Discussion Paper No. 16-035

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Abstract

We estimate the causal impact of restructuring aid granted by the European Commission between 2003 and 2012 on the survival and financial viability of aided firms. Using a comprehensive dataset we find that restructuring aid increases a firm's average survival time by 8 to 15 years and decreases the hazard rate by 58 to 68 percent, depending on the definition of firm survival. Further analysis finds strong support that, in the longer run, aid receiving firms have a significantly higher probability to improve their financial viability than the counterfactual group.

Keywords Government policy, state aid, ex-post evaluation, survival, European Union

JEL Class C41, D62, D73, G33, G38, H23, L52, L98, O52

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1 Introduction

The granting of state aid or subsidies[1] is a traditional and important tool of public policy. By reallocating funds – on a selective basis – to industries or firms, governments on the one hand may aim at compensating for market failures or market imperfections thereby improving market allocations and social welfare. However, on the other hand, such selective reallocations are not only generally suspected of causing incremental societal costs by damaging competition and distorting trade but may also be guided by less altruistic alternative governmental motives – such as, for example, the preservation of powers – typically associated with detrimental effects on social welfare.[2] This ambivalence in the motivations – together with increasing political pressures to reduce government spending – has led many countries to tie such transfers to the fulfilment of strict conditions.

For the European Union and its key objective of creating common European markets for goods and services, the control of state aid has always been of key interest. However, although the 1957 Treaty of Rome already included key provisions on state aid, it took until the end of the last century before the European Commission successfully started several stages of substantial reforms of the existing rules aiming at 'less and better targeted state aid' (European Commission, 2005) and 'good aid that supports growth' (European Commission, 2012).[3] The general success of these initiatives – such as the 2005-2009 State Aid Action Plan and the 2012-2014 State Aid Modernization Reform – is reflected not only in the development and implementation of stricter and more transparent state aid rules but also in a shrinking significance of (non-crisis related) state aid transfers from 1.10 percent of GDP in 1992 to 0.49 percent of GDP (EU-28) in 2013.

However, despite its decreasing share, state aid continues to be an important tool of government policy in the European Union reflected in overall (non-crisis related)

[1] As noted by the OECD (2010), there are no substantive differences in the definitions of 'state aid' and 'subsidies'. In the remainder of this paper, we will use the term 'state aid' (referring to the official wording of the European Commission).

[2] For detailed overviews of the (efficiency- or equity-related) rationales for granting state aid in general and the existence of a European State aid control in particular, see Nitsche and Heidhues (2006) or Friederiszick et al. (2007).

[3] See Kassim and Lyons (2013) for a detailed overview of the history of European state aid policy.

transfers of about 64.4 billion Euros in 2013.[4] While a large fraction of European state aid is granted for so-called horizontal objectives covering areas such as environmental protection, regional development as well as research and development (including innovation), sectoral aid (excluding both agricultural and transport sectors) still accounted for about 10 percent of European state aid transfers in 2013. In fact, as part of its sectoral aid activities, the European Commission considers rescue and restructuring (henceforth R&R) aid as key policy tool to support firms in difficulty aiming at avoiding their dissolution with all the expected negative (societal and economic) consequences such as loss of employment, technical knowhow and expertise or disruption to important services. However, a necessary precondition for the granting of R&R aid by the European Commission in a certain case is a sufficiently high likelihood that the respective aided firm will return to viability after going through the compulsory restructuring process.

In this context, we estimate the causal impact of 56 positive restructuring aid decisions – reached by the European Commission between 2003 and 2012 – on the survival probability and financial viability of aided firms. Based on the construction of a non-aid receiving counterfactual group through a matching procedure, our application of survival models shows that restructuring aid increases a firm's average survival time by 8 to 15 years and decreases the hazard rate by 58 to 68 percent, depending on the definition of firm survival. Subsequently, estimating ordered response models, we find strong support that, in the longer run, aid receiving firms have a significantly higher probability to improve their financial viability than the counterfactual group of non-aided firms. Our results therefore suggest that the European Commission was not only successful in saving a large fraction of the aided firms in difficulty from their dissolution but also that its evaluation procedure to grant restructuring aid is effective in the sense that aided firms have a significantly larger probability to return to (financial) viability than the control group of non-aided firms.

The remainder of this paper is structured as follows. In the second section, we provide an overview of the institutional background of R&R aid transfers in the European Union and briefly review the existing literature that aims at estimating the impact of R&R aid on firm survival and financial viability. The third section continues with the

[4] Sources: 1992 data stem from Tunali and Fidrmuc (2015) while 2013 data were retrieved from the European Commission's State Aid Scoreboard (available at http://ec.europa.eu/competition/state_aid/scoreboard/index_en. html (last accessed on 13 February 2016)).

presentation of our econometric analysis, subdivided further into a general characterization of our identification strategy in Section 3.1, the detailed description of our data set in Section 3.2, the matching procedure in Section 3.3 and our main empirical results of an application of, first, survival models in Section 3.4 and, second, ordered response models in Section 3.5. Selected policy implications of our empirical results are discussed in the fourth section, before Section 5 closes the paper with a review of its main insights and an identification of avenues for future research.

2 Institutional background and literature review

In this section, we first provide a description of state aid in the European Union in general and the concept of rescue and restructuring (R&R) aid in particular. Subsequently, we review the rather small existing literature which studies the impact of R&R aid on the survival and financial viability of aided firms.

2.1 State aid and rescue and restructuring aid in the European Union

According to Article 107 of the Treaty on the Functioning of the European Union (TFEU), state aid is defined as "… any aid granted by a Member State or through State resources in any form whatsoever which distorts or threatens to distort competition by favoring certain undertakings or the production of certain goods …". Granting state aid is generally prohibited unless it is justified by reasons of general economic development. To ensure that this prohibition is respected and exemptions are applied equally across the European Union, the European Commission is in charge of ensuring that state aid complies with EU rules.

Due to the broad and general character of state aid in the European Union, reaching the aim of a transparent and strict application procedure requires several regulations and different guidelines for different types of aid.[5] These different types are also reflected in the European state aid statistics which first subdivide state aid expenditures into non-crisis aid and crisis aid. Limiting our further discussions to the former category, a

[5] For example, the European Commission's State Aid Modernization (SAM) reform – launched in 2012 and completed in 2014 – aimed at providing 'more efficient decision making and procedures for granting growth-supporting aid' through the reform (or creation, respectively) of both key regulations (such as the Procedural Regulation or the General Block Exemption Regulation) and several more specific guidelines (such as Broadband, Regional Aid, R&D&I or R&R Guidelines). See European Commission (2015, pp. 4ff.) for further information.

further subdivision into horizontal objectives aid and sectoral aid is undertaken. Horizontal aid includes transfers for regional development, environmental aid, research and development (including innovation) and aid for small- and medium-sized enterprises. Sectoral aid, however, includes government transfers to agriculture and fisheries, transport, coal, steel and shipbuilding as well as R&R aid. Figure 1 below provides an overview of the development of the relative significance of the two main categories[6] over time as well as the absolute amount of government spending for R&R aid as part of sectoral aid.

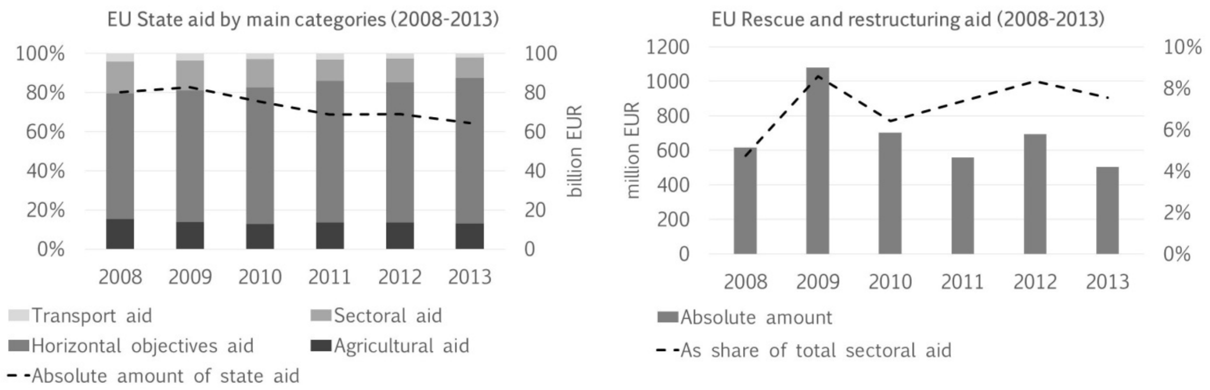

Figure 1: EU State aid and rescue and restructuring aid (2008-2013)

Data source: EC State Aid Scoreboard

As shown in the left-hand chart in Figure 1, the total sum of EU State aid peaked in the year 2009 with a value of 82.8 billion EUR; however, experienced a substantial downward trend in the following years reaching the smallest value of 64.4 billion EUR in 2013. Interestingly, the share of horizontal objectives aid increased from 64 percent in 2008 to 74 percent in 2013 leading to corresponding reductions in both agricultural aid (from 15 to 13 percent) and transport aid excluding railways (from 4 to 2 percent). Sectoral aid in the narrower sense – of which R&R aid is a significant fraction – is also found to have followed a decreasing trend from a share of 16 percent in 2008 to 10 percent in 2013.

Turning to the right-hand chart in Figure 1, it is on the one hand revealed that the share of R&R aid out of the (narrow-defined) sectoral aid category fluctuates between 5 percent in 2008 and 9 percent in 2009. In terms of the absolute amount of R&R aid granted by the European Commission, the average amount of 693 million EUR for the

[6] For illustrative purposes, agricultural aid and transport aid are reported separately (although technically part of sectoral aid).

entire time period from 2008 to 2013 is characterized further by a maximum value of 1,079 million EUR in 2009 and a minimum value of 504 million EUR in 2013.

Although rather small in size, R&R aid is an important policy tool for the European Commission. By definition, R&R aid can only be granted to firms in difficulty. According to the 2004 Rescue and Restructuring Guidelines[7] (hereafter referred as 2004 Guidelines), a firm in difficulty means a firm that "… is unable, whether through its own resources or with the funds it is able to obtain from its owner/shareholders or creditors, to stem losses which, without outside intervention by the public authorities, will almost certainly condemn it to going out of business in the short or medium term." (p. 3, para. 9 of the 2004 Guidelines). In particular, a firm is regarded as being in difficulty in the following circumstances:

a) "in the case of a limited liability company, where more than half of its registered capital has disappeared and more than one quarter of that capital has been lost over the preceding 12 months;
b) in the case of a company where at least some members have unlimited liability for the debt of the company, where more than half of its capital as shown in the company accounts has disappeared and more than one quarter of that capital has been lost over the preceding 12 months;
c) whatever the type of company concerned, where it fulfils the criteria under its domestic law for being the subject of collective insolvency proceedings" (p. 3, para. 10 of the 2004 Guidelines).

Also according to the 2004 Guidelines, R&R aid may only be regarded as legitimate subject to certain conditions. It may be justified namely by social or regional policy considerations, by the need to take into account the beneficial role played by small and medium-sized enterprises (SMEs) in the economy or, exceptionally, by the desirability of maintaining a competitive market structure when the demise of firms could lead to a monopoly or to a tight oligopolistic situation.

The 2004 Guidelines distinguish between rescue aid and restructuring aid. Rescue aid is designed to allow firms that are facing imminent collapse to stay in business for long

[7] Community Guidelines on State Aid for Rescuing and Restructuring Firms in Difficulty, Official Journal of the European Union (2004/C 244/02). The guidelines were adopted in 1994 and amended in 1999 and 2004. The current version of the guidelines became effective in 2014 (see Guidelines on State Aid for Rescuing and Restructuring Non-Financial Undertakings in Difficulty, Official Journal of the European Union (2014/C 249/01)).

enough to prepare a restructuring plan. It must be in the form of liquidity support (loans or guarantees) and has a maximum duration of six months. If further public support is needed after that, it must be in the form of restructuring aid. Restructuring aid aims at supporting a firm's restructuring and its return to long-term viability. It can be granted for a longer period, but must be accompanied by a detailed restructuring plan that meets a number of conditions (see p. 12, para. 82 of the 2004 Guidelines).

