Government Support and Bankruptcy*

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Abstract

This paper examines whether differences in access to governments' financial support during economic crisis affects firms' likelihood of bankruptcy. By exploiting quasi-random time differences between firms' application date and the government's decision date for support during the COVID-19 crisis, I find that waiting for support significantly and economically increases firms' likelihood of bankruptcy. In terms of magnitude, I estimate that the likelihood of bankruptcy increases by between 0.84 (0.0145) to 2.03 (0.0550) percent (percentage points), depending on the type of support and model specification when firms experience one extra day higher decision time to receive support. Overall, these results provide novel evidence of the causal effect of government support on firm survival.

Keywords: Bankruptcy, COVID-19, Government support

JEL Codes: G33, G38, G01, G32

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1 Introduction

In response to the economic impact of governments' COVID-19 pandemic restrictions, numerous governments have provided financial support to firms and individuals to prevent good firms from going bankrupt and to limit employment losses (see e.g., Barrios et al., 2020; Bennedsen et al., 2023). Despite the financial support provided to firms, governments and lenders still expected to observe increases in bankruptcies among small- and medium-sized firms because i) the global economy shrunk during the early months of the pandemic at a level resembling that of the Great Financial Crisis and because ii) the level of bankruptcies has historically been highly correlated with economic conditions.[1] Instead, many countries experienced a decline in the number of bankrupt firms, both during and after COVID-19 pandemic shutdowns, and thus the effects of government support on firms' survival remain a puzzle.

Isolating the effects of government support during crises is inherently difficult because of the endogenous nature between the heterogeneous impact of the crisis on firms, the targeting, timing, and size of government support, and concurrent events. For instance, during the COVID-19 health crisis, governments directed support to firms based on the impact of shutdowns and other COVID-19 restrictions; during the Great Financial Crisis, support was provided mostly to financial institutions to prevent a collapse of the financial system. Despite the economic magnitude of aid disbursement during crises, research lacks on the effectiveness of government support on firms' performance and survival as this link is highly susceptible to endogeneity issues.

In this study, I exploit a unique setting with quasi-random differences in firms' access to government support to mitigate these endogeneity concerns and provide estimates on the effectiveness of government support on firms' survival. Specifically, I investigate firms experiencing differences in the time between applying and receiving a decision for government

[1] The GDP of OECD countries shrunk by 4.6 percent in 2020 (see data at https://data.oecd.org/gdp/quarterly-gdp.htm), and Wang et al. (2021) show the strong correlation between economic growth and corporate bankruptcies.

support in Denmark during COVID-19 and find that firms experience between 0,84 (0.0145) to 2,03 (0.0550) percent (percentage points) higher likelihood of bankruptcy per extra day they wait for support, depending on the subsample, model specification, and support type.

Similar to other countries, the Danish Government decided at the outbreak of the pandemic to provide grants to firms based on the economic impact of shutdowns and other restrictions. The Danish government provided three major support types to cover fixed costs, lost revenue, and employee salaries, respectively, and they delegated the disbursement to the Danish Business Authority (DBA) based on an application process with transparent eligibility requirements and payout levels. According to DBA, applications were processed on a first-come-first-served basis within the three types of support, but, nevertheless, data on the support applications show that firms experienced great variation in the time between first applying for support and later receiving a decision—even within support types and months.

The use of time differences in decision time of support resembles the setting used in the early work of Bartik et al. (2021) and Granja et al. (2022), who exploits the differences in access to the two rounds of the U.S. Paycheck Protection Program (PPP).[2] This study adds several favorable properties to rule out endogeneity concerns. First, the Danish Business Authority (DBA) was the sole processor of support applications, which alleviates concerns of endogeneity between firms and the application processors. Specifically, the first-come-first-served processing basis allays concerns about the prioritization of certain support applications that correlate with factors impacting firms' likelihood of bankruptcy during the crisis.[3]

[2]The PPP provided eligible small businesses with forgivable loans if the firms retained or regained pre-COVID employment levels after the health crisis. The administration of the program was delegated to banks to enable swift disbursement of funds. But because the funds were initially limited and the program relied on the first-come, first-served principle, some firms had to wait until the second round to obtain support. Using the differences of firm survey recipients' access to the funds, Bartik et al. (2021) find that the PPP loans significantly improved survival rates.

[3]Similarly, it is unlikely that politically-connected firms received positive discrimination as Denmark ranks as one of the least corrupt countries in the world. Although Amore and Bennedsen (2013) find that political connections in Denmark provide firms with profitability benefits, the setting of this study differs significantly. The DBA operates on the law and thus DBA's application processes operationalize the law.

So where does the variation in decision time derive from? Some of the variations in decision times derive from DBA's control procedures to ensure that only eligible firms receive support. Based on the DBA's procedures to monitor accounting fraud, the DBA applies automatized checks and logical conditions to assign applications into three categories: immediate payout, manual control, or extended review.[4] The two latter categories, *ceteris paribus*, added to the length of the decision times as manual labor was required to assess firms' eligibility for receiving support before payout.

Part of the differences in decision times, however, appear quasi-random. Specifically, differences in decision time may emerge unrelated to firms' financial situation or behavior but because of differences in application reviewer speed, reviewer sickness, weekends and holidays, reviewer turnover, requests for additional documentation, simple processing errors, and the need to call for experts to assess support applications. Reviewers of applications had little to no experience with the analysis of financial statements and were hired within a few weeks.[5] Part of firms' application decision times thus likely varied because of differences in reviewer assignment. Moreover, in communication with the DBA about the application processes for government support, the DBA admits to having a limited overview of the decision processes, including who is responsible for the individual applications, which applications have been selected for manual or extended review, and the case history of applications. All together, variation unrelated to firms' characteristics likely permutated the decision time of applications. Under the assumption that these differences are quasi-random when controlling for firms' financial characteristics, this setting allows me to provide casual estimates of how much government support displaces firms' likelihood of bankruptcy—equivalent to

[4] A report by the Danish National Auditors ("Rigsrevisionen") describes the controls and the quality of DBA's handling of support applications. The report concludes that the DBA effectively set up a control procedure but criticizes i) that the DBA may still have paid out support to firms because of mistakes in manual controls, ii) that too many applicants for support to cover fixed costs had to wait more than 60 days, and iii) that many additional controls are postponed too long after the payout of support. All applications for support to cover fixed costs were assigned for at least manual control. See report (in Danish) https://rigsrevisionen.dk/Media/637733535437592963/SR0621.pdf

[5] Anecdotally, some reviewers have participated in basic accounting courses after engaging with application reviewing.

comparing firms that have received government support with similar firms that have not.

As a second favorable feature of the setting, my study relies on highly verifiable outcomes of firm survival, as I use data that stem directly from the government registry. Because of the availability of private firms' financial statements, I can control for firms' financial characteristics, which previous research shows have a critical impact on firm survival (e.g., Beaver et al., 2005). The impact of the crises and the access to government support may depend on firms' financial position through either a direct or indirect channel. As a direct channel, lack of funding may prevent firms from fulfilling their credit obligations. This channel may be even more pronounced for already financially constrained firms, as they would have difficulty obtaining new equity or new loans or extending existing lines of credit—although firms are eligible for government support even after bankruptcy. As an indirect channel, constrained access to government support may force firms to bypass attractive investment opportunities, which hurts their future performance. For instance, Granja and Moreira (2023) show that firms with credit restrictions introduce fewer product innovations, which leads to fewer products sold. Similarly, Campello et al. (2010) suggest that financially constrained firms during the Great Financial Crisis planned to reduce technology and marketing spending, capital investments, and employment costs significantly more than unconstrained firms.[6] Recent research consistently shows that reduction in credit supply to manufacturers causes them to invest less (Fakos et al., 2022). Deterioration of credit scores and ratings may inflate the impact of differences in access to government support. For instance, bank forbearance or delinquency of corporate borrowers, due to a late support decision, could cause firms to experience a higher cost of capital, as banks take prior lending history into consideration when negotiating new loans.

Third, my study alleviates concerns about concurrent events, as the support packages provided by the Danish government span over two years and several ongoing rounds of

[6] Kahle and Stulz (2013) argue that the firms' cuts to capital investments and other cost-saving actions could be explained by reductions in consumer demand rather than a shock to the credit supply. My study, however, focuses exclusively on variation in the supply of liquidity, alleviating any concerns of demand-driven changes to firm behavior.

funding. This allows me to implement time-fixed effects that control for concurrent events and unobservable time-variant differences in the processing times of applications and firms' survival outcomes.

Fourth, little selection of firm support recipients exists in the setting, as the eligibility for support relied on fixed and transparent requirements. Firms had little uncertainty about the amount they would receive in the Danish setting, as the government exclusively disbursed grants and not forgivable loans. Any uncertainty about the support amount and the ability to uphold the requirements for forgiveness might cause certain firms that correlate with particular outcomes to abstain from applying or conversely to take on more risk.

To allay concerns of firms' financial characteristics driving both decision time and the likelihood of bankruptcy, I follow Regenburg and Seitz (2021) and apply three accounting-based bankruptcy models. These models are the Altman model (1968), the Ohlson model (1980), and the Beaver et al. model (2005), which I estimate one at a time. I find that the effects of decision time are largely unchanged and that coefficient estimates continue to be significant and economically meaningful when I include controls for firms' financial and other characteristics. Even when splitting the sample on each support type—which returns fewer observations for bankruptcy model estimations—I still find significant results. This indicates that the parts of decision time explained by firm characteristics and the size of the support differ from the variation in decision time that affects firms' likelihood of bankruptcy.

