrupt in a "normal" year.

A6 Balance Improvement With Matching

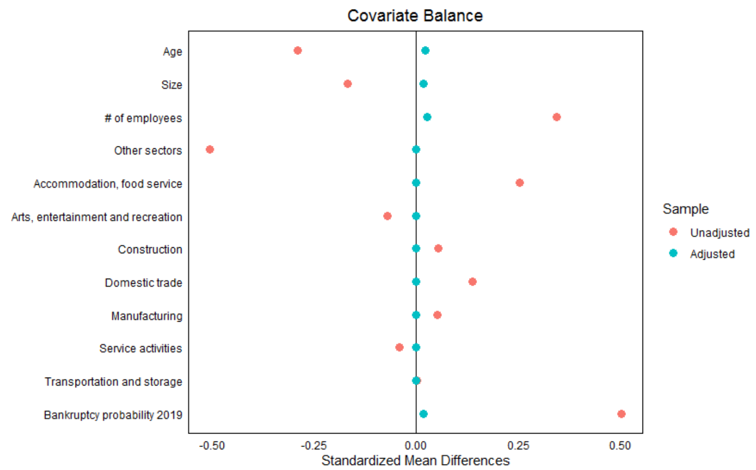
Figure A6.1: Improvement in balance for all matched samples



(a) Tax deferral in 2020



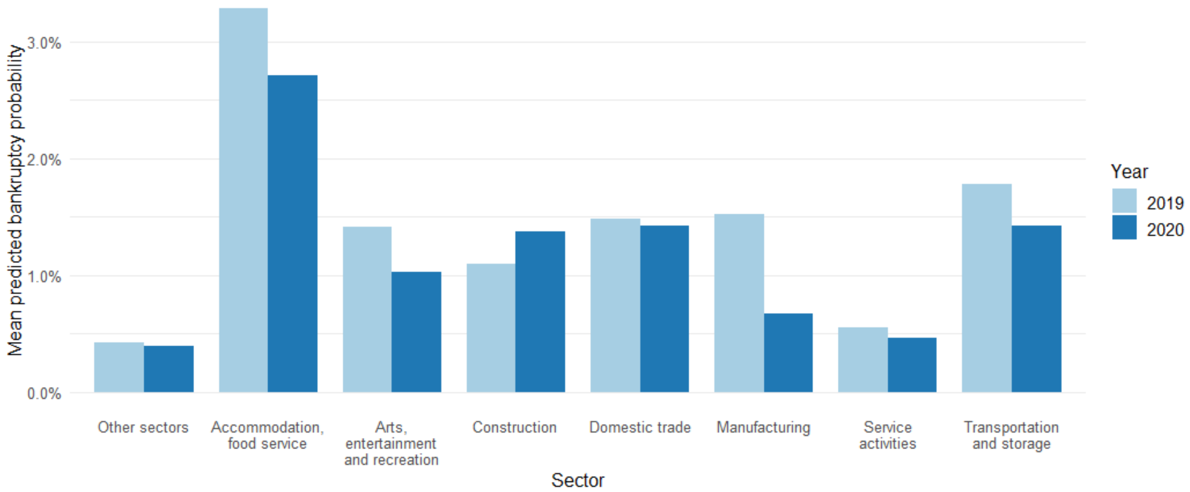
(b) Tax deferral in 2021



(c) Tax deferral in 2020 and/or 2021

A7 Predicted Bankruptcy Probabilities in 2019 vs. 2020

Figure A7.1: Change in mean predicted bankruptcy probabilities - 2019/2020



Note: The figure shows that in all sectors except for construction, the predicted bankruptcy probabilities based on the given year's Income Statements are lower in 2019 than in 2020. The probabilities in 2020 are based on the financial accounts in 2020, and show the expected bankruptcy frequencies in 2021 and 2022 Given the dramatic impact of COVID-19, this may indicate that the government support schemes have been excessive.