The overall objective of EU policy for restructuring aid to the non-financial sector is to contribute to successful restructuring of firms where this can be considered legitimate in the light of the justifications explained above. These justifications can only be met by firms that are viable. Moreover, the risks for distortive effects need to be minimized which implies that the amount of aid given is kept to the minimum necessary to implement the plan and appropriate measures are taken to minimize the adverse impact on competition.

In particular, the 2004 Guidelines therefore require the EC to verify the compatibility of restructuring aid according to three principles (p. 2, para. 7 of the 2004 Guidelines). First, return to viability, i.e., a restructuring plan must be submitted showing that after completing its restructuring, the firm will be able to cover all its costs and to compete in the market on its own merits. Second, an own contribution, i.e., the aid recipient must make a significant contribution to the costs of the restructuring (up to 50 percent in the case of large companies) from its own resources. Third, compensatory measures, i.e., the adverse effects of the aid on trading conditions are minimized by divestments of assets, reductions in capacity or market presence and reduction of entry barriers to the markets concerned.

2.2 Literature review

The ex-post evaluation of different types of state aid schemes has long been of interest in both academia and practice. In academia, the ex-post evaluation of the impact of, for example, R&D public policies on various outcome variables has long been attracting a substantial amount of research focusing on both various national levels and cross-country comparisons (see, e.g., Bronzini and Piselli, 2016, Czarnitzki and Lopes-Bento, 2012, 2013, Dimos and Pugh, 2016, as well as Zúñiga-Vicente et al., 2012, and the respective literature cited there). In practice, the European Commission itself commissioned studies evaluating the impact of its R&D aid (see CERES, 2005) or its regional aid (see Ramboll & Matrix, 2013) schemes and, most recently, implemented a compulsory evaluation process for certain categories of aid as part of its State Aid Modernization (SAM) reform (see European Commission, 2013, 2015).

Guided by our aim to study the particular impact of restructuring aid decisions, two general strands of research can be differentiated: first, studies that aim at investigating the *effectiveness question*, i.e., whether restructuring aid policies are found successful in avoiding (or delaying) market exit of aided firms. Second, studies focusing on the subsequent *efficiency question*, i.e., whether the respective (potentially effective) restructuring aid policies are likely to have promoted social welfare by, first, their direct impacts on the aid beneficiaries (including their respective industries or sectors) as well as, second, their various (positive or negative) indirect impacts on, e.g., competition, trade, employment, investment or economic growth.[8]

Limiting ourselves to a review of the former set of articles, in an early contribution, Glowicka (2006) studies the effectiveness of bailouts in preventing bankruptcy. Using a data set of 86 R&R aid cases decided by the European Commission between 1995 and 2003 she compares survival probability between firms that received only rescue aid and firms that also received restructuring aid finding that restructuring aid is significantly more likely to prevent firm's market exit than rescue aid. She also finds that the estimated hazard rate increases during the first four years after the aid was granted and drops after that (suggesting that some bailouts only delayed exit instead of preventing it). She concludes that a tougher European state aid control would likely increase social welfare through a reduction in the number of failing bailouts.

The study by Chindooroy et al. (2007) investigates the survival of firms after a positive R&R aid decision by the European Commission. Starting from the same data

[8] For qualitative as well as quantitative discussions of the efficiency question, see, e.g., London Economics (2004), Oxera (2009), Schweiger (2011) or Tunali and Fidrmuc (2015). Interestingly, the European Commission (2013, pp. 35ff.) itself proposes to study the efficiency question by differentiating between the positive direct impacts of the granting of R&R aid at the level of the beneficiaries as well as positive indirect impacts on broader policy objectives. While the 'maintenance of employment and activity at firm-specific and regional level' as well as 'changes in market share and productivity of aided firms' are explicitly mentioned as suitable result indicators for the direct impact, the broader category of indirect impacts of granting R&R aid is subdivided further into macroeconomic gains, advantages in the diversification of the regional economy, benefits of an increased cooperation between private and public enterprises or positive externalities (spill-over effects) of R&R aid on the European, national or regional economy. However, the European Commission is also explicit in discussing potential negative effects of R&R aid on competition and trade such as a possible sectoral bias, a bias towards loss-making (incumbent) firms or firms with low productivity ('prevention of exit') or a reinforcement of market power.

set as Glowicka (2006), the authors exclude nine cases – as the implementations of the compulsory restructuring plans were not finished yet – leaving 77 EC R&R aid cases between 1995 and 2003 for the empirical analysis. Applying a probit-model to evaluate the chances for survival, the authors find that almost 50 percent of the firms having received rescue aid did not survive while only 20 percent of the restructuring aid-receiving firms had to exit the market for good at some point. The mortality rate is also found to vary considerably over time. While firms receiving rescue aid show a high mortality particularly in the first three years after the aid was granted, restructuring aid-receiving firms have a lower mortality and – if they nevertheless had to exit – they tend to do so between three and six years after receiving the aid.

Last but not least, in a recent contribution, Nulsch (2014) also studies particularly the effectiveness of state aid in the European Union. Starting from all R&R aid cases available in the European State Aid Register for the period from 2000 to 2010, she eventually identified 141 approved R&R aid cases for her econometric analysis. By estimating survival rates for aided firms and subsequently comparing the results with the survival rates of a subset of comparable non-aid receiving firms, she finds that – despite the granting of R&R aid – a firm's market exit is often only postponed (although the ratio is still higher for the non-aided firms). Interestingly, the best survival rates are found for firms with long-term restructuring, firms in Eastern Europe as well as smaller and more mature firms.

We contribute to this literature by identifying the causal impact of 56 restructuring aid decisions by the European Commission between 2003 and 2012 on firm survival through a matching procedure. Additionally, based on the sample of matched non-aid receiving firms and aided firms, we estimate duration models in order to predict the difference in survival length for aided firms and the counterfactual group of non-aid receiving firms. Last but not least, we complement our estimations of the impact of restructuring aid on firm survival with an analysis of its impact on the likelihood of a firm to recover in terms of financial viability by estimating an ordered logit model.

3 Econometric analysis

In this section, we present our econometric analysis of the impact of restructuring aid on the survival and financial viability of aided firms. Following a first characterization of our identification strategy in Section 3.1, we continue with a detailed description of the data set in Section 3.2. Our matching procedure – explained and executed in Section 3.3

– provides the basis for an application of, first, both parametric and semi-parametric survival models in Section 3.4 and, second, ordered response models aiming at investigating the financial viability of the aided firms compared to the counterfactual group of non-aided firms in the final Section 3.5.

3.1 Identification

In developing our empirical approach we aim at identifying the causal effect of restructuring aid on firm survival. Therefore, we have to address a potential selection bias since aid is not granted randomly. Although several potentially valuable ex-post evaluation techniques exist that generally address the problem of selection bias, a meaningful application of either instrumental variable estimation (IV) or selection models, a Regression Discontinuity Design (RDD) or a (conditional) difference-in-difference estimator (DiD) to our research question – given the available data – faces severe methodological problems.

For an application of an IV estimator or a selection model, a valid instrument or an exclusion restriction, respectively, is required which could not be identified in our case. Furthermore, an application of RDD, e.g., with a 'firms in difficulty' measure as a threshold variable, is unlikely to yield reliable estimates. The reason is that the application of the EC's definition of firms in difficulty (according to the 2004 Guidelines on rescue and restructuring aid) is too fuzzy and does not provide a clear cut threshold which would be essential for RDD estimations. Finally, a DiD estimator is not appropriate in our case as all aid recipients (by definition) have to be alive at the time the aid is granted in order to receive meaningful results.

We therefore chose an empirical strategy which makes use of matching techniques in order to identify the counterfactual group and determine the average treatment effect on the treated (ATT). Subsequently, on the basis of the matched firms we specify duration as well as ordered response models in order to deeper investigate the impact of restructuring aid on the firm's survival and financial viability. With respect to the ATT our evaluation question can be defined by the subsequent equation

$$E(a_{TT}) = E(Y^T|S = 1) - E(Y^C|S = 1) \tag{1}$$

where Y^T depicts the outcome variable *firm survival* while S indicates whether the firm has received state aid (1) or not (0). Y^C is the potential outcome of the treatment group $(S = 1)$ if it had not been treated. Because $E(Y^C|S = 1)$ is not observed, in contrast to $E(Y^T|S = 1)$, it has to be estimated. As state aid is not randomly assigned, we cannot simply estimate $E(Y^C|S=1)$ as the average survival of non-aid recipients. Therefore, the conditional independence assumption (CIA) has to be valid in order to overcome the selection problem (see Rubin, 1977). The CIA implies that treatment assignment and potential outcome are statistically independent for firms with the same set of exogenous characteristics X. Matching techniques make use of this concept and enable the identification of a counterfactual group of non-treated firms by restricting the relevant counterfactual group to firms with the same exogenous characteristics X as the treated firms. Then, the remaining difference in the outcome can directly be attributed to the treatment if the CIA is valid, which is the case when selection is based on observable variables ('selection on observables'). Thus, formally we can write

$$E(Y^C|S=1,X) = E(Y^C|S=0,X) \tag{2}$$

with

$$E(a_{TT}) = E(Y^T|S=1,X=x) - (Y^C|S=0,X=x) \tag{3}$$

denoting the average treatment effect on the treated (ATT).

3.2 Data and variables

The construction of our data set was conducted in several steps. Before characterizing both dependent and independent variables in greater detail in Sections 3.2.2 and 3.2.3, it is important to identify and characterize the European Commission's restructuring aid cases included into our data set.

3.2.1 Characterization of restructuring aid cases

Referring to our categorization of state aid in the European Union introduced above, we concentrate on restructuring aid decisions by the European Commission between 2003 and 2012. Using the European Commission's online database, we first accessed the entire set of decided restructuring aid decisions. Out of this group of cases, we identified all positive restructuring decisions for individual firms (not aid schemes such as those that exist for SMEs). We exclude decisions in the financial sector as these are subject to specific rescue and restructuring rules. Since the 2004 Guidelines are not valid for firms in the coal and steel sector either, we exclude these firms from the analysis as well. Furthermore, the agricultural sector and the fishery industry – as defined in Section 5 of the 2004 Guidelines – as well as cases in which aid was granted to firms in the former

German Democratic Republic in connection with the reunification of Germany were also excluded due to their status as special types of restructuring aid.

In total, our case selection procedure eventually identified 67 firms that received restructuring aid and fit to the above criteria. Figure 2 below characterizes the respective cases in terms of both their decision year as well as the amounts of aid granted.

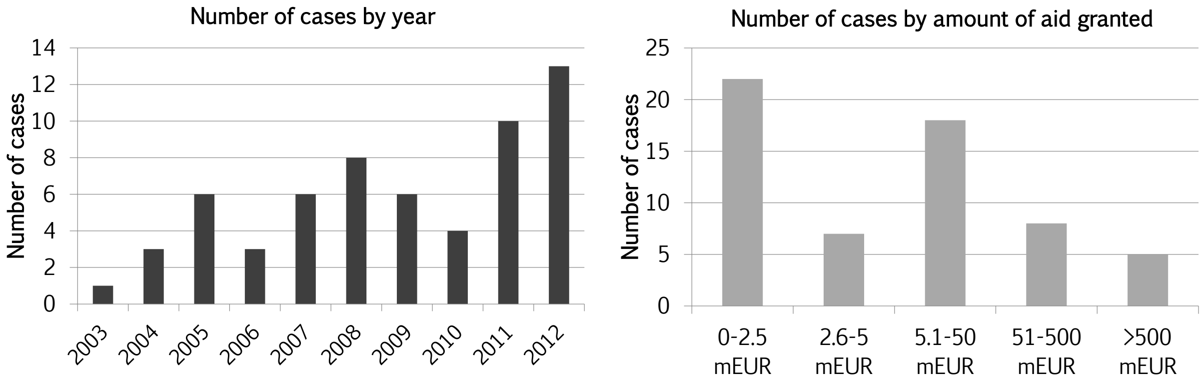

Figure 2: Restructuring aid cases by year and amount of aid granted (2003-2012)

Data source: EC restructuring aid decisions

As shown in the left-hand chart in Figure 1, in general terms, the number of restructuring aid cases has experienced an overall growth since 2003, with the last year (2012) representing the highest number of decisions taken by the EC. Nevertheless, there has been some volatility as shown by declining trends from 2005 to 2006 and 2008 to 2010. Over the last three years (2010 to 2012), there was consistent growth from 4 to 13 cases.