In addition, I take several steps to further strengthen the validity of the setting. First, I focus exclusively on firms that receive approval for support to alleviate concerns about fraudulent behavior or ineligible firms confounding both decision time and bankruptcy from driving the results. Second, I estimate a determinants model of decision time and find that only the type of support consistently explains the variation in decision time while the significance of size and the amount of support vary across tests, consistent with application length increasing with size and DBA's additional control procedures of very large support sizes.[7] Third, I employ alternative specifications of decision time with splits of decision time into intervals and log transformation. The results show that the estimated effect of the decision time increases monotonically over intervals of decision in the pooled regression and for salary applications. The results are, however, less consistent in tests with only fixed costs or revenue applications. And the findings are unchanged when employing log-transformation. Fourth, I test whether the effect of decision time varies across the size of support and find in the main specification with financial statement information available, that the effects of decision time on the likelihood of bankruptcy are prevalent in the three highest quartiles of support while the effects in the full sample and samples split by support type show mixed results, in the latter case likely because of power issues. Fifth, I find largely consistent results when I exclude the five percent highest decision times per year-month and support type to remove applications selected for extended controls. This is after winsorization, meaning that the influence of the most extreme cases is already limited. Similarly, the findings are unchanged when I remove zero-day decisions to remove potential rubber stamping.

This paper contributes to the recent literature on how government interventions affect firm outcomes following crises (Alstadsæter et al., 2020; Barrios et al., 2020; Bartik et al., 2021; Bennedsen et al., 2023; Granja et al., 2022; Wang et al., 2021). My study presents evidence from a unique setting with clean identification, which allows me to infer the causal effects of government financial support on firms' survival during crises. While the studies on heterogeneous disbursement provide great insights for the U.S. setting, the PPP differed substantially from most other support packages in Western countries. Similar to Denmark, many countries relied on grants with fixed eligibility requirements and a government-based application process. This study also avoids concerns from highly endogenous methods that either rely on simulation or surveyed outcome expectations of firms to develop counterfac-

[7] In the report presented in footnote 4, the Danish National Auditor also states that the DBA has extra control procedures for salary (fixed costs) applications with a support amount of more than DKK 1 (2.5) million. I perform additional tests to estimate the effect of these additional controls on the decision time and find longer decision times above the thresholds. The number of firms above the threshold is, however, too low to have enough power for regression discontinuity design tests of the impact of the thresholds on the likelihood of bankruptcy.

tuals. For instance, Alstadsæter et al. (2020) rely on self-reported declines in revenue to simulate estimates of profit changes for Norwegian and U.S. firms during COVID-19. Gourinchas et al. (2024) use past accounting information, survey data, and GDP projections to predict bankruptcy rates in 17 EU countries in absence of government support and compare the estimates with the actual outcomes to determine the effect of government support. And Wang et al. (2021) provide correlation estimates on the effects of U.S. support programs by implementing a naive, counterfactual model using 2019 bankruptcy rates. My study provides casual inferences, as I exploit exogenous variation in firms' access to government support, effectively comparing firms that receive support to those that will receive support but have not yet. Moreover, I investigate actual bankruptcy rates over time, which, combined with time-fixed effects, alleviates concerns of concurrent events and other endogenous time-variant differences.

This study also relates to other studies investigating the effect of random allocation of credit, grants, and money prizes (such as lotteries) on financial distress and prosperity. For instance, this study relates to the findings of Paravisini (2008), who investigates how random variation in local banks' access to support in Argentina in the 1990s affected their lending. My study explores a similar trait in the allocation of government support but instead focuses on intervention effects on firms across many industries and with diverse sets of characteristics. Other studies explore labor and personal finance outcomes and find that random access to transportation credit creates positive labor mobility and employment effects (Van Doornik et al., 2024) as well as negative effects on the financial stability of individuals' peers (Agarwal et al., 2020). My study provides causal evidence on firms' financial disadvantage of receiving support grants late, compared to peers.

Although governments provide astronomical amounts of support to firms, regulators have limited knowledge of the causal effect of these efforts. This study has implications for government authorities and their handling of their support programs. Firms' survival sensitivity to the timing of support indicates that authorities should pay extremely close attention to their decision processes during economic crises. My findings show that decision time greatly impacts the number of bankruptcies and that firms in Denmark during the COVID-19 crisis experienced great variation in decision times, which produced arbitrary differences in the likelihood of bankruptcy.

The remainder of the paper proceeds as follows. Section 2 describes the institutional setting of the Danish government support initiatives and the pertinent data. Section 3 presents the research design. Section 4 presents the empirical results, while section 5 concludes.

2 Related research and the institutional setting

2.1 Related research

Across all major economies, countries implemented support measures to counter the effects of the COVID-19 pandemic on consumer behavior and the effects of lockdowns on firm performance and employment.[8] Two key goals of the support packages were to prevent good firms from going bankrupt and to keep workers employed. These support packages resulted in astronomical amounts being allocated to firms and employees. In the U.S. alone, the government has paid more than USD 800 billion in direct aid to firms.[9]

Several studies investigate the effects of government support on firm survival and employment. For instance, recent work by Wang et al. (2021) attributes lenders' loan forbearance to the reduction in bankruptcies during the COVID-19 crisis. Gourinchas et al. (2024) estimate the impact of government support using a baseline model to approximate the counterfactual number of bankruptcies and show differences between the observed and estimated bankruptcy rates, which they attribute to governments' support. Bennedsen et al. (2023)

[8]See OECD paper for an overview of SMEs' responses to COVID-19: https://www.oecd-ilibrary.org/docserver/6407deee-en.pdf?expires=1643212341&id=id&accname=guest&checksum=E6DFFEA3198E07C93F73BE7FBDC0749D

[9]The U.S. government has paid out more than USD 790 billion in 2020 and 2021 through the PPP and more than USD 28 billion from the Restaurant Revitalization Fund (RRF) to cover lost revenue in the restaurant and bar industry. These amounts equate to about 3.82 percent of the U.S. GDP in 2019 (pre-crisis) numbers.

find that government support mitigates employment terminations. They survey firms' managers on their expected number of layoffs in the absence of government support and estimate the number of furloughed employees helped by government support.

Indeed many studies have focused on the PPP and exploited i) heterogeneity across banks' processing of applications (Bartik et al., 2021; Granja et al., 2022; Joaquim and Netto, 2021; Elenev et al., 2022; Barrios et al., 2020) or ii) variation in receiving funds around the eligibility threshold of the less-then-500-employees requirement (Autor et al., 2022; Bartik et al., 2020; Faulkender et al., 2020). Specifically, the PPP provided small- and medium-sized firms with loans that are forgivable if those firms retained or rehired employees after the initially expected end of the pandemic. The U.S. government required firms to have less than 500 employees and delegated the application process of the program to banks. Exploited by studies has been the fact that the first round of PPP funds was limited,[10] and consequently some firms did not initially obtain support (without knowledge of subsequent rounds) because of differences in banks' processing of PPP applications but instead received support in the second round. Studies also exploit that the government allowed firms in certain industries to obtain PPP funds, although they had more than 500 employees.

These studies provide great insight though a few limitations persist. First, the lack of strong identifications and counterfactuals inhibits most of the PPP studies from providing causal estimates of the impact of both the pandemic and the government support initiatives. In the PPP settings, banks' application processing imposes incentive concerns, which, for instance, materialize in banks favoring certain firms (e.g., Granja et al., 2022, footnote 15 and section II of Bartik et al., 2021). Moreover, bank-specific characteristics may also endogenously relate to firms' choice of banks and how banks prioritize PPP applications. In efforts to investigate the labor effects of COVID-19 and overcome endogeneity issues, Granja et al. (2022) exploit differences in local bank access to the PPP based on banks' uptake of the

[10] The U.S. Congress had initially limited the fund allocation to USD 349 billion, which was exhausted in two weeks on April 16, 2020. The government quickly extended the program by an additional USD 310 billion, which opened April 27, 2020, and later added a third round. See Barrios et al. (2020) for more info on the PPP.

PPP and firms' dependence on the supply of credit from local banks. They find that banks' labor intensity, previous experience as intermediaries of state-guaranteed loans, the intensity of this intermediation, and active enforcement actions affect banks' PPP processing. Based on these factors, they create a synthesized exposure to the PPP and find that the PPP had a limited effect on employment.

Second, studies on the impact of government COVID-19 support of firms struggle to separate their findings from concurrent events and thus likely suffer from omitted variable problems. For instance, studies investigating the differences in PPP receipt times focus on a single point in time when firms had to wait for support though the effect of support likely depends on the intensity of crises.

Third, the scarcity of detailed and universal data on firms, especially in the U.S. setting, affects the validity of research design. Bartik et al. (2021) rely on firms' self-assessment of their expected survival probability, which may be overstated. Granja et al. (2022) instead employ data from a specific provider of schedule management software.

Fourth, some studies do not observe government support at the firm level. Both Wang et al. (2021) and Gourinchas et al. (2024) exploit cross-sectional differences on either state- or country-level observations. While the aggregate approaches have their own merits, these studies cannot directly identify how government support affects individual firms. Bennedsen et al. (2023) use employee-level observations but only in the context of one, namely employment support, out of a mix of government support initiatives that firms may have received.

Fifth, the studies provide results on short-window effects, which may reverse in the future. Greenwood et al. (2020) suggest that the final impact of the COVID-19 pandemic on firms has not yet played out. Ultimately, government support may not affect firm outcomes in the short run (e.g., up to six months), but the long-term effects of support could just be temporarily delayed. Based on these limitations and the magnitude of support during the crises, clearer identification to provide causal inferences is called for.