With respect to the amount of restructuring aid granted, the right-hand chart in Figure 2 shows that in almost half of all cases, the firms benefited from an amount of up to EUR 5 million, while about 30 percent of the companies were granted aid between EUR 5.1 million and EUR 50 million. At the upper end of the spectrum, we find about 13 percent of the firms receiving an amount between EUR 51 million and EUR 500 million leaving the remaining about 8 percent for restructuring aid granted above EUR 500 million.

In terms of aided firm size, we find that the majority of about 78 percent of all aided firms were large according to the official categorization by the European Commission, leaving the remaining 22 percent for medium or small firms. In terms of number of employees – as an alternative measure of firm size – about 44 percent of the aided firms have less than 250 employees with about 17 percent of the benefitting companies having between 250 and 499 employees thus leaving the remaining about 39 percent for firms with a number of employees above 499.

Location wise, it is important to note that almost 40 percent of the aided firms have their headquarters in Poland, with Italy and France representing an additional almost 22 percent. The remaining EU Member States generated relatively few or no restructuring aid cases (after executing our selection procedure). From the total of 17 countries represented in our analysis, six countries (Cyprus, Denmark, Finland, Germany, Malta and Slovakia) only had one company receiving aid during the observation period with the same number of countries (Austria, Belgium, Czech Republic, Lithuania, Slovenia and the United Kingdom) having two benefiting companies. In addition, five Member States (France, Greece, Italy, Spain and Poland) had three or more aided companies

3.2.2 Dependent variables

Our main outcome variables are *firm survival* in general and *firm financial viability* in particular. As there are no unique definitions of either of these two variables, we characterize our measurement approaches in greater detail in the following.

Definition of firm survival

Although on the surface, firm survival appears to be clearly defined, a closer look reveals that especially the treatment of firms that either merged with (or were taken over by) another firm or are in liquidation (or under bankruptcy protection) requires a richer set of alternative definitions of survival shown in Table 1.

Table 1: Alternative definitions of survival

	Def. 1a	Def. 2a	Def. 1b	Def. 2b
Active	×	×	×	×
In Liquidation/Insolvency Procedure/ Bankruptcy/Default of Payment/Dormant	-	×	-	×
Merger or Takeover	×	×	-	-
Dissolved	-	-	-	-

Note: Crosses indicate that the respective status is included in the survival definition.

In implementing these four definitions of survival, we use the information provided in the AMADEUS database[9] to first generate a dummy variable that indicates a firm's operating status in 2014 (the final year of our analysis). Firms are considered as being alive (i.e., the dummy equals 1) if AMADEUS reports that a firm is either 'active' or was 'acquired' (Definition 1a).

However, in applying this definition, firms that are in 'insolvency proceedings' and firms that were 'finally dissolved' are treated equally. This may be a too narrow definition of a firm being active since firms can possibly recover after going through insolvency proceedings. Hence, we generate an additional dummy variable which considers a firm as being alive if AMADEUS reports that this firm is either 'in liquidation' or 'bankrupt'[10]. However, the firm is considered dead if AMADEUS either reports it as 'finally dissolved' (Definition 2a).

Additionally, it might create additional value in the empirical analysis below to distinguish between active firms that were target of a successful take-over bid and firms that remained legally independent. For this reason, we introduce additional classifications of firm survival, based on the two remaining definitions above, as part of which we exclude acquired firms from the definition of firm survival. Therefore, Definition 1b considers firms as being alive only if AMADEUS reports that a firm is 'active' (and neither 'acquired' nor 'in liquidation' nor 'bankrupt' nor 'finally dissolved') and Definition 2b counts firms as being alive only if AMADEUS reports that a firm is 'active', 'in liquidation' or 'bankrupt' (but considers them dead if they were acquired or finally dissolved).

Definition of firm financial viability

In order to assess a firm's financial viability we apply the z-score concept of Altman (1968, 2002). Altman proposes a multivariate procedure to predict a firm's probability of going bankrupt within two years. This probability can be separated into three categories: Low, mid-level and high. We consider firms with a high probability of going

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[9] The Amadeus database, provided by Bureau van Dijk, contains comprehensive financial and business information on around 21 million companies across Europe. In particular, it includes standardized annual accounts, financial ratios, sectoral activities and ownership data. See http://www.bvdinfo.com/en-gb/our-products/company-information/international-products/amadeus for further information (last accessed on 13 February 2016).

[10] Please note that the term 'bankruptcy' in this section refers to the AMADEUS definition and does not perfectly coincide with our definition of a firm's market exit in this paper.

bankrupt as firms with insufficient financial viability, firms with a mid-level probability of going bankrupt as firms with normal financial viability, and firms with a low probability of going bankrupt as firms with high financial viability.

According to Altman, the probability of going bankrupt can be determined by z-scores. The calculation of z-scores depends on the legal form of the company. For *publicly listed firms*, z-scores (Z) are calculated by the following equation:

$$\mathrm{Z} = 1.2 * \mathrm{X}_1 + 1.4 * \mathrm{X}_2 + 3.3 * \mathrm{X}_3 + 0.999 * \mathrm{X}_4 + 0.6 * \mathrm{X}_5 \tag{4}$$

X_1 represents the ratio of working capital to total assets, X_2 is the ratio of retained earnings to total assets, X_3 is defined as the ratio of earnings before interest and taxes (EBIT) to total assets, X_4 represents the ratio of total revenue to total assets and X_5 is the ratio of the market value of equity to total liabilities.

With respect to *private companies*, z-scores are given by the following equation:

$$\mathrm{Z} = 0.717 * \mathrm{X}_1 + 0.847 * \mathrm{X}_2 + 3.107 * \mathrm{X}_3 + 0.998 * \mathrm{X}_4 + 0.42 * \mathrm{X}_6 \tag{5}$$

with X_6 being the ratio of the book value of equity to total liabilities. Hence, the differences between equations (4) and (5) are the weights attached to the five balance sheet ratios as well as the different kinds of ratios of equity to total liabilities. While the market value of equity is taken into account for publicly listed firms, the book value is used for private firms. The final categorization of a firm's financial viability is shown in Table 2.

Table 2: Categorization of a firm's financial viability according to Altman z-scores

Category	Description	Z-Score Range for Publicly Listed Firms	Z-Score Range for Private Firms
1	Insufficient financial viability	$Z < 1.81$	$Z < 1.23$
2	Normal financial viability	$1.81 < Z < 2.99$	$1.23 < Z < 2.9$
3	High financial viability	$Z > 2.99$	$Z > 2.9$

Source: Altman (1968).

In applying Altman's z-score method[11] to our data set, we use information provided by AMADEUS[12] to determine the legal form of the firms in our sample and to calculate the corresponding z-scores following equations (4) and (5) stated above. Specifically, we make use of the following balance sheet figures from AMADEUS: 1) Total revenue, 2) EBIT, 3) Non-current assets, 4) Current assets, 5) Non-current liabilities, 6) Current liabilities, 7) Book value of equity and 8) Other equity. Total assets are calculated as the sum of 3) and 4), total liabilities as the sum of 5) and 6), and working capital as the difference of 3) and 6). Information regarding retained earnings and the market value of equity are not provided by AMADEUS. However, since retained earnings are part of the balance sheet figure 'Other equity', we use 8) as a proxy for retained earnings. In addition, we use the book value of equity for both groups of firms, publicly listed and private. Last but not least, we assign all firms in our data set to the above mentioned three categories – insufficient, normal or high financial viability – defined by Altman.

3.2.3 Independent variables

Turning to the independent variables, we use – in addition to the above mentioned variables 1) Total revenue, 5) Non-current liabilities and 6) Current liabilities – the following further financial and business information in our econometric analysis (which we also obtained from AMADEUS): 9) Net earnings (profits), 10) Liquidity ratio, 11) Solvency ratio, 12) Employment level, 13) Year established, 14) Firm size, 15) NACE Code, and 16) Country.

The liquidity ratio is the ratio of quickly marketable assets (e.g., cash) to non-current liabilities. Hence, the financial viability should be positively linked to a higher liquidity ratio. The solvency ratio is defined as the ratio of the sum of net earnings and depreciation to total liabilities. As with liquidity ratios, high solvency ratios imply a higher financial viability. Firm size is categorized by AMADEUS into four types: Small,

[11] Even though Altman's method to predict bankruptcy is sometimes criticized due to its simplicity in general and its failure to consider the general market environment (e.g., local bankruptcy laws) in particular, it is still viewed as a reliable (and frequently applied) tool to assess a firm's financial stress condition (see, e.g., Grice and Ingram, 2001). In fact, recent research suggests that the efficacy of the Altman z-score in predicting financial distress is high with bankruptcy filings being accurately predicted in 94 percent of the cases and financial distress in over 90 percent of the cases (see Hayes et al., 2010). Furthermore, the z-score continues to enjoy great popularity in the finance literature and is a crucial part of contemporary commercial rating models (e.g. Agrawal 2013, Altman and Hotchkiss, 2006 or Bemmann, 2005).

[12] As AMADEUS only provides information for the most recent ten years – and also drops firms that have exited the market after several years – we also use historical AMADEUS data.

medium, large and very large. The NACE Code, which indicates a firm's main area of activity, is obtained on the four-digit level.

Additional country-level data is drawn from Eurostat. In particular, we obtain the following three variables: 17) Average unemployment rate of the last three years, 18) Ratio of subsidies to governmental expenditures, and 19) GDP per capita. These variables are measures which might affect the propensity of a national government to provide aid to firms. For example, when the economy is in a bad state (i.e., it faces low GDP growth and high unemployment), political pressures to grant aid are expected to be higher. However, governments with a general tendency (or culture) to support firms through transfers – for example, as part of an industrial policy approach – might generally be more prone to grant restructuring aid.

In sum, by using the name of the aid receiving firms, we were able to identify 63 out of 67 restructuring aid receiving firms in AMADEUS and obtained the respective financial and business information for the years between 2000 and 2013. The pool of possible matching partners forms, together with the observations for the aid receiving firms, the sample for the subsequent matching. It includes firms that (a) have its company headquarters within the EU-28 and (b) operate in a similar industry (measured by the first two digits of the NACE Code) as the aid receiving firms (see Section 3.3 below).

We had to cope with certain challenges in terms of data availability with respect to both dependent and independent variables as AMADEUS does not consistently report the respective information throughout our time period of interest (2000 to 2014). For some firms, there are gaps in the data with respect to specific years or variables. It is partly also the case that, in a given year, one or more variables are missing.

Due to the large number of possible matching partners, we are less concerned about data availability of non-aid receiving firms. However, we aim at avoiding missing values with respect to the independent and dependent variables of aid receiving firms in order to keep as many aid-receiving firms as possible in our analysis. In particular, the values of variables for the years before state aid was granted are of relevance for the identification of appropriate matching partners for the aid-receiving firms. As a consequence, we imputed a small number of data points with respect to the variables used in the matching procedure to avoid severe reductions in the subsample of aid receiving firms. A full documentation of the imputed data points can be found in Table 10 in the Annex.

3.3 Matching procedure and Average Treatment Effect on the Treated (ATT)

The construction of counterfactuals for treated firms that received restructuring state aid will be conducted by matching methods in order to mitigate problems arising from selection bias. Matching rests on the following identifying assumptions: i) the selection into the treatment group is only driven by observable variables ('selection on observables') and ii) based on the selection on covariates, selection into treatment is random (the 'conditional independence assumption' (CIA) discussed above). Matching further requires iii) a large enough sample size to ensure that there is an overlap ('common support') as regards the observables in both groups, treated and untreated units, as well as sufficient information on covariates that affect both the treatment decision and the outcome.

In our case, (i) and (ii) implies that we observe all relevant factors why one firm receives aid and another one does not. The analysis can be confounded, e.g., when aided firms have systematically better political connections and we do not account for this. Then, the measured treatment effect not only captures the effect of aid, but also of this unobserved firm characteristic. In practice, this concern might not be particularly relevant as it alleges favoritism by the European Commission. Finally, iii) is violated if, e.g., all large firms in our data set receive aid. In such a case, there is no common support for firm size.

When treatment assignment depends on a vector of discrete and continuous covariates, the concept of propensity score matching becomes particularly useful. Whereas exact matching methods (which require identical values for each variable for treatment and control group) suffer from the curse of the dimensionality problem (lack of common support), less restrictive matching methods – such as propensity score matching (PSM) – reduce this problem by defining a single distance metric based on the covariates. Functions of relevant observed covariates are referred to as balancing scores. One type of balancing score is the propensity score which measures the conditional probability of treatment assignment (see Caliendo and Kopeinig (2008) for an overview).

In order to predict the probability of receiving state aid, we estimate a probit model with the following list of covariates (using the data sources described above):

- *Firm level financials:* ln Profit; ln Fixed Liabilities; ln Current Liabilities; Revenue per Employee; Altman z-score category; Liquidity ratio; Solvency ratio; dummy 'Public firm' indicating whether the firm is listed on the stock exchange
- *Firm level structural characteristics:* ln Employment; ln Age; firm size dummies ('Medium Firm'; 'Large Firm'; 'Very Large Firm')
- *Industry level:* Industry dummies based on 1-digit NACE industry codes
- *Country level:* Dummies for the country where the firm is headquartered
- *Macro level:* Unemployment level of the last 3 years; Share of subsidies from governmental expenditures; GDP per capita

Firm level financials include size measures (in logs) as well as financial key ratios, productivity and ownership measures. Firm performance in terms of the financial key ratios and productivity approximates financial viability. One would expect that the higher a firm´s financial viability is the lower is the likelihood that it will receive restructuring aid. A firm´s liquidity and solvency ratio directly captures a company´s risk of default and hence the probability to receive state aid. Similarly, whether a firm is listed on the stock exchange as well as the financial structure in terms of liabilities in general reflects the firm´s ability to access capital markets. The way firms have access to capital markets might be crucial for the survival of firms in financial distress and hence also exerts a potential impact on receiving restructuring aid.

Firm level structural characteristics provide different measures of firm size that influence the economic and political consequences of firm bankruptcy and hence the likelihood of receiving state aid. Firm characteristics such as firm size and the age of a company will also likely influence the adjustment process of firms in financial distress and hence firm survival.

Industry level dummies capture any industry specific heterogeneity such as differences in industry growth rates or industry specific risks. Similarly, country level dummies capture any institutional and macroeconomic effects that are peculiar to individual EU Member States and which are not covered by the other macro level controls. The latter control for different income levels, national labor market conditions as well as the proneness of national governments to provide public subsidies in general. It appears that this group of controls also exerts a potential impact on both, the likelihood to receive state aid as well as firm survival. Table 12 in the Annex reports the results of the probit regressions.

First, our main probit regression produced a reasonably good model fit (McFadden Pseudo-R2 ~ 0.39) indicating a high predictive power of the included covariates. Furthermore, due to the large number of Polish bus operators (NACE Code 4939) among restructuring aid recipients (7 out of 67), we performed the probit regression both with (regression (1)) and without (regression (2)) public Polish bus operators in order to ensure the robustness of our empirical analysis. The total number of observations used in the probit estimation contains 57 firms comprising the treatment group in regression (1) and 53 treated firms in regression (2).[13]

Based on the results of the probit regressions, we can identify the group of counterfactual firms for the firms that received restructuring aid ('treated' firms). We first construct different counterfactual groups starting with the nearest neighbors (NB = 1). We then extend the counterfactual group to a total number of three neighbors (NB = 3) in order to examine whether our estimates are robust towards different specifications of neighbors. We apply nearest neighbor matching with replacement meaning that each observation of the control group can be matched with more than one of the treated observations.

To identify the nearest neighbors, we do not solely rely on the estimated propensity scores but – in order to avoid 'bad' matches where, e.g., a treated observation is matched to a completely different industry – also conduct direct matching on the following arguments: same 2-digit NACE Codes, firm size (small, medium, large or very large as classified in AMADEUS), a binary variable that indicates whether a firm is publicly listed, and the year which represents the start date of the restructuring measure. This ensures that the nearest neighbor belongs to the same industry category, has the same legal form, the same size and that the counterfactual outcome is observed in the same year the treated firm received state aid. All steps conducted for the matching procedure are summarized in the matching protocol in Table 11 in the Annex.

A necessary condition for the validity of the matching procedure refers to the common support requirement. In our case, we deleted observations whose propensity score is smaller than the minimum and larger than the maximum of the other group (see Caliendo and Kopeinig, 2008). This basic criterion avoids incomparable matches and discards one observation from the unrestricted treatment group and two observations for

[13] Three of the four aid receiving firms which we could not identify through AMADEUS were Polish bus operators. Thus, we only exclude four out of the seven Polish bus operators in regression (2). Furthermore, we lose six further firms in the probit estimations due to insufficient data availability.

the restricted treatment group which precludes the four restructuring aid cases of Polish bus operators. This ultimately results in a total number of 56 (51) treated firms for the subsequent treatment evaluation analysis.

Further assessments of the quality of the matching procedure refer to the performance measures of the probit model. The Pseudo R^2 measures the explanatory power of the covariates which should be substantially lower after the matching procedure (see Sianesi, 2004). Indeed, comparing the Pseudo R^2 in Table 12 (Pseudo R^2 ~ 0.39) with the respective value of the probit regression after matching based on the sample of treated units and counterfactuals in Table 13 (Pseudo R^2 ~ 0.17 for NB = 1 and Pseudo R^2 ~ 0.16 for NB = 3) indicates that the systematic differences between both groups decreased substantially after controlling for covariates. Similarly, one can compare likelihood ratio tests on the joint significance of all covariates in the probit model before and after matching (see Caliendo and Kopeinig 2008, p. 49). As required, the null hypothesis ('all covariates are jointly insignificant') is rejected before (p = 0.00) but not after matching (p = 0.83 for NB = 1 and p = 0.28 for NB = 3).

Finally, we apply ordinary two-sample t-tests to check the balancing properties of our matching procedure. The tests examine whether the mean values of the included covariates differ statistically significant for treated and untreated groups before and after matching (H0: 'means are equal for both groups'). For obvious reasons, matching is designed to ensure that for units with a similar propensity score, the assignment to treatment is random and independent of the covariates. This would closely re-establish the conditions of a controlled randomized experiment. If this is satisfied then firms with the same propensity score must have the same distribution of covariates independently of the treatment status. This balancing condition can be tested by the differences in means for each covariate.

The last column of Table 14 in the Annex reports the result of the mean tests applied to the full sample, i.e., before matching is conducted. As expected, almost all means of the covariates are significantly different between treated firms (N = 57) and untreated firms (N = 1,132,360). In contrast, the last two columns of Table 3 below report the mean test applied to the sample generated by the matching (for nearest (NB = 1) and three neighbor (NB = 3) matching).

Table 3: Mean difference tests after matching

	Aid receiving firms $N = 56$		Selected control group (NB = 1) $N = 56$		Selected control group (NB = 3) $N = 168$		*t*-tests on mean differences	
Variables	Mean	S.D.	Mean	S.D.	Mean	S.D.	NB=1	NB=3
Financial Figures								
ln Profit	-3.69	7.27	-2.50	8.11	-3.20	7.26	-	-
ln Fixed liabilities	7.60	4.12	7.24	4.89	7.61	4.22	-	-
ln Current liabilities	9.95	2.71	10.12	2.82	9.90	2.46	-	-
Revenue per employee	153.89	218.74	184.85	187.04	211.72	275.24	-	-
Altman Z-Score category	1.36	0.59	1.39	0.65	1.49	0.71	-	-
Public firm	0.66	0.48	0.66	0.48	0.66	0.47	-	-
Liquidity ratio	0.68	0.65	0.62	0.41	0.90	2.57	-	-
Solvency ratio	9.53	36.39	15.19	30.41	14.26	28.24	-	-
Firm Characteristics								
ln Employment	6.09	1.77	5.92	2.32	5.75	2.00	-	-
ln Age	3.05	1.14	2.67	0.91	2.88	0.93	*	-
Medium firm	0.30	0.46	0.30	0.46	0.30	0.46	-	-
Large firm	0.29	0.46	0.29	0.46	0.29	0.45	-	-
Very large firm	0.34	0.48	0.34	0.48	0.34	0.47	-	-
Macro level Information								
Unemploy. last 3 years	9.64	4.25	9.78	4.02	9.40	3.34	-	-
% subs. from gov. exp.	62.67	11.22	63.97	8.29	64.48	8.65	-	-
GDP per capita	2.16	2.50	2.01	2.37	1.64	2.59	-	-
Outcome								
Stat. 2014 Def. 1a	*0.82*	*0.39*	*0.68*	*0.47*	*0.67*	*0.47*	*	**
Status 2014 Def. 2a	*0.88*	*0.33*	*0.73*	*0.45*	*0.73*	*0.44*	*	**
Status 2014 Def. 1b	*0.80*	*0.40*	*0.63*	*0.49*	*0.62*	*0.49*	**	***
Status 2014 Def. 2b	*0.86*	*0.35*	*0.68*	*0.47*	*0.68*	*0.47*	**	***

Notes: Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. H_0: equal means for both groups. As the nearest neighbor matching procedure is performed with replacement, we also impose Lechner´s variance approximation (Lechner, 2001) on the outcome variables.

As shown in Table 3, only for one of all covariates (log of firm age), there is a (weakly) significant difference between the selected control group and aid receiving firms (as indicated by one star in the NB = 1 column). Therefore, and in line with the above tests, we are confident that our matching procedure was successful in identifying valid counterfactuals for the group of treated (i.e., restructuring aid receiving) firms.

The outcome variable is the variable of interest in determining the treatment effect. As explained above and illustrated in the bottom of Table 3 we analyze four different outcome variables. The outcome variable (firm survival) is equal to 1 if AMADEUS reports that the status of a firm in 2014 is 'active' or 'acquired' (Definition 1a), 'active', 'acquired', 'in liquidation' or 'bankruptcy' (Definition 2a), 'active' (Definition 1b) or 'active', 'in liquidation' or 'bankruptcy' (Definition 2b). Hence, in Definition 2a, only firms are defined as having exited the market if their status is 'dissolved'. The justification for this definition of outcome is that full recovery is possible for firms with status 'in liquidation' or 'bankruptcy' and such firms can even receive state aid under certain conditions. Furthermore, the outcome Definitions (.)a differ from their Definitions (.)b counterparts in the sense that they consider acquired firms as having exited the market. The motivation behind this differentiation is that it may depend on the ultimate aim of granting restructuring aid whether an acquisition of a restructured (aided) firm is evaluated as a success of the measure or not.

The parameter of interest is the average treatment effect on the treated (ATT), where the mean average outcome of the untreated group – identified through the matching procedure – defines the relevant counterfactual for the outcome of the treated group (see equation 3 above). The lower part of Table 3 reports the outcome values for aid receiving firms (column 2) and different control groups with one (column 3) and three (column 4) nearest neighbor(s). One can infer that treatment in terms of receiving state aid exerted a significantly positive impact which is robust to the choice of definition of the outcome variable (Definitions 1a, 1b, 2a and 2b) suggesting that restructuring aid measures significantly increase the survival probability and reduce the probability of a firm's market exit, respectively.