2.2 Government support in Denmark

The Danish support packages provide such a setting. Similar to other nations, the Danish government promptly provided financial support to firms to counter the economic consequences of the lockdown restrictions.[11] The Danish Business Authority (DBA) implemented seven government support initiatives, which disburse grants to firms, contingent on certain application requirements. I investigate the three largest support packages, which constitute compensation for lost revenue, aid to cover fixed costs, and salary support for employees during pandemic shutdowns. The remainders include three types of support for freelancers and one support initiative specifically to the event industry to cover costs of already planned events, including festivals and concerts.[12] The three support types in focus of my analysis account for about 96.3% or DKK 53,430 (USD 7,834) million out of the total of DKK 55.466 (USD 8,133) million paid out in government support as of June 30, 2023. This is equivalent to 2.4 percent of Denmark's GDP in 2019 (pre-crisis).

The DBA exclusively processes the applications, and the allocation of the three major support packages depends on whether firms fulfill eligibility requirements. 1) For fixed costs, the DBA required that the firm experience a 30 percent to 45 percent decline in revenue during the compensation period (depending on the time of the COVID-19 crisis they experienced the decline) to be eligible to receive up to DKK 30 million per month to cover fixed costs. The size of the support depends on the size of the decline in revenue. The DBA also required the application to be certified by an auditor if the application amount was more than DKK 150,000 per month.[13] 2) to cover lost revenue, firms must have had less than 25 employees and must have lost more than 30 percent of their revenue to receive between DKK 23,000 to 33,000 per month (depending on the decline in revenue) to owners with

[11] Based on the knowledge from the previous financial crisis, the government reacted fast after the beginning of the COVID-19 pandemic. Just four days after the first announcement of major lockdowns, the Danish government proposed a compensation scheme for workers unable to work from home.

[12] See https://www.erhvervsstyrelsen.dk/statistik-kompensationsordninger for details (in Danish).

[13] There were only seven applications for fixed costs support without an auditor certification, making any regressions of audit effects on the outcomes infeasible.

more than 25 percent of the shares. 3) for firms to receive up to DKK 30,000 per employee who cannot work, firms must have expected—in absence of support—to lay off more than 30 percent of the employees or 50 employees in the compensation period. Bennedsen et al. (2023) use survey data in the Danish setting to show that many used to this option and that the support package prevented more than 80,000 people (∼2.8% of the workforce) from being laid off in Denmark.

This setting allows me to investigate the causal effects of government support on firm survival for the following reasons. First, only the DBA processed applications, which allays concerns about some firms receiving preferential access to support based on such as prior banking relationships. Second, the DBA (a separate part of the organization than the one managing support applications) provides daily operational status data on all firms, enabling the extraction of firms' exact bankruptcy dates. In addition, the DBA requires all limited liability firms to file annual financial statements, which the agency provides free-of-charge to everyone. This allows me to control for firms' financial characteristics, which research suggests affect the likelihood of bankruptcy (Regenburg and Seitz, 2021). Third, firms obtained support as grants based on simple and transparent eligibility requirements. Contingent grants might have induced differences in when firms chose to apply for support based on firm characteristics. Fourth, I use the differences in the time the DBA took to process applications. This resembles the design of the PPP studies. However, the applications in the Danish setting were scattered over time, enabling me to implement time-fixed effects, which alleviates concerns of concurrent events and time-variant omitted variables across applications. But the differences in decision times in this raises another concern.

Why did the support applicants experience different decision times? The DBA's time to decide on applications likely derives from several sources. In an extensive report, the Danish National Auditors ("Rigsrevisionen" in Danish. DNA hereafter) analyze DBA's decision times and application processes. Reusing much of the control procedures of the DBA's monitoring of financial statement filings, the DBA implemented three levels of controls to balance the timely disbursement of support and the detection of ineligible applications, such as attempts to commit fraud. All applications went through the initial control level, which consisted of an automatized control of the application information and firm characteristics. Besides an initial check of application eligibility, the automatized control assessed the risk of fraudulent behavior, and then, based on that assessment, the support was either paid out or assigned for manual control or extended review.[14] Manual control and extended review, *ceteris paribus*, added extensively to the decision because of the demand for manual labor to fulfill these steps.

Other differences in decision time may emerge unrelated to any firm-specific characteristics. For instance, firms may experience different decision times because of varying reviewer speed, reviewer sickness, weekends and holidays, reviewer turnover, requests for additional documentation, simple processing errors, and the need to call for experts to assess support applications. Reviewers of applications had little to no experience with the analysis of financial statements and were hired within a few weeks.[15] Part of firms' application decision times thus likely varied because of differences in reviewer assignment. Relatedly, the DNA report states that the application process was hastily implemented, which likely negatively contributed to the number of unintentional differences in decision times. In freedom of information responses, the DBA acknowledges their lack of overview of the decision processes and describes that they cannot identify who is responsible for the individual applications, obtain an overview of which applications have been selected for manual or extended control, or observe the case history of applications. In sum, the part of the differences in decision times likely exists as a result of inconsistencies in DBA's application handling.

[14] All support applications for compensation of fixed costs underwent manual control.

[15] Anecdotally, some reviewers have participated in basic accounting courses after engaging with application reviewing.

3 Research design

3.1 Data

To test the effect of government support on firms' likelihood of bankruptcy, I obtain application-level data from DBA on all three major COVID-19 support programs explained in section 2. The data cover 453,594 support applications and represent all applications of these support programs received by the DBA. I receive accounting data from Experian on limited liability firms. Most of the applicant firms are unlimited liability companies that do not report financial statements to the DBA. I exclude those from the bankruptcy model tests. I obtain bankruptcy data and industry information from the Danish Business Registry.[16] I also remove observations with less than 365 days between day of application and June 30, 2023, which constitutes my last updated sample of the status data. After these steps, I am left with 272,639 applications (full sample) of which 113,529 have financial statement data available (FS sample). Applicants without financial statement information available are unlimited liability firms that do not voluntarily report their financial statements. All limited liability firms in Denmark, on the other hand, are required to file an annual report to the DBA, which explains the large number of applicants with financial statement data. I include tests of both the full sample and the financial statement (FS) sample for completeness.

3.2 Decision time

This study exploits the quasi-random variation in decision times across firms' applications to estimate firms' access to governments' financial support. The intuition is in concept to the heterogeneous effects documented by the PPP literature. The longer (less) it takes for the government to process a firm's support application, the less (more) access that firm has to financial support. Figure 1 illustrates this for hypothetical firms A and B where t is the

[16] I obtain operational status and identify firms as bankrupt if their status changes from *normal* to *under bankruptcy*, *bankrupt*, *under liquidation*, or *liquidated* and remove any applicants without any status records.

application date and $t + x$ is the decision date. That means x represents the decision time (in days) that the government uses to provide a decision for the specific applications, which varies between applications.

3.3 Bankruptcy models

To answer whether differences in access to government support affect firms' likelihood of bankruptcy, I estimate equation 1 in a logit regression as follows.

$$\begin{aligned} Bankrupt_{i,t+365} = \beta_0 + \beta_1 Decision\ time_a + \beta_2 Support\ type_a + Controls_a \\ + Fixed\ Effects + \epsilon_{i,t+365} \end{aligned} \quad (1)$$

where *Bankrupt* is an indicator of one if firm i goes bankrupt between time *t+1* and *t+365* days after the DBA receives application a. *Decision time* is the number of days it takes the DBA to provide a decision on application a for firm i.[17] Controls represents a control variable for the support size measured by the natural logarithm of the support amount. *Fixed Effects* include month-year fixed effects to account for time-variant differences in decision times and bankruptcies and industry fixed effects to control for time-invariant industry differences. All continuous variables are winsorized at the 1% and 99% levels to mitigate the effect of outliers. I estimate all models with standard errors clustered at the month-year and industry if not otherwise stated. Variables are defined in table A.1 of the appendix.

I expect government support to reduce firms' likelihood of bankruptcy. The endogenous relation between firms that receive support and the bankruptcy rate prevents prior research

[17] I use the decision date and not the actual payout date because decisions essentially provide firms with a government guarantee of the allocated amount. According to the DNA report, approved applications are usually paid out within 1–2 days. Moreover, I use the raw number of days and not a log-transformation of decision time because the data include observations with zero-day decisions. In untabulated analyses, I log-transform a sample without zero-days observations. An alternative method is to apply a log plus one method on decision times. However, theory does not provide any explanation to whether this produces biased coefficient estimates. I use decision time for the ease of interpretations, as I can estimate marginal effects at the mean to obtain the percentage point effect on how much extra wait time affects the likelihood of bankruptcy.

from providing causal inferences. The estimate of β_1 shows whether the time from applying to receiving a decision from the DBA affects the bankruptcy rate of firm that ultimately obtains government support. I predict that $\beta_1 > 0$, indicating that firms with earlier access to support are less likely to go bankrupt. The effect of *Decision time* could be less pronounced if the DBA takes longer time to process applications for firms that are marginally eligible for support, as opposed to those that are easy to assess, which would work against finding any results.

To mitigate concerns of other firm characteristics driving the decision times and the bankruptcy rate, I implement three accounting-based bankruptcy models. These models are from Altman (1968), Ohlson (1980), and Beaver et al. (2005) following Regenburg and Seitz (2021). I use three distinct bankruptcy models to triangulate the results, alleviating concerns that the results on the lack of access to government support depend on a single model's specifications. Accordingly, for the bankruptcy models, I estimate a logit regression based on equation 1 but where *controls* represents the firm-specific controls for each bankruptcy model and a control variable for the size of the support. The control variables in the three bankruptcy models depend on financial statement data. To ensure all figures depict pre-crisis financials and thus are unaffected by the government support itself, I use the latest available statements before March 2020. I predominately refer to the Ohlson model for the test results in robustness tests and additional analyses, as Regenburg and Seitz (2021) show that it has the highest predictability in comparable samples of private firms.