For instance, the absolute difference in the probability of a firm to survive until at least 2014 is $0.82 - 0.68 = 0.14$ if we compare the outcome according to Definition 1a of the treated firms with the counterfactual group with one nearest neighbor. This means that whilst 82 percent of aided firms were active in the year 2014, only 68 percent of the matched non-aided firm were active, implying a difference of 14 percentage points with respect to firms' operating status. As noted above, the difference of 14 percent, however, is the absolute difference meaning that from 100 firms 14 firms survive due to restructuring aid which otherwise had exited the market. In relative terms, the interpretation is that the average survival probability increases by 21 percent when a firm receives restructuring aid (0.14/0.68).

An alternative interpretation looks at the probability of a failure which is 1 minus the survival probability. Thus, aid recipients will exit the market with a probability of 18 percent and non-aid receiving firms with 32 percent probability. In other words, receiving restructuring aid decreases the average risk of a failure by 44 percent (1-0.18/0.32) or, alternatively expressed, a non-aid receiving firm from the counterfactual group has 78 percent (0.14/0.18) higher relative risk of failure than an aid recipient.

The differences in average outcome variables of the treated firms is statistically significant according to two-sided t-tests (column 5) throughout all definitions and for both, the counterfactual groups with one and with three nearest neighbors, while there was no significant difference before in the full sample (see Table 3). Comparing the results for the different outcome definitions, we find the largest value for Definition 2b, the outcome definition which considers acquisitions as market exits. In other words, aid receiving firms are less frequently acquired compared to non-aid receiving firms. Table 4 below exemplary provides the respective calculations for the nearest neighbor (NB = 1).

Table 4: Differences in survival probability and failure risk (NB = 1)

	a Absolute difference	*b* Survival prob. for non-aid recipients	*c=a/b* Aid increases survival prob. by:	*d=1-b* Failure risk for non-aid recipients	*e=a/d* Aid reduces failure risk by:
Def. 1a	14%	68%	21%	32%	44%
Def. 2a	15%	73%	21%	27%	55%
Def. 1b	17%	63%	27%	37%	46%
Def. 2b	18%	68%	26%	32%	56%

Limiting our discussion of the results to the very right of Table 4, it is shown that restructuring aid reduces the failure risk by between 44 and 56 percent. Also, the different definitions of survival reveal that the probability of being taken over is lower for aid recipients as is the probability to be in liquidation or under bankruptcy protection.

3.4 Estimating the impact of state aid on firm survival

In this section, we continue investigating this relationship by using survival analysis. Survival analysis – also referred to as 'time to event' analysis or more generally duration analysis – provides a alternative perspective on our subject of study. These methods represent a common tool to analyze the time until the occurrence of an event and are frequently applied not only in economics but also in a variety of other research disciplines such as pharmaceutical statistics (e.g., to assess the efficacy of a new therapy in a clinical trial) or engineering (e.g., to study the lifetime of machine components).

In our application, the event is the market exit of firms. There are two main concepts in the field of survival analysis. The first is the survivor function which is used to determine the probability of an individual to survive beyond a certain point in time (i.e., a firm is still active after a specific time period). The second concept is the hazard rate or hazard function which is the probability that an individual will experience the event while that individual is at risk for having an event(i.e., the probability that a firm will exit the market in t and it was operating in t-1).

Survival analysis enables us to effectively consider right censoring. Right-censoring means that some individuals do not experience the event until the end of the observation period (see Allison 2010, pp. 413ff.). In our case, firms are said to be right-censored if they do not exit the market until the last year of our observation period (i.e., 2014), but potentially will do so afterwards. To adequately consider right-censoring the dependent variable in survival analysis has two components: 1) the time to event and 2) the event status, which records if the event of interest occurred during the observed time period or not.

The aim of our survival analysis is to estimate and compare survival functions and hazard rates, respectively, of treated and matched control firms in our data set. Using survival analysis in this section, we aim at answering the question how the granting of restructuring aid affects the overall survival time of firms. Survival analysis can be either conducted non-parametrically, parametrically or semi-parametrically with all approaches having their specific advantages and drawbacks. In the following, we limit the discussion of our estimation results to the parametric (Section 3.4.1) and semi-parametric (Section 3.4.2) duration methods (since we are also interested in studying the impact of covariates on survival).[14]

[14] The results of an application of non-parametric survival methods, i.e., Kaplan-Meier and Nelson-Aalen estimates, are available from the authors upon request.

3.4.1 Parametric analysis

Generally, parametric survival models enable us to control for co-factors with potential impact on survival probability. More importantly, they also allow to estimate the baseline hazard from which we can predict the average survival time of a firm with certain characteristics. Having chosen the appropriate model, parametric survival models deliver the highest efficiency compared to either non-parametric or semi-parametric methods. As a drawback, the accuracy of parametric survival models depends on the distributional assumptions with regard to the survival time (most common are exponential, Weibull, Gompertz, loglogistic and lognormal distributions). Parametric survival methods are implemented in a regression framework and estimated by maximum likelihood. Regression analysis steps involve i) the identification of the distribution that best fits the underlying data and ii) the identification of relevant covariates.

With respect to the first step – finding the optimal distribution – we ran parametric regressions with several distributions and computed the corresponding information criteria. The model with the lowest information criteria provides the best model fit. In our case, as shown in Table 15 in the Annex, the Akaike Information Criterion and the Bayesian Information Criterion are lowest for the lognormal model while the exponential model fits the data worst. This finding is independent of the definition of outcome and the inclusion of covariates. Thus, in the second step, the parametric regressions are conducted using a lognormal model of the form

$$\ln(T_i) = \beta_0 + \boldsymbol{x_i}\boldsymbol{\beta_x} + u_i$$

where T_i represents the survival time of firm i, $\boldsymbol{x_i}$ is a vector of firm specific characteristics and u_i is an error term which follows a normal distribution with mean 0 and a standard deviation of σ. This specification implies the survivor function $S(t) = 1 - \Phi\left(\frac{\ln(T_i)-(\beta_0+\boldsymbol{x_i}\boldsymbol{\beta_x})}{\sigma}\right)$, where $\Phi(.)$ is the cumulative distribution function for the standard normal distribution.

Besides the treatment variable ‘aid’, we also let the survival time depend on additional covariates such as macro-level information as well as firm age and dummies for public firm and firm size (dummies for Medium Firm, Large Firm and Very Large Firm with Small Firms being the reference category). Thus, we can also investigate which factors may have an impact on survival probability and length, respectively. However, excluding those does not substantially change the results with respect to the ‘aid’ variable as – due to the matching procedure – both groups do not differ with regard to the control variables.

The corresponding estimation results are reported in Table 5 below. It is important to note that parametric survival models with a log-normal distribution are parametrized in accelerated failure time (AFT) metric, i.e., the coefficients measure to what extent the treatment accelerates or decelerates a firm’s survival time – with the underlying assumption being that a firm’s survival time is generally limited. In Table 5, we report the exponentiated coefficients from our estimates to make them interpretable as time ratios. This means they represent the factor by which the (expected) survival time is multiplied after a one-unit increase of the explanatory variable. Thus, a time ratio of 1.68 for ‘aid’ as estimated in Definition 1a can be interpreted as follows: restructuring aid prolongs the survival time by 68 percent (1.68-1=0.68) in comparison to the control group and approximately doubles survival time if we consider Definition 2a (107 percent lifetime expansion), respectively. For the models which consider acquisitions as market exit, we also find that public firms have a significantly longer survival time than private firms. The corresponding graphical illustrations of the survival functions computed with the means of the covariates from Table 5 are shown in Figure 3 in the Annex.

Table 5: Parametric survival function based on log-normal distribution (NB = 3)

	(1) Def. 1a	(2) Def. 2a	(3) Def. 1b	(4) Def. 2b
Aid	1.68***	2.07**	1.70***	2.08***
	(0.33)	(0.74)	(0.33)	(0.53)
Public Firm	1.29*	1.31	1.29*	1.30
	(0.20)	(0.28)	(0.19)	(0.24)
Age	1.00	1.00	1.00	1.00
	(0.00)	(0.00)	(0.00)	(0.00)
Medium Firm	1.10	1.08	1.09	1.07
	(0.37)	(0.59)	(0.29)	(0.56)
Large Firm	0.95	1.00	0.95	1.00
	(0.32)	(0.56)	(0.26)	(0.53)
Very Large Firm	1.57	1.43	1.50	1.37
	(0.53)	(0.80)	(0.42)	(0.72)
Share of subsidies from gov. expenditures (%)	1.00	1.00	1.00	1.00
	(0.01)	(0.01)	(0.01)	(0.01)
GDP per Capita	1.03	1.05*	1.03	1.05*
	(0.03)	(0.03)	(0.03)	(0.03)
Unemployment level last 3 years	1.04*	1.05	1.04*	1.04
	(0.03)	(0.03)	(0.02)	(0.03)
Intercept	4.52**	5.40**	4.58**	5.47**
	(3.04)	(4.41)	(3.00)	(4.35)
ln_sig	-0.19**	-0.06**	-0.22***	-0.09
	(0.83)	(0.09)	(0.08)	(0.09)
Sigma	0.83	0.95	0.80	-0.92
	(0.07)	(0.07)	(0.81)	(0.08)
N	1,438	1,464	1,406	1,432

Note: Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Coefficients are parametrized in accelerated failure time metric (AFT) and reported as Time Ratios (exponentiated coefficients).

As mentioned above, parametric survival models have the advantage that the intercept term is also explicitly estimated and defines the baseline survival time which enables the prediction of a firm's survival time conditional on covariates in general and the reception of aid in particular. Table 6 shows the respective results for all four definitions of a firm's survival.

Table 6: Average survival time

	Def. 1a	Def. 2a	Def. 1b	Def. 2b
Predicted average survival duration for aid=0 (years)	11.59	14.12	11.09	13.43
Predicted average survival duration for aid=1 (years)	19.53	29.20	18.86	27.96
Difference in average survival duration (years)	7.93**	15.09**	7.78**	14.53**

Table 6 reveals that the average time-to-failure (or survival time) is roughly between 11 and 14 years for the non-aid counterfactual. For the aid recipients, it is approximately twice as high with average times-to-failure between 20 and 29 years, depending on the specification of our survival variable.

3.4.2 Semi-parametric analysis

In this section, we complete our estimations of duration models with an application of Cox proportional hazard models. Cox models (see Cox, 1972) are semi-parametric as they leave the baseline hazard function $h_0(t)$ unspecified meaning that they do not impose restrictions on the shape of the baseline hazard and therefore allow the baseline hazard to be as flexible as possible (however, at the cost of not explicitly estimating the baseline hazard). Thus, this class of models does not allow making any predictions on survival time. The covariates, however, enter the model parametrically:

$$log(h_t) = log(h_0(t)) + \beta_1 x_{i1} + \cdots + \beta_k x_{ik} \tag{6}$$

or equivalently

$$h_i(t) = h_0(t) \cdot exp(\beta_1 x_{i1} + \cdots + \beta_k x_{ik}) \tag{7}$$

There is no constant term in the linear predictor $\eta_i = \beta_1 x_{i1} + \cdots + \beta_k x_{ik}$ as the constant is absorbed in the baseline hazard $h_0(t)$ which gives the hazard (or the occurrence) of an event in t if all other predictors are equal to zero. Thus, Cox models enable us to produce covariate-adjusted hazard ratios without imposing any assumption on the baseline hazard which yields generally more robust estimates compared to parametric analysis. In terms of interpretation, it is important to note that in contrast to the AFT metric from the log-normal parametric survival model, we report the coefficients in the Cox model as Hazard Ratios (HR), i.e., the ratio of a hazard rate with a one-unit increase of an explanatory variable and a hazard rate without such an increase. Hence, the HR represents the factor by which the hazard rate is multiplied as a result of a one-unit increase of an explanatory variable. With respect to our evaluation question, the

HR is the ratio of the probability of an event (in our case market exit) in the treatment group (i.e., aid recipients) to the control group (i.e., matched non-aid receiving firms) at any duration. Thus, the hazard ratio does not depend on the time survived in the proportional hazard model, i.e. the hazard ratio is constant over time. If this condition holds, the parameters can be estimated without consideration of the baseline hazard function. In our case, the proportional hazard assumption cannot be rejected as indicated by the test statistics presented in Table 7 below.[15]

Table 7 also reports the results for a Cox model with covariates, applied to the dataset with three neighbor matching and all four definitions of survival. We include a dummy for public firm, dummies for firm size (medium to very large), a firm's age as well as the macro-level variables unemployment level in the last 3 years, share of subsidies from government expenditures (%) and GDP per capita. We report hazard ratios (exponentiated coefficients) rather than the actual coefficients in Table 7 since their interpretation is more straightforward.

[15] The conducted tests are based on the scaled Schoenefeld residuals from the Cox models. If the test would reject the null hypothesis of proportional hazards one would interact the covariates with time or alternatively divide the data into strata. Since our dataset is discrete in time (calendar years), we apply the Efron method to handle tied failures.

Table 7: Cox regressions with covariates (NB = 3)

	(1) Def. 1a	(2) Def. 2a	(3) Def. 1b	(4) Def. 2b
Aid	0.416**	0.326***	0.398***	0.315***
	(0.160)	(0.155)	(0.153)	(0.150)
Public Firm	0.710	0.687	0.712	0.691
	(0.220)	(0.241)	(0.219)	(0.241)
Age	0.997	0.997	0.996	0.996
	(0.005)	(0.006)	(0.006)	(0.006)
Medium Firm	0.647	0.696	0.658	0.700
	(0.312)	(0.370)	(0.317)	(0.372)
Large Firm	0.850	0.714	0.846	0.710
	(0.415)	(0.395)	(0.412)	(0.392)
Very Large Firm	0.366*	0.495	0.388*	0.526
	(0.188)	(0.276)	(0.198)	(0.291)
Share of subsidies from gov. expenditures (%)	1.002	1.002	1.002	1.003
	(0.017)	(0.018)	(0.017)	(0.018)
GDP per Capita	0.934	0.918*	0.936	0.919*
	(0.041)	(0.044)	(0.042)	(0.044)
Unemployment level last 3 years	0.934	0.954	0.934	0.954
	(0.044)	(0.049)	(0.044)	(0.049)
Test of prop. hazard assump. p> χ^2 for all cov..	✓	✓	✓	✓
LR $\chi 2$	20.54	16.53	20.66	16.86
p> $\chi 2$	0.01	0.06	0.01	0.05
# subjects	224	224	224	224
# observations	1,436	1,462	1,404	1,430

Notes: Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01. Bootstrapped standard errors in parentheses (1,000 repetitions). Coefficients are exponentiated and to be interpreted as hazard ratios.

As revealed by Table 7, we find that restructuring aid significantly reduces the hazard regardless of the outcome definition. The hazard rate for those firms who received aid is only between 32 percent and 42 percent of the hazard rate for those firms that had not received the aid, or alternatively expressed, restructuring aid reduces the hazard rate between 58 percent and 68 percent – other things equal – which is measurably higher than our initial findings from the matching where we found restructuring aid to reduce the risk of a failure by 44 percent to 56 percent. In contrast to the findings from the parametric survival models, we do not find that a public firm has a statistically significant lower risk of a failure, however, the 'very large firm' coefficient is significant for Definitions 1a and 1b indicating that these firms also have a lower failure risk if ‘bankruptcy’ and ‘in insolvency procedure’ are not considered as market exit.

3.5 Estimating the impact of state aid on financial viability

Although the analysis of survival rates certainly provides useful insights on the impact of restructuring aid on the aided firms, it is a relatively general measure in the sense that a firm on the verge to bankruptcy – but still alive – is treated equally to a firm that prospered again. In this section, we therefore aim at introducing a financial performance indicator in the form of the Altman z-score, i.e., we now additionally consider the development of aid receiving and non-aid receiving firms’ financial situation over time. Whereas the outcome variable corresponded to the binary categorization in Definitions 1a, 1b, 2a, and 2b, this section employs a multinomial categorization of the dependent variable based on the Altman-z score as characterized in Section 3.2.2 above.

Although the Altman z-score is a continuous variable (which can be negative and take the value of zero), we construct the ordinal scale from Z-score categories as described in the data section above – suggested by Altman (1968, 2002) – in order to enable a reasonable consideration of market exit within this framework. We start this section with a descriptive overview of the Altman z-score differences between aid receiving and non-aid receiving firms over time as well as the general data availability required for the computation of z-scores followed by the estimation of ordered response regression models.

3.5.1 Descriptive information on Altman z-scores

Aiming at providing an initial descriptive overview of Altman z-scores, Table 8 below presents – for Definition 1a and three nearest neighbors (NB = 3)[16] – an overview of data availability of the dependent variables in the post-treatment period and also provides initial insights into the trend of financial viability of aid receiving firms in comparison to their matched non-aid receiving counterparts. In case of a firm’s bankruptcy or acquisition, respectively, we consider its market exit to take place one year after the last annual financial report is available in AMADEUS. As this procedure is conducted for both, aid receiving and non-aid receiving firms, it does not bias our results.

[16] The results for the remaining three definitions of survival are provided in Tables 16 to 18 in the Annex.

Table 8: Mean value of Altman z-scores per year, Def. 1a, NB=3

Time Cat	Year	$\overline{Z_N}$	$\overline{Z_A}$	P-val.	Number of firms from N: in $\overline{Z_N}$	died	acq	miss	total	Number of firms from A: in $\overline{Z_A}$	died	acq	miss	total
1	0	1.49	1.36	0.1544	168	0	0	0	168	56	0	0	0	56
2	1	1.52	1.36	0.1254	154	11	0	3	168	50	0	0	6	56
	2	1.59	1.47	0.2561	143	18	1	6	168	49	1	0	6	56
	3	1.62	1.48	0.2682	116	25	2	16	159	42	3	0	8	53
3	4	1.68	1.47	0.1395	94	27	3	5	129	36	4	0	3	43
	5	1.65	1.63	0.8836	77	27	5	5	114	32	3	0	3	38
	6	1.51	1.63	0.5580	51	30	5	7	93	24	2	0	5	31
4	7	1.67	1.70	0.8774	39	27	6	6	78	20	4	0	2	26
	8	1.75	1.58	0.5692	20	26	5	9	60	12	2	0	6	20
	9	1.83	2.14	0.4721	12	24	5	7	48	7	3	0	6	16
	10	2.20	2.38	0.6550	5	23	5	6	39	8	2	0	3	13

In Table 8, the column *Year* shows the number of years that have elapsed since restructuring aid was granted to an aid receiving firm or, in case of a non-aid receiving firm, to the matched partner in the treatment group. The columns $\overline{Z_N}$ and $\overline{Z_A}$ show the mean value of the Altman z-score category of the non-aid receiving (N) and aid receiving (A) firms, respectively. *P-values* refer to a two tailed t-test with assumed unequal variances, where the null hypothesis states that $\overline{Z_N} = \overline{Z_A}$. Separated by treatment status (i.e., non-aid receiving (N) and aid receiving (A)), the subsequent columns display the number of firms that (i) are included in the calculation of the mean value of the Altman z-scores (in $\overline{Z_N}$ and in $\overline{Z_A}$), (ii) have the status 'not active' (*died*), (iii) were acquired (acq), (iv) have the status 'active' and were not acquired but do not have enough financial variables to calculate a z-score (*miss*) and (v) are in the sample (*total*).[17]

As Table 8 reveals, data availability of z-scores depends largely on the considered time horizon. We have a higher number of observations for the first years after restructuring aid was granted, which decreases in later years. This has implications for the following time-dependent multinomial outcome analysis of the effect of restructuring aid on the financial viability of firms (which requires a high degree of data availability for the different time periods). Therefore, to increase the number of observations in each

[17] Mean values of Altman z-scores can only be calculated for firms that are active, not acquired and provide all relevant financial variables to calculate a z-score. Therefore, columns (i) to (iv) add up to (v).

time period, we cluster the observations of our sample into four time dependent categories, as shown in the column *Time Cat.* It is important to note that, in these tables, we did not drop observations for the years after a firm has exited the market or was acquired. Hence, the number of firms in the sample decreases over time solely due to right censoring, i.e., reaching the end of our observation period in the year 2014. The reason is that we can still use the information that a firm has exited the market in one particular period in the subsequent periods and we do not lose information for these firms.

However, while the start year of granting aid varies over time in the sample, the final year of our analysis is fixed to 2014 – which implies that we observe less firms over a longer time period. Additionally, this is also the reason why the number of firms with status 'not active' is not monotonically increasing. For instance, a firm that received aid in 2008 and had to exit the market in 2010 is only listed as 'not active' for the years 2 to 5. In year 6, the firm drops out of the sample – as the end of our observation period is reached – lowering the number of non-active firms due to right-censoring. The same is true for the number of firms that were acquired.

Table 8 also indicates a positive trend of financial viability for both groups of firms (if a company has survived). However, while $\overline{Z_N}$ is slightly higher than $\overline{Z_A}$ before restructuring aid was granted, the aid receiving firms $\overline{Z_A}$ (those which have survived) get ahead of those of $\overline{Z_N}$ (which have survived) after 5 years on average; then they are always higher but the difference between $\overline{Z_A}$ and $\overline{Z_n}$ never gets significant. However, there is a potential reason for this finding: From the previous estimations we know that non-aid receiving firms have a statistically significant lower survival probability. Because firms with low financial viability are apparently more likely to exit the market, putting the focus only on the Altman z-score categories per year without considering market exits would positively bias the financial viability measures in favor of the non-aid receiving firms.

This can be shown by the following example. Let us assume we have two aided firms, one with a good financial viability, one with a bad financial viability and also two non-aided firms, one with good and one with bad financial viability. If the aided firm with bad viability survives until time t because of the aid and the non-aided with bad viability dies prior to t, only looking at the Altman z-score categories would indicate that aid-receiving firms are more likely to be in a bad financial situation after three years. Thus, one has to take a look at both at the same time – surviving rates and Altman z-score categories per year – to get a full picture.

3.5.2 Ordered response

In the following we classify the dependent variable into three distinct outcomes which follow a natural ordering. Therefore, with regard to the bias before discussed, we re-classify the outcome variable and construct a separate category for firms that have exited the market. Furthermore, we group Altman categories 2 and 3 ('normal financial viability' and 'high financial viability') to one single category called 'save zone' in order to avoid a lack of observations the longer the period under review. This categorization enables us not only to analyze whether the probability of exiting the market differs between aid receiving and non-aid receiving firms but also whether full recovery is more likely for aid receiving firms or not. To summarize, the categories determining the outcome variable in the multinomial logit are as follows:

- *Category 1:* The firm has exited the market (Definitions 1a, 1b, 2a and 2b, respectively).
- *Category 2:* The firm is in the 'red zone' which is the Altman z-score category 'insufficient financial viability'. This is also the baseline category.
- *Category 3:* The firm is in the 'save zone' which encompasses the Altman z-score categories 'normal financial viability' and 'high financial viability'.

With three outcome categories, the ordered logit model estimates a set of coefficient vectors β_1, β_2 and β_3 corresponding to the respective outcome category. Following our brief discussion of non-feasible estimation methods in Section 3.1 above, it is difficult to interpret coefficients of interaction terms in discrete choice models (as required for the classical difference-in-difference estimator; see Greene, 2010). However, recall that after conducting the matching procedure, no significant difference in Altman-z score categories between treatment group and control group (before treatment) was received. Accordingly, the ordered logit approach may be interpreted as a conditional difference-in-difference approach.

Thus, the estimates from the ordered logistic models allow for an attractive way to work around the problem of the interaction terms in discrete-choice models by deriving marginal effects from the estimated results. Marginal effects refer to the effect of a unit increase in the explanatory variable on the probability of selecting the respective outcome category expressed in percentage terms. With a dichotomous explanatory variable (restructuring state aid is received or not), the marginal effect of receiving aid is the difference in the adjusted predictions for the two groups of firms, i.e., for treated and non-treated firms.