4 Empirical results

4.1 Descriptive statistics and correlation matrix

Table 1 provides descriptive statistics of the variables used in estimating equations. The mean decision time for the DBA to process approved COVID-19 support applications is 19.73 days, with a standard deviation of 18.21 for the full sample, indicating great variation in decision time across support applications. This is similar to the sample of applications with financial statement data available with a mean decision time of 19.48 and a standard deviation of 18.98. In the full sample, 1.66 percent of support applicants enter bankruptcy proceedings or go bankrupt within a year after the application date, while those applicants reporting financial statements have a mean bankruptcy rate of 2.66 percent (decimals tabulated in table 3 and 4). The DBA rejects about 8 percent of applications (untabulated), suggesting that most firms receive support either because they likely were well aware of the eligibility requirements or because most firms were eligible.

Figure 2 depicts the bankruptcy rate of split in quartiles based on decision time and for the full sample and the sample with financial statement data available. The graph shows that the bankruptcy rate is steady for the first three quartiles and them increases for the last quartile in the full sample. The bankruptcy rate, however, monotonically increases for the sample limited to applications with financial statement data available. Both samples convey an increasing trend from the first to the fourth quartile, providing initial evidence that longer decision times lead to a higher likelihood of bankruptcy.

Table 2 reports the correlation matrix, which reveals that bankruptcies are correlated with decision times when assessed individually. However, I do not expect the correlation to fully depict how decision times affect bankruptcy, as bankruptcy appears seasonal, especially during crisis times (e.g., Wang et al., 2021). Moreover, decision time correlates with several of the bankruptcy model controls. These indicate the importance of including firm characteristics into the bankruptcy models and the effects of access to government support.

4.2 Differences in access to government support

Table 3 shows the estimation of equation 1 for the full sample (column 1–4) and for samples split on the support type (column 5–7). Column 1 shows the estimation of equation 1 on the full sample but without any fixed effects and with standard errors assumed naively to be independent and identically distributed (iid., i.e., without any adjustment of standard errors for heteroskedasticity). As I gradually include time and industry fixed effects, the Pseudo R^2 increases. This highlights the importance of including both industry and time fixed effects. The following specifications include both.

Columns 1–4 include indicators for each support type *revenue*, *salary*, and *fixed costs*—where the latter is the baseline—to account for differences in the bankruptcy rate of firms applying for each support type. The indicator variables show that firms applying for salary support have the highest likelihood of bankruptcy, across all fixed-effect specifications in columns 1 through 4. In columns 5–7, I split the sample by each support type to obtain support-type specific variation in the coefficients and controls of decision times. The log-likelihood coefficient estimates for decision time vary between 0.010 and 0.019. The marginal effect at the mean depicts a similar inference. Here an extra standard deviation of wait time to receive a decision increases the likelihood of bankruptcy between 0.26 to 0.39 percentage points for applicants, depending on the support type. Using the sample-specific bankruptcy rate, this translates into a 15.83 to 25.05 percent higher likelihood of bankruptcy. For ease of interpretation, I also calculate the percentage change to the bankruptcy when firms wait an extra day for support (untabulated but calculated by dividing ΔSD decision time on bankruptcy by the SD of decision time or the marginal effect of the bankruptcy rate).

To mitigate concerns that firm characteristics explain the variation in decision time that drives firms' likelihood of bankruptcy, I estimate the three bankruptcy models in equation 1. The sample size is reduced to 103,140 observations because the majority of firms applying for support do not disclose financial statements (i.e., are unlimited liability firms) and due to singletons. Table 4 shows the results, including observations with available financial statement data.[18] *Decision time* continues to be highly significant in all specifications, except for fixed costs applications in the cross section. Notably, the coefficients in column 1 resemble closely the coefficients in column 1 of table 3 on the full sample. This provides

[18]The table shows a slightly smaller number of observations than the descriptive statistics in table 1 because of singletons across months and industries (i.e., some industries in the sample did not experience any bankruptcies in certain months).

some evidence that firms are hit similarly by heterogeneity in decision times, regardless of whether they produce financial statements, which is likely determined by whether they are incorporated and have limited liabilities. Moreover, including the bankruptcy control variables in columns 2–4 produces largely unchanged coefficients of decision time, further indicating that the variation in decision time explained by firm characteristics is unrelated to the variation of decision time that explains the likelihood of bankruptcy. These findings show that access to government support significantly affects firms' likelihood of bankruptcy.

In columns 5–7, I again separate applications by their type and estimate equation 1 using the Ohlson model, as Regenburg and Seitz (2021) show that Ohlson provides the highest AUC. The power of these tests is lower, as separating the applications by type greatly reduces the sample size and increases the occurrences of singletons. In light of the reduced power, the decision time for fixed costs in column 5 is insignificant, while the coefficient of decision time of revenue and salary support remains significant in columns 6 and 7. These results are robust to using the Altman and the Beaver et al. bankruptcy models (untabulated).

The marginal effect at the mean estimates are highly economical across all bankruptcy models. Specifically, the estimates show that the increased likelihood of bankruptcy for one extra standard deviation wait time varies between 0.48 to 0.70 of a percentage point. Using the bankruptcy rate of the specific samples, these estimates translate into a between 17.85 to 21.93 percent higher likelihood of bankruptcy per day of extra wait time.

Overall these estimations provide evidence of government COVID-19 support decreasing firms' likelihood of bankruptcy. Notably, the coefficients of the bankruptcy model controls appear to vary across support types. For instance, the sign of logged total assets is positive for fixed costs and salary but negative for revenue. This indicates that the pools of applicants for each support type fundamentally differ from each other.

The control variable for the support amount also reveals interesting but descriptive findings about the effectiveness of the support types. Specifically, the significant coefficients of support amount for fixed costs and salary show that more support paid out leads to a higher likelihood of bankruptcy. This may indicate that the government disbursed too little support for fixed costs and salary expenses to firms hit hard by the COVID-19, compared to firms that were hit mildly. In contrast, firms that received more revenue support were less likely to go bankrupt, suggesting that the government may have overfunded this compensation program.[19]

4.3 Determinants of decision time

Despite table 4 includes controls on firms' financial characteristics, I cannot completely rule out that unobservable factors affect both applicants' decision time and their likelihood of bankruptcy. The institutional setting and the consistency in the coefficients when estimating bankruptcy models, however, do not suggest that this is the case. Instead DBA's incredibly short window to implement an application process and the lack of overview of the responsible reviewers and application handling stage point towards many opportunities for variation in decision times that are unrelated to firms' characteristics. These include but are not limited to reviewer speed, reviewer sickness, weekends and holidays, reviewer turnover, requests for additional documentation, simple processing errors, and the need to call for experts to assess support applications. To gain insight into what explains the decision time, I estimate a determinants model, which I explain in detail and present in Appendix B. Here, I find that only the type of support consistently is associated with the variation in decision time while the significance of size and the amount of support vary across tests, consistent with application length increasing with size and DBA's additional control procedures of very large support sizes.

[19] I should caution the reader that, compared to decision time, I do not claim that the support amount is exogenous, and thus I cannot infer causality from the effectiveness of the disbursed government support sizes.

4.3.1 Decision time intervals

Next, I test the effect of decision time split into intervals between 0, 10, 20, 30, 40, and ∞ to account for skewness in the distribution of decision times. Table 5 shows the results, and decision times between 0 and 10 days are the baseline. Column 1 employs the full sample and shows a monotonically increasing effect of higher decision time intervals[20]. In column 2, I implement the financial statement sample and test the effect of the decision time intervals in the Ohlson bankruptcy model. The results also indicate an increasing trend, as the decision time intervals include higher decision-time observations. Although less robust, the rising trend persists when I split the financial statement sample by support type and estimate the Ohlson model. These results corroborate the graphical trends shown in figure 2 and suggest that the findings of previous tests are not driven by skewness in the distribution of decision days.

4.3.2 Effect of decision time across support size

Next I test whether the coefficient of decision time increases over higher support amounts and support intensity, measured as the support amount scaled by total assets. Assuming that the support amount and intensity are fair proxies for the severity of the financial impact on firms during the COVID-19 crisis, I expect that the importance of decision times increases for firms that wait for higher levels of support. Table 6 shows the test results. Column 1 shows the results for the full sample, and decision time continues to be significant. The interaction terms are, however, insignificant for the second and fourth support quartile interactions, while marginally significant for the third support quartile interaction, which indicates that the effect of decision time on firms' likelihood of bankruptcy is uniform across the size of support. Instead the level variable of support is marginally significant for the second support quartile (quartile 1 is the baseline), which yields inconclusive evidence of the size of support

[20]Not all differences between interval coefficients are significantly different from neighboring intervals or the baseline.

on firms' likelihood of bankruptcy.[21] Column 2 employs the financial statement sample and includes Ohlson bankruptcy controls. Interaction terms with support quartiles 2 through 4 in column 2 are significant although the baseline decision time is insignificant but positive, consistent with the expectations. Columns 3 through 5 split the financial statement sample by application type. Separating by application type greatly reduces the sample size and increases the occurrences of singletons, which reduces the power of the results. With those caveats in mind, the effect of decision time is positive, consistent with the main results but only significant for salary applications in column 5. The interaction terms between support and decision time across the support types elicit varying results. The interaction of decision time and the second (fourth) quartile of support in the fixed costs (revenue) is significant. The rest of the coefficient estimates of interactions are insignificant but mostly positive.

4.4 Robustness tests

4.4.1 Removing very high decision times.

One concern is that differences in decision times relate to the DBA requiring supplemental documents in cases where the firms' support amount applied for differs from what the DBA deems appropriate. To test this, I construct the measure *disagree*, which is an indicator set to one if the applied-for amount differs from the paid-out amount and estimate cross-sectional regressions conditioned on the indicator. Table 7 shows the results. Columns 1 through 3 for both cross-sections of the full sample and the sample limited to applications with available financial statement data continue to show significant coefficients of decision time. However, decision time in the limited sample is insignificant, likely due to the paucity of observations. These results indicate that the decisions are not driven by disputes between the firms and the DBA.

[21]The effect of the support amount on the likelihood of bankruptcy may stem from the government program composition and thus decision time may be irrelevant. Similar to footnote 19, the support amount may be endogenous to firms' likelihood of bankruptcy.

4.4.2 Amount of support

For consistency, I run the main specification (table 4 column 3) with the scaled support amount as a control (support intensity explained above in section 4.2). The coefficient of decision time continues to be highly significant, and the scaled support measure is insignificant. The effect of the support intensity is, however, insignificant.

4.4.3 Zero-days observations

The most frequent decision time is zero days. One concern may be that firms receiving zero-day decisions are those without any remarks that receive rubber-stamped approvals by the DBA, while applications requiring reviews take more time. To alleviate this concern, I re-estimate table 4 using only nonzero decision time observations, and all inferences are unchanged (untabulated).

4.4.4 Log-transformation of decision time

Table 1 shows right-skewness in the distribution of decision time, and the typical solution is to log-transform the predictor.[22] However, zero-day observations prevent the implementation of such an approach. Instead I use the sample of nonzero day observations to re-estimate the models with the log of decision time as the independent variable of interest.[23] Re-estimations with log-transformed decision time of the three bankruptcy models applied in table 4 show highly significant coefficients (untabulated), consistent with previous inferences. Separating the sample by application type, removing zero-day decision times, and log-transforming the decision time variable weakens the result (untabulated). Specifically, the coefficient of decision time in fixed cost applications now appears marginally significant at the 10% level, while the coefficient estimates are insignificant for revenue support applications in two out

[22] A common mistake is to require independent variables to be normally distributed. However, the assumptions for logit regression only require the error term and the outcome variable to be normally distributed. Instead linearity usually improves model performance.

[23] An alternative approach is the inverse hyperbolic sine transformation, which assimilates $ln(2) + ln(x)$ and allows for nonpositive (i.e., $x \leq 0$) inputs.

of three bankruptcy models. These differences are likely an effect of fewer observations, leading to lower power or the reduced influence of extreme values on the coefficients in the log-transformed estimations.

5 Conclusion

This study shows that differences in access to government financial support affect firms' likelihood of bankruptcy. I exploit plausibly exogenous variation in decision times of firms' support applications and find that higher decision times significantly and economically increase bankruptcy likelihood. In terms of magnitude, marginal effects at the mean coefficients show that the likelihood of bankruptcy increases between 0,84 (0.0145) to 2,03 (0.0550) percent (percentage points), depending on the subsample and model specification, when firms face an extra day of wait time on application decisions for government support.

This study contributes to the literature on how government support affects firm survival. The setting allays limitations that prevent recent research to provide causal inferences on the impact of government support on firm outcomes because of the endogenous nature between selection of recipients of government support, firms' survival, concurrent events, and limited access to data on firm outcomes. Specifically, this study exploits properties of the Danish government support program, one application entry, access to the universe of support recipients, and their characteristics and outcomes. The setting also provides for application processing across time and no upper limit to the government's funding of applications across time, which may encourage some firms to apply earlier.

The findings have implications for governments and their support efforts during crises. I show that decision times highly affect firms' likelihood of bankruptcy and that the heterogeneity in decision times across firms creates arbitrary differences in firms' survival. Governments should thus in future crises not only be aware of the speed of processing support applications but also the consistency in the processing speed across applicants.

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Appendix A Variable definitions

Table A.1: Variables definitions

Variable name	Definition
Variables of interest	
Bankrupt	An indicator variable of one if the firm goes bankrupt between $t+1$ and $t+x$ days after the Danish Business Authorities receives the applications for the government support initiative.
Decision time	The number of days the authorities use to provide a decision on a support application
Decision time$_d$	Indicator for variables for whether decision time is between 0, 10, 20, 30, 40, and ∞ days, respectively.
Support type	A categorical value of the government support type, which is either 'salary', 'revenue', or 'fixed costs'
Other variables	
Support	The natural logarithm of the paid out support amount. If the paid-out amount is missing, I use the applied amount instead.
Support/TA	The natural logarithm of the support amount scaled by total assets. I use the application amount if the paid amount is missing.
Support$_q$tr	Support amount or support/TA split into quartiles within each support type.
Disagree	An indicator that is set to one if the paid-out support amount is different from the amount applied and zero otherwise. In cases where either one is missing, the indicator is set to zero.
Bankruptcy model variables	
EBIT/TA (Altman, BMR)	Earning before interest and tax scaled by the beginning of period total assets, $\frac{EBIT}{TA_{t-1}}$

Variable name	Definition
NWC/TA (Altman, Ohlson)	Net working capital scaled by total assets, $\frac{NWC_t}{TA_t}$ $NWC_t = WCA_t - WCL_t$ WCA=Working Capital Assets =Current Assets -cash and cash equivalents -properties held for sale -receivables from closely related parties WCL=Working Capital Liabilities =current liabilities -current part of mortgage -current part of bank debt -liabilities to closely related parties -dividends if included in current liabilities
RE/TA (Altman)	Retained earnings scaled by total assets, $\frac{RE_t}{TA_t}$
BVE/TL (Altman)	Book value of equity scaled by total liabilities, $\frac{BVE_t}{TL_t}$
GP/TA (Altman)	Gross profit scaled by total assets at time $t-1$, $\frac{GP_t}{TA_{t-1}}$
TL/TA (Ohlson, BMR)	Leverage. Total liabilities scaled by total assets, $\frac{TL_t}{TA_t}$
EBITDA/TL (Ohlson, BMR)	Earnings before interest, tax, depreciation, and amortization scaled by total liabilities, $\frac{EBITDA_t}{TL_t}$
Log TA (Ohlson)	The natural logarithm of total assets, $Log(TA_t)$.
CL/CA (Ohlson)	The current ratio. Current liabilities scaled by current assets, $\frac{CL_t}{CA_t}$.

Variable name	Definition
NITWO (Ohlson)	An indicator variable that is set to one if the sum of the last two years' earnings is negative and zero otherwise, $NITWO = \begin{cases} 1, & Net\ income_{t-1} + Net\ income_t < 0 \\ 0, & Otherwise. \end{cases}$
OENEG (Ohlson)	An indicator that is set to one if owners' equity is negative and zero otherwise, $OENEG = \begin{cases} 1, & Total\ liabilities_t > Total\ assets_t \\ 0, & Otherwise. \end{cases}$
Chin (Ohlson)	The change in net income scaled by the sum of the absolute net income at time t and $t-1$, $Chin = \frac{\Delta Net\ income_t}{\lvert Net\ income_{t-1}\rvert + \lvert Net\ income_t\rvert}$

Appendix B Determinants of decision time

Although the variation in decision time is quasi-random, some variation may be explained by firm characteristics. Specifically, I expect some variation in decision time to be driven by firm size as presumably larger firms may provide more voluminous applications and require greater scrutiny (e.g., the DBA requires a manager to approve fixed costs applications above DKK 2.5 million). However, I argue that the legitimacy of using decision time as a plausibly exogenous treatment remains as the coefficients of decision times are largely unchanged when including determinants of decision time in the bankruptcy models.

I investigate the legitimacy in three steps. First, I estimate determinant models using the controls of the main specifications, which include the full sample test, estimation of the Ohlson model, and the applications split by support type. Columns 1–5 of table B.1 show the results of Poisson regressions. Only the support type (columns 1 and 2) consistently explains the decision time, while the significance of the effects of firm size, the support amount, and the net working capital (NWC) on decision time varies. Consistent with DNA's report on the DBA's handling of the applications, the highly negative coefficients of the indicator of revenue and salary support show that the fixed costs application took the longest to process. That is because all applications for fixed costs support were assigned to manual control.

In the second step, I investigate four distinct characteristics of the applications or applicants that should assign firms to manual control or manager approval, according to the DNA report, and thus resolve in higher decision times. The goal of this step is to assert to what degree being assigned for manual control affects higher decision times. These thresholds include an automatic assignment to manual control for revenue applications if I) the beneficiary ownership for the largest owner is less than 25 percent, II) if the number of employees is above 25, and for application types, if III) the application amount is different from the actual support amount. Only this threshold is seemingly unrelated to firms' financial characteristics. For fixed costs support, applications IV) require manager approval if the support amount exceeds DKK 2.5 million.

Columns 6–9 show the tests of these criteria. Column 6 includes an indicator for both I and II, and the results suggest that only the applicants with above 25 employees experience a marginally higher decision time, while the indicator for the beneficiary owner threshold is insignificant. Column 7 presents the result of threshold IV when fixed cost applications require manager approval. The results are highly significant suggesting that manager approval increased the decision time. Caution should, however, be exercised as the support amount likely correlates with the size of firms. Columns 8 (for the full sample) and 9 (for the sample with financial statements available) show the test results of whether disagreement between the application amount and the paid-out amount is associated with the decision time. The indicator estimates are both insignificant in the full sample and in the sample limited to applications with financial statement data available. Taken together, these four tests indicate that assignment to manual control does not seem to explain the variation in decision time.

In the third step, I rely on an in-depth investigation of the institutional setting described in DNA's report on the DBA's application handling. Concretely, lengthy correspondence with the DBA and anecdotal interviews with auditors. They reveal that the DBA had a limited overview of the application process, including who was responsible for individual applications and whether applications were assigned for manual control, corroborating the insignificant and marginally significant results of thresholds I, II, and IV. Moreover, the auditors were not able to determine why some applications were handled swiftly while others were not, even when assisting simple firms, and no additional documents were requested by the DBA.