In order to examine the dynamics of firm survival, we estimate the ordered logit model for different time intervals of our period of analysis. In other words, for each of our three Altman z-score categories – dead, red zone and save zone – and for each time interval, we estimate the probability for both groups to be in the respective Altman z-score category and subsequently calculate whether the difference in the probability of being in the same category differs statistically significant between aid recipients and the counterfactual group.

Table 9 below reports the ordered logit estimation results for the alternatives definitions of firm survival, i.e., Definitions 1a, 1b, 2a and 2b, respectively. The row 'Margins' reflects the difference in the adjusted predictions of both groups of firms while 'Av. Pr.' is the average probability for an aid receiving and a non-aid receiving firm, respectively, to be in the respective category.

Table 9: Ordered logit estimates for different definitions of survival (NB = 3)

Definition 1a

Year	0			1-3			4-6			>6		
Z-Cat.	1	2	3	1	2	3	1	2	3	1	2	3
Av. Pr. No Aid	-	0.63	0.37	0.14	0.50	0.35	0.25	0.42	0.32	0.46	0.25	0.29
		(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.06)	(0.05)	(0.06)
Av. Pr. Aid	-	0.70	0.30	0.13	0.48	0.39	0.18	0.40	0.42	0.30	0.25	0.45
		(0.06)	(0.07)	(0.03)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)	(0.07)	(0.05)	(0.09)
Margin		0.07	-0.07	-0.02	-0.02	0.04	-0.07	-0.03	0.10*	-0.16*	0.00	0.16*
		(0.07)	(0.08)	(0.03)	(0.03)	(0.06)	(0.05)	(0.02)	(0.06)	(0.09)	(0.01)	(0.10)
N		224	224	221	221	221	163	163	163	92	92	92

Definition 1b

Year	0			1-3			4-6			>6		
Z-Cat.	1	2	3	1	2	3	1	2	3	1	2	3
Av. Pr. No Aid	-	0.63	0.37	0.16	0.50	0.34	0.29	0.42	0.30	0.52	0.22	0.26
		(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)	(0.04)	(0.05)
Av. Pr. Aid	-	0.70	0.30	0.13	0.48	0.39	0.18	0.39	0.43	0.31	0.23	0.46
		(0.06)	(0.07)	(0.03)	(0.04)	(0.05)	(0.04)	(0.04)	(0.06)	(0.07)	(0.05)	(0.08)
Margin		0.07	-0.07	-0.03	-0.02	0.05	-0.10**	-0.03	0.13*	-0.21**	0.01	0.19**
		(0.07)	(0.07)	(0.03)	(0.03)	(0.06)	(0.05)	(0.02)	(0.07)	(0.09)	(0.02)	(0.09)
N		224	224	221	221	221	166	166	166	98	98	98

Definition 2a

Year	0			1-3			4-6			>6		
Z-Cat.	1	2	3	1	2	3	1	2	3	1	2	3
Av. Pr. No Aid	-	0.63	0.37	0.12	0.53	0.35	0.23	0.44	0.33	0.40	0.29	0.31
		(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)	(0.07)	(0.05)	(0.06)
Av. Pr. Aid	-	0.70	0.30	0.10	0.50	0.40	0.15	0.40	0.45	0.26	0.28	0.46
		(0.07)	(0.07)	(0.02)	(0.04)	(0.06)	(0.03)	(0.05)	(0.06)	(0.07)	(0.05)	(0.10)
Margin		0.07	-0.07	-0.02	-0.03	0.05	-0.08*	-0.04	0.12*	-0.14*	-0.01	0.15*
		(0.07)	(0.07)	(0.03)	(0.04)	(0.06)	(0.04)	(0.03)	(0.07)	(0.08)	(0.02)	(0.08)
N		224	224	221	221	221	158	158	158	88	88	88

Definition 2b

Year	0			1-3			4-6			>6		
Z-Cat.	1	2	3	1	2	3	1	2	3	1	2	3
Av. Pr. No Aid	-	0.63	0.37	0.13	0.53	0.34	0.27	0.43	0.30	0.47	0.26	0.28
		(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.06)	(0.05)	(0.06)
Av. Pr. Aid	-	0.70	0.30	0.11	0.50	0.40	0.16	0.39	0.45	0.28	0.26	0.47
		(0.06)	(0.07)	(0.02)	(0.05)	(0.05)	(0.04)	(0.05)	(0.07)	(0.07)	(0.05)	(0.07)
Margin		0.07	-0.07	-0.03	-0.03	0.06	-0.11**	-0.05*	0.15**	-0.19**	0.00	0.19**
		(0.07)	(0.08)	(0.03)	(0.03)	(0.07)	(0.05)	(0.03)	(0.07)	(0.10)	(0.02)	(0.09)
N		224	224	221	221	221	161	161	161	94	94	94

Notes: Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01. Bootstrapped standard errors in parentheses (1,000 repetitions). 'Z-Cat.' represents the categories *market exit* (Z-Cat.=1), *red zone* (Z-Cat.=2) according to Altman z-score category 'firm with insufficient financial viability' and *save zone* (Z-Cat.=3) encompassing the Altman-z-score categories 'normal financial viability' and 'high financial viability'. 'Year' is the corresponding time period elapsed after the beginning of the restructuring measures. 'Av. Pr. Aid' and 'Av. Pr. No Aid', respectively, are the average probabilities of aid recipients and non-aid recipients to be in the corresponding category. Estimations applied to the dataset including the three nearest neighbors (NB=3).

When looking at the Altman categories 1 (Z-Cat.) in Table 9 ('firm has exited the market'), one infers that the probability of firm bankruptcy becomes significantly lower three years after the start of restructuring measures for firms that received restructuring aid. A unit change in the independent variable, i.e., aid received instead of no aid received, decreases the probability of a market exit by 21 percent in absolute terms (Altman cat. 1) after more than six years of restructuring while the difference is only 10 percent in absolute terms in the period from three to six years after restructuring (column 2). There is no significant difference observed in the first three years after the start of a restructuring measure. Accordingly, there is evidence of a positive treatment effect in terms of reducing the likelihood of market exit which starts after four years and then increases with the years elapsed since restructuring aid was granted.

This result therefore suggests that restructuring aid measures have a long-term rather than a short term impact on survival (conditional on a firm's survival in the first years). Furthermore, the probability of a firm's full recovery from financial distress – measured in categories of the Altman z-score – is also significantly higher for restructuring aid recipients in the long-term. Again referring to Table 9, we find a 19 percent higher probability for aid recipients to fully recover and reach the save zone six years after the restructuring aid was granted compared to the counterfactual, however, only a 13 percent difference 4 to 6 years after the start year and no significant impact in the first 3 years.[18]

4 Policy implications

Turning from the description of our empirical results to their policy implications, our main message is the following: state aid granted by the European Commission to firms in difficulty is effective in significantly increasing both the probability that these aided firms survive and that they return to a status of financial viability. In the light of the European Commission's aim to only grant state aid in the case of a firm "… which, without outside intervention by the public authorities would almost certainly condemn it to go out of business in the short- or medium term" (Section 2.1, para. 9 of the 2004 Guidelines), it can therefore be concluded that we find evidence consistent with the European Commission reaching this aim.

Our empirical results can further be put into perspective in light of earlier results reported in Glowicka (2006). Based on a data set of 86 R&R aid cases decided by the European Commission between 1995 and 2003, she finds that a significant fraction of the aid receiving firms eventually had to exit the market within the first four years despite receiving state aid. Thus, bailouts appear to have only delayed firm exit instead of

[18] The results from the ordered logit estimations are robust to the inclusion of covariates (i.e., age of the firm, dummy for public firms, GDP per capita, share of subsidies from government expenditures, three year unemployment rate). They are available from the authors upon request. Financial covariates were excluded because they are logically related to the dependent variable (as the Altman z-score is defined on the basis of a linear combination of financial covariates). Due to missing observations, we refrain from including the number of employees and, due to perfect prediction in some cases, firm size is also excluded. As the focus is on firm survival and financial viability (and the matching shows no mean difference for these variables), this does not bias our results.

preventing it. In this respect, our (partly) diverging results – using a more recent data set of 56 EC R&R aid cases decided between 2003 and 2012 – are consistent with the hypothesis that recent state aid reforms were successful in improving the evaluation process inside the European Commission leading to a better identification of those firms in difficulty – out of the entire group of applicants – that have an increased probability of survival (as, e.g., suggested by convincing restructuring plans). However, the fact that between 12 and 20 percent of the aided firms – according to our matching results – eventually still had to leave the market for good suggests that further incremental improvements in the effectiveness of the EC's process of granting R&R aid are still possible.

In addition to these main policy conclusions, prior research by Chindooroy et al. (2007) and Nulsch (2014) also aim at identifying factors that significantly influence the survival probability of aided firms. Our estimates from a parametric survival model partly suggest that public firms have a significantly longer survival time than private firms.[19] Furthermore, as part of our estimations of a semi-parametric survival model, we find limited evidence that very large firms have a lower failure risk. While the latter finding could be related to the well-known 'too big to fail' argument – suggesting that politicians have a strong incentive to bailout very large firms in fear of the severe social and economic consequences of their market exits – the former finding could reflect that public firms have better access to various financing sources leading to a significant increase in the survival probability.

In addition to these two main sets of results, two further policy-relevant implications can be drawn from our empirical analysis. First, our application of the matching procedure in combination with the four different definitions of survival reveals that aid receiving firms are less frequently acquired compared to non-aid receiving firms. This finding suggests that state aid is not consistently abused as windfall profit by firms who were planning to acquire the respective firm in difficulty anyway. Second, our empirical assessment of the financial viability of aided firms find that restructuring aid have a long-term rather than a short term impact on survival – conditional on a firm's survival in the first years – implying that the granting of restructuring aid often reaches the desired long-term survival of firms in difficulty.

[19] However, the respective coefficient loses its significance when applying semi-parametric estimation methods.

Thus, we can conclude that while we find evidence supporting the hypothesis that the European Commission only grant restructuring aid conditional on "… a feasible and coherent and far-reaching plan to restore a firm's long-term viability" (Section 2.2. para. 17 of the 2004 Guidelines), we have to leave the question whether this aim was achieved by limiting " … the amount and intensity of the aid … to the strict minimum of the restructuring costs necessary to enable restructuring to be undertaken …" (Section 3.2, para. 43 of the 2004 Guidelines) for future research.

5 Conclusion

In May 2012, the European Commission announced its State Aid Modernization (SAM) reform aiming at fostering growth in the internal market through streamlined rules and faster decisions. "State aid control should more effectively target sustainable growth-enhancing policies while encouraging budgetary consolidation, limiting distortions of competition and keeping the single market open" (European Commission, 2012, p. 4). Interestingly, in working towards these goals, the Commission's strategy does not only envisage the identification of common principles for assessing the compatibility of aid with the internal market – in combination with the creation or revision of guidelines and frameworks – but it explicitly includes an ex-post evaluation program as key tool to ensure an effective EU State aid policy (see European Commission, 2014).

From an academic perspective, the ex-post evaluation of state aid policies in general and rescue and restructuring (R&R) aid in particular can be subdivided further into two main research questions: First, from an effectiveness perspective, the question whether the granting of state aid had the desired direct effect suggests itself; i.e., in the case of R&R aid, did the granting of financial aid to firms in difficulty have a positive impact on their survival and financial viability? Second, from an efficiency perspective, the broader question is posed whether the respective state aid scheme or policy as such is socially desirable. In the case of R&R aid, such a broader assessment of social costs and benefits would have to go beyond the direct effects of the aid on the beneficiaries themselves (as well as their industries and sectors) and would additionally have to take various (positive or negative) indirect effects of the granting of aid on, e.g., competition, trade, employment, investment or economic growth into account.