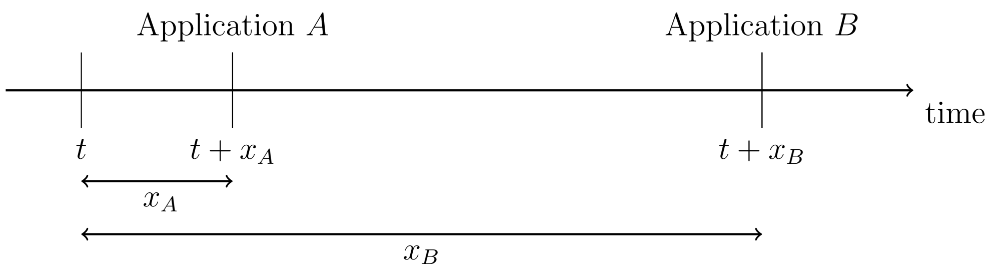
Table B.1: Determinants of decision time

	Decision time								
	(1) Full	(2) Ohlson	(3) Fixed costs	(4) Revenue	(5) Salary	(6) Revenue	(7) Fixed costs	(8) Full	(9) Ohlson
Support	0.038***	0.013	0.022	0.068**	0.013	0.064*	0.007	0.038***	0.012
	(0.007)	(0.016)	(0.018)	(0.033)	(0.017)	(0.034)	(0.018)	(0.007)	(0.016)
Real ownership						0.028			
						(0.087)			
>25 employees						0.180*			
						(0.095)			
>2.5 million in support							0.409***		
							(0.073)		
Disagree								0.075	0.156
								(0.106)	(0.112)
Support type$_{revenue}$	-0.763***	-0.734***						-0.763***	-0.734***
	(0.117)	(0.122)						(0.117)	(0.122)
Support type$_{salary}$	-0.823***	-0.767***						-0.823***	-0.769***
	(0.068)	(0.063)						(0.068)	(0.063)
TL/TA		0.006	0.003	0.015	0.015	0.003	0.004		0.006
		(0.011)	(0.013)	(0.014)	(0.021)	(0.017)	(0.014)		(0.011)
EBITDA/TL		-0.010	-0.019**	-0.005	-0.002	-0.002	-0.018*		-0.010
		(0.009)	(0.009)	(0.009)	(0.015)	(0.011)	(0.009)		(0.009)
NWC/TA		-0.050***	-0.028	-0.001	-0.087***	-0.013	-0.018		-0.050***
		(0.015)	(0.017)	(0.012)	(0.025)	(0.016)	(0.016)		(0.015)
Log TA		0.043***	0.009	-0.048***	0.101***	-0.040***	-0.001		0.043***
		(0.014)	(0.012)	(0.008)	(0.023)	(0.007)	(0.012)		(0.014)
CL/CA		-0.002	-0.002**	0.005**	-0.006*	0.005**	-0.001*		-0.002
		(0.002)	(0.001)	(0.002)	(0.003)	(0.002)	(0.001)		(0.002)
NITWO		0.009	0.012	0.018	-0.007	0.012	0.011		0.009
		(0.008)	(0.009)	(0.016)	(0.016)	(0.017)	(0.009)		(0.008)
OENEG		0.024*	0.022	-0.021	0.031	0.001	0.016		0.024*
		(0.013)	(0.014)	(0.022)	(0.029)	(0.025)	(0.013)		(0.013)
CHIN		0.005	-0.001	-0.001	0.011	-0.002	0.000		0.005
		(0.008)	(0.007)	(0.005)	(0.013)	(0.008)	(0.007)		(0.008)
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	272,637	113,527	33,493	25,369	54,659	22,520	33,493	272,637	113,527
Pseudo R^2	0.25	0.25	0.24	0.27	0.17	0.27	0.24	0.25	0.25

This table shows the Poisson regression estimates of the determinants of decision time. Column 1 and 8 show the estimations on the full sample, and columns 2–7 and 9 show the estimates of the Ohlson bankruptcy model. Column 2 shows the estimation of the sample with financial statements available, while columns 3, 4, and 5 show the results of the samples split by fixed costs, revenue, and salary applications, respectively. Columns 6–9 investigate four application or applicant characteristics that should lead to higher decision times. These include an indicator for whether the beneficiary owner owns more than 25 percent of the firm and whether the number of employees exceeds 25 in column 6, an indicator for whether the support amount is above DKK 2.5 million in column 7, and an indicator for whether the application amount is different from the support amount in column 8 and 9. The dependent variable *Decision time* is the number of days it takes the authorities to provide a decision on a support application. All other variables are defined in table A.1 of Appendix A, and all continuous variables are winsorized at the 1% and 99%-level. ***, **, and * represent significance levels at 0.01, 0.05, and 0.10, respectively (two-tailed test).

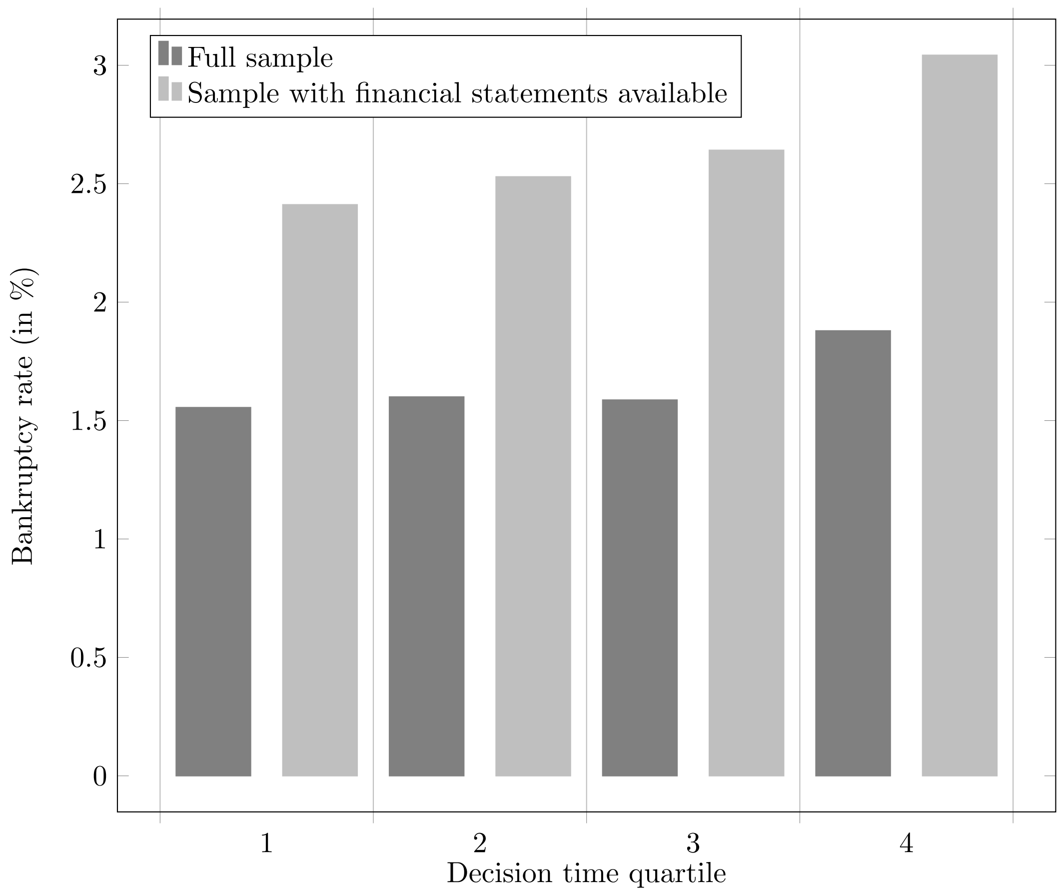
Figures

Figure 1: Decision time



This figure depicts the construction of the decision time measure based on two hypothetical applications that are aligned at the application date and observed over time. For application A the decision arrives early, producing a low decision time, whereas the decision time is high for application B as it has a late decision time.

Figure 2: Decision time quartiles and bankruptcy rates



This graph depicts the bankruptcy rate of subsamples split into quartiles by decision time of the full sample and the sample limited to applications with available financial statement data.

Tables

Table 1: Descriptive statistics

	N	Mean	StdDev	P5	P25	Median	P75	P95
Full sample								
Bankrupt	272,639	0.02	0.13	0	0	0	0	0
Decision Time	272,639	19.73	18.21	0.0	5.0	16	27	55.0
Support	272,639	174,726	1,213,752	10,517	30,679	66,000	113,597	477,285
Disagree	272,639	0	0.06	0	0	0	0	0
FS sample								
Bankrupt	113,529	0.03	0.16	0	0	0	0	0
Decision Time	113,529	19.48	18.98	0	4	15	27	56
Support	113,529	207,039	429,346	13,774	43,804	78,571	174,065	787,874
Support/TA	113,529	0.08	0.13	0.00	0.01	0.04	0.09	0.31
Disagree	113,529	0.01	0.07	0	0	0	0	0
NWC/TA	113,529	-0.16	0.63	-1.22	-0.37	-0.06	0.21	0.58
TL/TA	113,529	0.84	0.68	0.22	0.48	0.71	0.93	1.98
EBITDA/TL	113,529	0.11	0.54	-0.57	-0.11	0.04	0.25	1.08
Total assets (in 000's)	113,529	16,159	56,231	208	873	2423	7209	63,321
CL/CA	113,529	1.61	2.59	0.24	0.54	0.84	1.46	5.47
NITWO	113,529	0.32	0.47	0	0	0	1	1
OENEG	113,529	0.20	0.40	0	0	0	0	1
CHIN	113,529	0.02	0.67	-1.00	-0.50	0.02	0.56	1.00

This table shows descriptive statistics of the main samples used in the estimations of the equations. All other variables are defined in table A.1 of Appendix A, and all continuous variables are winsorized at the 1% and 99%-level.

Table 2: Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	Bankrupt		**0.02**	**-0.03**	-0.01	**0.11**	**-0.07**	**-0.06**	**-0.06**	**0.08**	**0.09**	**0.11**	**-0.02**
(2)	Decision time	**0.02**		**0.12**	0.00	**0.05**	**-0.02**	**-0.06**	**0.01**	**0.07**	**0.02**	**0.03**	**0.01**
(3)	Support	**-0.03**	**0.12**		**0.02**	**-0.04**	0.01	**0.08**	**0.44**	**0.01**	**-0.06**	**-0.09**	0.00
(4)	Disagree	-0.01	0.00	**0.02**		-0.01	0.00	**0.02**	**0.04**	-0.01	0.00	**-0.01**	0.00
(5)	TL/TA	**0.10**	**0.03**	**-0.09**	**-0.01**		**-0.42**	**-0.52**	**-0.22**	**0.76**	**0.45**	**0.69**	**-0.01**
(6)	EBITDA/TL	**-0.05**	**-0.02**	0.00	0.00	**-0.26**		**0.24**	**0.07**	**-0.43**	**-0.58**	**-0.34**	**0.39**
(7)	NWC/TA	**-0.07**	**-0.05**	**0.09**	**0.02**	**-0.76**	**0.20**		**0.37**	**-0.65**	**-0.26**	**-0.46**	**-0.03**
(8)	Log TA	**-0.06**	**0.03**	**0.48**	**0.04**	**-0.29**	**0.04**	**0.37**		**-0.14**	**-0.18**	**-0.30**	**-0.01**
(9)	CL/CA	**0.04**	**0.04**	**-0.03**	**-0.01**	**0.52**	**-0.18**	**-0.58**	**-0.10**		**0.37**	**0.50**	**-0.01**
(10)	NITWO	**0.09**	**0.02**	**-0.06**	0.00	**0.41**	**-0.44**	**-0.32**	**-0.17**	**0.26**		**0.48**	0.00
(11)	OENEG	**0.11**	**0.03**	**-0.10**	**-0.01**	**0.70**	**-0.23**	**-0.56**	**-0.29**	**0.37**	**0.48**		0.00
(12)	CHIN	**-0.02**	**0.01**	0.00	0.00	-0.01	**0.30**	**-0.02**	**-0.01**	0.00	0.00	0.00	

This table shows the correlation matrix based on the sample of applications with financial statements available. All variables are defined in table A.1 of Appendix A, and all continuous variables are winsorized at the 1% and 99%-level. Significant correlations at the 5% level are marked in bold. The lower-left corner is Pearson correlations, while the upper-right corner includes Spearman-rank correlations.

Table 3: Bankruptcy and decision times

	Bankrupt						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full	Full	Full	Full	Fixed costs	Revenue	Salary
Decision time	0.009***	0.012***	0.008***	0.011***	0.010***	0.019***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)
Support amount	0.056***	0.067***	0.012	0.032	0.077	-0.120**	0.033
	(0.013)	(0.021)	(0.018)	(0.027)	(0.047)	(0.049)	(0.033)
Support type$_{revenue}$	0.173***	0.209**	0.090	0.101			
	(0.043)	(0.088)	(0.055)	(0.085)			
Support type$_{salary}$	0.467***	0.499***	0.306***	0.323***			
	(0.039)	(0.093)	(0.070)	(0.099)			
Year-month FEs	No	Yes	No	Yes	Yes	Yes	Yes
Industry FEs	No	No	Yes	Yes	Yes	Yes	Yes
SE Clusters	None	Year-month	Industry	Year-month & Industry			
Observations	272,639	272,574	256,383	256,322	70,593	76,436	93,506
Pseudo R^2	0.006	0.02	0.06	0.06	0.07	0.08	0.07
Decision time$_{MEM\times100}$	0.0153***	0.0200***	0.0145***	0.0182***	0.0167*	0.0298*	0.0248**
	(0.0014)	(0.0071)	(0.0037)	(0.0067)	(0.0093)	(0.0159)	(0.0248)
SD of decision time	18.21	18.21	18.21	18.21	21.71	12.16	15.60
Bankruptcy rate (%)	1.66	1.66	1.66	1.66	1.21	1.47	1.99
ΔSD decision time on bankruptcy (pp.)	0.28	0.36	0.26	0.33	0.36	0.36	0.39
ΔSD decision time on bankruptcy (%)	16.76	21.96	15.83	19.97	25.05	24.65	19.47

This table shows the logit estimations of equation 1 to answer whether decision time predicts firms' likelihood of bankruptcy. Column 1 shows the results of the full sample with no fixed effects and standard errors assumed to be IID. Columns 2 and 3 show the results including fixed effects for (and standard errors clustered by) year-month and industry, respectively, while column 4 includes both. Columns 5–7 show the estimation results on samples split by the support type. The dependent variable *Bankrupt* is an indicator of one if the firm goes bankrupt between *t+1* and *t+365* days after the authorities receive the application. The variable of interest is *Decision time*, measured as the number of days it takes the authorities to provide a decision on a support application. The bottom part of the table shows the effects of one standard deviation change in decision time on the likelihood of bankruptcy (for both percentage-point and percent changes) compared to the sample-specific bankruptcy rate based on the marginal effects at the mean. All other variables are defined in table A.1 of Appendix A, and all continuous variables are winsorized at the 1% and 99%-level. Standard errors are in parentheses and are two-way clustered at the year-month and industry level. ***, **, and * represent significance levels at 0.01, 0.05, and 0.10, respectively (two-tailed test). For ease of interpretation, Decision time$_{MEM\times100}$ provides marginal effects at the mean times a hundred, while the parentheses below show standard errors.

Table 4: Bankruptcy models

				Bankrupt			
	(1) Full	(2) Altman	(3) Ohlson	(4) BMR	(5) Fixed costs	(6) Revenue	(7) Salary
Decision time	0.010***	0.009***	0.010***	0.010***	0.007***	0.016***	0.013***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Support	-0.118***	-0.083**	0.020	-0.074*	0.116*	-0.376***	0.088**
	(0.040)	(0.039)	(0.037)	(0.040)	(0.065)	(0.080)	(0.042)
	(0.052)	(0.052)	(0.051)	(0.051)	(0.123)	(0.138)	(0.053)
Support type$_{revenue}$	0.313***	0.299***	0.235***	0.292***			
	(0.087)	(0.077)	(0.079)	(0.080)			
Support type$_{salary}$	0.100	0.063	0.162**	0.081			
	(0.087)	(0.075)	(0.072)	(0.075)			
RE/TA		-0.130**					
		(0.064)					
BVE/TL		-0.439***					
		(0.094)					
GP/TA		0.097***					
		(0.017)					
EBIT/TA		-0.437***		-0.026			
		(0.072)		(0.106)			
TL/TA			0.192***	0.424***	0.158	0.216**	0.193**
			(0.073)	(0.032)	(0.103)	(0.086)	(0.092)
EBITDA/TL			-0.207**	-0.507***	-0.289**	-0.035	-0.276*
			(0.094)	(0.105)	(0.147)	(0.077)	(0.143)
NWC/TA		0.071	0.203**		0.136	0.009	0.375***
		(0.085)	(0.096)		(0.126)	(0.097)	(0.123)
Log TA			-0.142***		-0.215***	0.039	-0.229***
			(0.030)		(0.045)	(0.042)	(0.043)
CL/CA			0.010		0.007	-0.005	0.027**
			(0.012)		(0.021)	(0.024)	(0.013)
NITWO			0.469***		0.422***	0.607***	0.402***
			(0.104)		(0.136)	(0.101)	(0.127)
OENEG			0.740***		0.611***	0.543***	0.934***
			(0.124)		(0.175)	(0.135)	(0.148)
CHIN			-0.067		-0.004	-0.120*	-0.083
			(0.067)		(0.105)	(0.072)	(0.074)
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	103,140	103,140	103,140	103,140	27,758	21,559	46,101
Pseudo R^2	0.05	0.09	0.10	0.08	0.10	0.11	0.12
Decision time$_{MEM \times 100}$	0.0284*	0.0251**	0.0265*	0.0264*	0.0197	0.0550	0.0352
	(0.0284)	(0.0126)	(0.0155)	(0.0135)	(0.0131)	(0.0391)	(0.0221)
SD of decision time	18.98	18.98	18.98	18.98	22.54	12.72	16.10
Bankruptcy rate (%)	2.66	2.66	2.66	2.66	2.36	3.24	2.59
ΔSD decision time on bankruptcy (pp.)	0.54	0.48	0.50	0.50	0.44	0.70	0.57
ΔSD decision time on bankruptcy (%)	20.25	17.85	18.91	18.80	18.85	21.58	21.93

This table shows logit estimations of equation 1 to answer whether decision time predicts firms' likelihood of bankruptcy. Column 1 shows the result of the full sample but is limited to applicants with financial statements available. Columns 2–4 show the estimates of each bankruptcy model: Altman, Ohlson, and BMR. Columns 5–7 show estimations of the sample split by support type using the Ohlson model. The dependent variable *Bankrupt* is an indicator of one if the firm goes bankrupt between *t+1* and *t+365* days after the authorities receive the application. The variable of interest is *Decision time*, measured by the number of days it takes the authorities to provide a decision on a support application. The bottom part of the table shows the effects of one standard deviation change in decision time on the likelihood of bankruptcy (for both percentage-point and percent changes) compared to the sample-specific bankruptcy rate based on the marginal effects at the mean. All other variables are defined in table A.1 of Appendix A, and all continuous variables are winsorized at the 1% and 99%-level. Standard errors are in parentheses and are two-way clustered at the year-month and industry level. ***, **, and * represent significance levels at 0.01, 0.05, and 0.10, respectively (two-tailed test). For ease of interpretation, Decision time$_{MEM \times 100}$ provides marginal effects at the mean times a hundred, while the parentheses below show standard errors.

Table 5: Bankruptcy models with decision time thresholds

	Bankrupt				
	(1)	(2)	(3)	(4)	(5)
	Full	Ohlson	Fixed costs	Revenue	Salary
Decision time$_{10-20}$	0.082	0.144**	0.210	-0.042	0.220*
	(0.064)	(0.072)	(0.216)	(0.064)	(0.131)
Decision time$_{20-30}$	0.181***	0.170**	0.032	0.011	0.302***
	(0.052)	(0.068)	(0.210)	(0.083)	(0.103)
Decision time$_{30-40}$	0.329***	0.352**	0.134	0.238	0.576***
	(0.104)	(0.140)	(0.175)	(0.243)	(0.169)
Decision time$_{>40}$	0.571***	0.532***	0.426***	0.868***	0.695***
	(0.087)	(0.099)	(0.158)	(0.118)	(0.136)
Support	0.036	0.023	0.121*	-0.373***	0.091**
	(0.026)	(0.037)	(0.065)	(0.080)	(0.043)
Support type$_{revenue}$	0.104	0.237***			
	(0.085)	(0.081)			
Support type$_{salary}$	0.327***	0.171**			
	(0.100)	(0.076)			
TL/TA		0.191***	0.159	0.212**	0.189**
		(0.073)	(0.105)	(0.084)	(0.092)
EBITDA/TL		-0.206**	-0.287**	-0.033	-0.275*
		(0.094)	(0.146)	(0.078)	(0.143)
NWC/TA		0.202**	0.135	0.008	0.372***
		(0.097)	(0.125)	(0.096)	(0.124)
Log TA		-0.144***	-0.217***	0.037	-0.234***
		(0.030)	(0.044)	(0.041)	(0.044)
CL/CA		0.010	0.007	-0.003	0.027**
		(0.012)	(0.021)	(0.024)	(0.013)
NITWO		0.467***	0.422***	0.608***	0.399***
		(0.105)	(0.136)	(0.100)	(0.128)
OENEG		0.741***	0.608***	0.539***	0.937***
		(0.124)	(0.174)	(0.135)	(0.148)
CHIN		-0.067	-0.004	-0.120*	-0.083
		(0.067)	(0.104)	(0.071)	(0.075)
Year-month FEs	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes
Observations	256,322	103,140	27,758	21,559	46,101
Pseudo R^2	0.06	0.10	0.10	0.11	0.12

This table presents estimations of equation 1 but with decision time replaced by indicator variables *Decision times*$_d$ of applications with decision times between 0, 10, 20, 30, 40, and ∞, respectively. The threshold of less than 10 decision days is the baseline. Column 1 employs the full sample, while column 2 implements the Ohlson model using the FS sample. Columns 3 through 5 separate the financial statement sample by the government support type and estimate the Ohlson model. The dependent variable *Bankrupt* is an indicator of one if the firm goes bankrupt between *t+1* and *t+365* days after the authorities receive the application. The variable of interest is *Decision time*, measured by the number of days it takes the authorities to provide a decision on a support application. All other variables are defined in table A.1 of Appendix A, and all continuous variables are winsorized at the 1% and 99%-level. Standard errors are in parentheses and are two-way clustered at the year-month and industry level. ***, **, and * represent significance levels at 0.01, 0.05, and 0.10, respectively (two-tailed test).

Table 6: Support and decision time interaction

	Bankrupt				
	(1) Full	(2) Ohlson	(3) Fixed costs	(4) Revenue	(5) Salary
Decision time	0.009***	0.004	0.006	0.007	0.011***
	(0.002)	(0.003)	(0.004)	(0.008)	(0.004)
Support_{Q2}	0.177*	-0.104	0.021	-0.435*	0.169
	(0.100)	(0.105)	(0.160)	(0.249)	(0.147)
Support_{Q3}	0.071	-0.091	0.243	-0.619**	0.227*
	(0.098)	(0.115)	(0.265)	(0.252)	(0.131)
Support_{Q4}	0.118	-0.119	0.534***	-1.033***	0.262
	(0.120)	(0.127)	(0.204)	(0.286)	(0.181)
$\text{Support type}_{revenue}$	0.097	0.233***			
	(0.086)	(0.078)			
$\text{Support type}_{salary}$	0.332***	0.152**			
	(0.101)	(0.066)			
Decision time × Support_{Q2}	0.002	0.007**	0.007**	0.009	0.000
	(0.003)	(0.003)	(0.003)	(0.007)	(0.005)
Decision time × Support_{Q3}	0.005*	0.006**	0.003	0.006	0.001
	(0.002)	(0.003)	(0.005)	(0.009)	(0.003)
Decision time × Support_{Q4}	0.001	0.007***	-0.004	0.014**	0.004
	(0.002)	(0.002)	(0.005)	(0.007)	(0.005)
TL/TA		0.193***	0.154	0.197**	0.197**
		(0.073)	(0.105)	(0.090)	(0.092)
EBITDA/TL		-0.207**	-0.288**	-0.039	-0.280*
		(0.094)	(0.145)	(0.077)	(0.143)
NWC/TA		0.200**	0.135	0.005	0.373***
		(0.096)	(0.126)	(0.093)	(0.123)
Log TA		-0.132***	-0.103*	-0.180***	-0.153***
		(0.044)	(0.060)	(0.064)	(0.053)
CL/CA		0.010	0.008	-0.006	0.027**
		(0.012)	(0.021)	(0.025)	(0.013)
NITWO		0.470***	0.418***	0.612***	0.399***
		(0.104)	(0.136)	(0.102)	(0.127)
OENEG		0.739***	0.608***	0.557***	0.932***
		(0.124)	(0.176)	(0.138)	(0.148)
CHIN		-0.067	-0.003	-0.118	-0.082
		(0.067)	(0.105)	(0.073)	(0.074)
Ohlson model	No	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes
Observations	256,322	103,135	27,758	21,559	46,101
Pseudo R^2	0.07	0.10	0.10	0.10	0.12

This table presents estimations of equation 1 in column 1 and in columns 2–5, I include interactions between decision time and quartiles of the support amount either unscaled or scaled by total assets. Column 1 shows estimations on the full sample with unscaled quartiles of the support amount. Column 2 includes only applications with financial statement data available. Columns 3–5 split the sample on the application type and implement the scaled support amount. The dependent variable *Bankrupt* is an indicator of one if the firm goes bankrupt between *t+1* and *t+365* days after the authorities receive the application. The variable of interest is *Decision time*, measured by the number of days it takes the authorities to provide a decision on a support application. All other variables are defined in table A.1 of Appendix A, and all continuous variables are winsorized at the 1% and 99%-level. Standard errors are in parentheses and are two-way clustered at the year-month and industry level. ***, **, and * represent significance levels at 0.01, 0.05, and 0.10, respectively (two-tailed test).

Table 7: Main tests without the five percent highest decision times

	Bankrupt							
	(1) Full	(2) Fixed costs	(3) Revenue	(4) Salary	(5) Ohlson	(6) Fixed costs	(7) Revenue	(8) Salary
Decision time	0.008***	0.012***	0.011	0.010**	0.006***	0.009**	0.007	0.012***
	(0.002)	(0.003)	(0.008)	(0.004)	(0.002)	(0.004)	(0.007)	(0.005)
Support type$_{revenue}$	0.030				0.165**			
	(0.086)				(0.079)			
Support type$_{salary}$	0.262***				0.075			
	(0.091)				(0.082)			
Support	0.028	0.082	-0.083	0.024	0.006	0.126*	-0.315***	0.067
	(0.026)	(0.051)	(0.051)	(0.030)	(0.039)	(0.067)	(0.090)	(0.043)
TL/TA					0.187**	0.134	0.203**	0.186**
					(0.077)	(0.103)	(0.087)	(0.094)
EBITDA/TL					-0.241***	-0.323**	-0.063	-0.306**
					(0.093)	(0.145)	(0.082)	(0.152)
NWC/TA					0.194*	0.137	-0.029	0.373***
					(0.100)	(0.113)	(0.106)	(0.130)
Log TA					-0.135***	-0.228***	0.049	-0.226***
					(0.033)	(0.043)	(0.044)	(0.043)
CL/CA					0.010	0.009	-0.008	0.029**
					(0.012)	(0.022)	(0.024)	(0.015)
NITWO					0.475***	0.402***	0.669***	0.403***
					(0.113)	(0.142)	(0.113)	(0.136)
OENEG					0.761***	0.646***	0.587***	0.946***
					(0.131)	(0.185)	(0.136)	(0.160)
CHIN					-0.068	-0.014	-0.127*	-0.073
					(0.070)	(0.108)	(0.074)	(0.078)
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	240,890	66,652	70,785	87,723	96,775	26,077	20,150	43,070
Pseudo R^2	0.06	0.07	0.08	0.07	0.10	0.10	0.11	0.12

This table reestimates column 4–7 in table 3 and 4 but without the five percent highest decision times within year-month and support type. Columns 1 through 4 are based on the full sample while columns 5 through 8 are based on the sample with financial statements available to estimate the Ohlson model. Columns 2 through 4 and 6 through 8 are based on the samples split by the support types. Specifically, columns 2 (3) [4] and 6 (7) [8] are based on the fixed costs (revenue) [salary] support applications. The dependent variable *Bankrupt* is an indicator of one if the firm goes bankrupt between *t+1* and *t+365* days after the authorities receive the application. The variable of interest is *Decision time*, measured by the number of days it takes the authorities to provide a decision on a support application. All other variables are defined in table A.1 of Appendix A, and all continuous variables are winsorized at the 1% and 99%-level. Standard errors are in parentheses and are two-way clustered at the year-month and industry level. ***, **, and * represent significance levels at 0.01, 0.05, and 0.10, respectively (two-tailed test). For ease of interpretation, Standard errors are presented in the parentheses.