In this paper, we concentrate on answers to the first research question by investigating whether 56 positive restructuring aid decisions – reached by the European Commission between 2003 and 2012 – had a measurable impact on the survival and financial viability of the aided firms. Confronted with the challenge of a causal identification of the treatment effect of aided firms, we follow an empirical approach based on matching techniques. We first employ the matching on the whole population of firms in the AMADEUS database of European companies in order to identify non-aided – but otherwise comparable – firms which act as control group. Subsequently, we apply both survival models and ordered response models on the sample of aid receiving firms and the constructed counterfactual group to empirically investigate the impact of restructuring aid on firm survival and financial viability. Our estimates suggest that restructuring aid increases a firm's average survival time by approximately 8 to 15 years or, putting it differently, decreases the exit rate by 58 percent to 68 percent. With respect to financial viability – measured by categories of the Altman z-scores – we find evidence that aid recipients not only have higher survival probabilities in the long-term but that they are also more likely to improve their financial viability compared to non-aid receiving firms.

From a policy perspective, our empirical results directly support the conclusion that the European Commission's R&R aid policy is effective in significantly increasing both the probability that firms in difficulty will survive as well as the probability that they return to a status of financial viability (in the long-term). Based on these findings on the effectiveness of R&R aid, the consequential next step – left for future research – is an ex-post evaluation of the efficiency of R&R aid. Although both data availability as well as methodological issues are expected to be substantial, a thorough and complete evaluation of state aid polices and schemes will have to provide the best possible answers to the ultimate question – namely whether such government policies are likely to generate positive or negative net total effects on social welfare.

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Annex

Table 10: Documentation of imputed data points in the group of treated firms

Name of the firm	Changes made
Cyprus Airlines	Copy employment, liquidity ratio, solvency ratio from 2005 to 2004
Götzke Natursteinwerke	Copy revenue, profit, EBIT from 2004 to 2007 and employm. from 2008 to 2007
Air Aland	Copy employment from 2008 to 2010
British Energy	Copy all variables of interest from 2004 to 2003
Macedonian Publishing	Copy all variables of interest from 2008 to 2010
Fluorite	Copy all variables of interest from 2007 to 2006
Air Malta	Copy all variables of interest from 2011 to 2010
Zaklad Naprawczy	Copy non-current assets from 2010 to 2011
Fabryka Samochobow	Copy employment from 2003 to 2004
Stocznia Gdansk	Copy employment from 2004 to 2005
Zaklady Miesne	Copy employment from 2010 to 2011
Fabryka Lozysk	Copy employment from 2005 to 2009
Konas	Copy all variables of interest from 2005 to 2004
Bull	Copy solvency ratio from 2003 to 2004
Krakowskie Zaklady	Copy solvency ratio from 2004 to 2007

Table 11: Matching protocol

Step 1	Specify and estimate the probit model to obtain the propensity scores $\hat{p}(\mathbf{x})$.
Step 2	Restrict the sample to common support: delete all observations of treated firms with propensity scores larger than the maximum and smaller than the minimum of the propensity scores in the control group.
Step 3	Choose one observation from the subsample of treated firms and delete all other observations from that subsample.
Step 4	Restrict the subsample of control firms to firms that have the same size (small, medium, large, very large) and operate in a similar industry (measured by the 2-digit NACE code) as the chosen treated firm. In addition, delete all observations that are not in the same year as the year in which the chosen treated firm received restructuring state aid.
Step 5	Calculate the difference of the propensity scores between the chosen treated firm and the remaining control firms.
Step 6	*For NB=1:* Select the observation with the minimum distance from the remaining control group. *For NB=3:* Select the three observations with the minimum distance from the remaining control group.
Step 7	Repeat steps 3-6 for all treated firms.

Table 12: Probit estimation before matching

	(1) Full Sample		(2) Without Polish Bus Operators	
Financial figures				
ln Profit	-0.0295***	(0.0068)	-0.0290***	(0.0069)
ln Fixed Liabilities	-0.0576***	(0.0189)	-0.0475**	(0.0198)
ln Current Liabilities	0.0128	(0.0516)	0.0314	(0.0515)
Revenue per Employee	-0.0002	(0.0002)	-0.0002	(0.0002)
Altman Z-Score category	-0.2368***	(0.0867)	-0.2511***	(0.0916)
Public Firm	0.2324**	(0.1107)	0.2550**	(0.1155)
Liquidity ratio	0.0035	(0.0314)	0.0079	(0.0235)
Solvency ratio	-0.0092***	(0.0016)	-0.0092***	(0.0016)
Firm characteristics				
ln Employment	0.2878***	(0.0554)	0.2533***	(0.0553)
ln Age	-0.0118	(0.0502)	-0.0355	(0.0507)
Medium Firm	0.0805	(0.1715)	0.0084	(0.1732)
Large Firm	-0.0706	(0.1920)	-0.0829	(0.1917)
Very Large Firm	-0.0632	(0.2566)	-0.0974	(0.2581)
Industry information				
NACE Industry Code 0	-0.0303	(0.4859)	-0.0249	(0.4824)
NACE Industry Code 1	-0.9418**	(0.3698)	-0.9177**	(0.3681)
NACE Industry Code 2	-0.8827**	(0.3539)	-0.8684**	(0.3527)
NACE Industry Code 3	-0.7224**	(0.3638)	-0.7128*	(0.3629)
NACE Industry Code 4	-0.8956**	(0.3552)	-1.0081***	(0.3602)
NACE Industry Code 5	-0.7546**	(0.3651)	-0.7542**	(0.3644)
NACE Industry Code 6	-0.5962	(0.5096)	-0.6237	(0.5104)
NACE Industry Code 7	-0.6800*	(0.3717)	-0.6906*	(0.3707)
Country information				
Belgium	-0.9548**	(0.3766)	-0.9893***	(0.3739)
Cyprus	0.1383	(0.7630)	0.1410	(0.7623)
Czech Republic	-1.0654***	(0.4001)	-1.0598***	(0.3982)
Germany	-1.3527***	(0.4437)	-1.3969***	(0.4444)
Denmark	-0.5638	(0.7137)	-0.5923	(0.7150)
Spain	-1.1296***	(0.3799)	-1.2017***	(0.3797)
Finland	-0.8810**	(0.4223)	-0.9195	(0.4224)
France	-1.3984***	(0.3980)	-1.4465***	(0.3967)
UK	-1.5745***	(0.4191)	-1.5881***	(0.4188)
Greece	-0.7936*	(0.4565)	-0.8620*	(0.4559)
Italy	-1.1410***	(0.3401)	-1.2121***	(0.3386)
Malta	0.5994	(0.8888)	0.5226	(0.8843)
Poland	-0.1504	(0.3483)	-0.2564	(0.3512)
Slovenia	0.5666	(0.4799)	0.5368	(0.4784)
Slovakia	-0.8110*	(0.4598)	-0.8920*	(0.4607)
Macro level information				
Unemployment level last 3 years	-0.0503***	(0.0173)	-0.0383**	(0.0175)
Share of subsidies from gov. expend. (%)	-0.0077	(0.0120)	-0.0081	(0.0120)
GDP per capita	0.0426**	(0.0201)	0.0434**	(0.0204)
Intercept	-1.5939	(1.0030)	-1.5812	(1.0028)
McFadden R^2	0.386		0.382	
LR χ^2	479.06		433.59	
p> χ^2	0.00		0.00	
#Observations	1,132,417		1,132,413	

Notes: Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table 13: Probit estimation after matching

	(1) N=1		(2) N=3	
Financial figures				
ln Profit	-0.0204	(0.0212)	-0.0104	(0.0165)
ln Fixed Liabilities	0.0527	(0.0709)	-0.0476	(0.0534)
ln Current Liabilities	0.0212	(0.222)	0.0701	(0.142)
Revenue per Employee	-0.000432	(0.00109)	-0.000168	(0.000682)
Altman Z-Score category	0.0185	(0.385)	-0.300	(0.221)
Public Firm	-0.172	(0.455)	-0.137	(0.321)
Liquidity ratio	0.703**	(0.339)	0.0382	(0.0643)
Solvency ratio	-0.0155**	(0.00661)	-0.0113**	(0.00448)
Firm characteristics				
ln Employment	0.102	(0.208)	0.206	(0.149)
ln Age	0.119	(0.174)	-0.102	(0.127)
Medium Firm	1.064	(1.002)	-0.747	(0.563)
Large Firm	0.909	(1.093)	-0.631	(0.628)
Very Large Firm	0.476	(1.288)	-0.779	(0.788)
Industry information				
NACE Industry Code 0	0.135	(1.800)	-0.187	(1.306)
NACE Industry Code 1	-0.577	(1.316)	-1.327	(1.026)
NACE Industry Code 2	-0.553	(1.204)	-1.202	(0.957)
NACE Industry Code 3	-0.114	(1.190)	-0.608	(0.943)
NACE Industry Code 4	-0.457	(1.246)	-1.161	(0.970)
NACE Industry Code 5	-0.809	(1.191)	-1.186	(0.960)
NACE Industry Code 6	0.135	(1.800)	-0.187	(1.306)
NACE Industry Code 7	-0.577	(1.316)	-1.327	(1.026)
Country information				
Belgium	-4.668	(742.7)	-4.746	(233.6)
Cyprus	0	(.)	0	(.)
Czech Republic	-4.944	(742.7)	-5.812	(233.6)
Germany	0	(.)	-5.387	(233.6)
Denmark	0	(.)	0	(.)
Spain	-5.341	(742.7)	-5.669	(233.6)
Finland	0	(.)	-5.867	(233.6)
France	-6.638	(742.7)	-7.239	(233.6)
UK	-6.539	(742.7)	-7.443	(233.6)
Greece	-5.510	(742.7)	-6.167	(233.6)
Italy	-5.975	(742.7)	-6.594	(233.6)
Malta	0	(.)	0	(.)
Poland	0	(.)	0	(.)
Slovenia	-4.306	(742.7)	-4.815	(233.6)
Slovakia	0	(.)	0	(.)
Macro level information				
Unemployment level last 3 years	-0.0706	(0.0658)	-0.0909*	(0.0498)
Share of subsidies from gov. expend. (%)	-0.0473	(0.113)	-0.0728	(0.0828)
GDP per capita	-0.00487	(0.0880)	0.0865	(0.0634)
Intercept	6.830	(742.7)	11.64	(233.7)
McFadden R^2	0.17		0.16	
LR χ^2	24.42		38.24	
$p > \chi^2$	0.83		0.28	
#Observations	105		217	

Notes: Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table 14: Mean difference tests before matching with unequal variances

Variables	Aid receiving firms, N=57		Non-aid receiving firms, N=1,132,360		Results of t-tests on mean difference
	Mean	S.D.	Mean	S.D.	
Financial Figures					
ln Profit	-3.8104	7.2691	2.0825	4.3054	***
ln Fixed liabilities	7.6584	4.1073	5.0288	2.6484	***
ln Current liabilities	9.9896	2.7099	6.8662	1.9918	***
Revenue per employee	155.0788	216.9677	532.5130	21760.775	***
Altman Z-Score category	1.3509	0.5822	2.0916	0.7455	***
Public firm	0.6667	0.4756	0.2847	0.4513	***
Liquidity ratio	0.6708	0.6469	1.5428	3.2522	***
Solvency ratio	7.9504	37.9917	33.3579	25.0619	***
Firm Characteristics					
ln Employment	6.1066	1.7635	2.6816	1.5603	***
ln Age	3.0551	1.1371	2.6719	0.7853	**
Medium firm	0.2982	0.4616	0.3967	0.4892	-
Large firm	0.2807	0.4533	0.1639	0.3702	*
Very large firm	0.3509	0.4815	0.0429	0.2027	***
Macro level Information					
Unemploy. level last 3 years	9.5842	4.2290	10.7737	4.3288	**
Share of subs. from gov. exp.	62.2212	11.6203	66.7845	9.7499	***
GDP per capita	2.1772	2.4827	0.4537	2.4405	***
Outcome					
Status 2014 Def. 1a (1=act.)	0.8246	0.3837	0.8304	0.3753	-
Status 2014 Def. 2a (1=act.)	0.8772	0.3311	0.8555	0.3516	-
Status 2014 Def. 1b (1=act.)	0.8070	0.3981	0.8143	0.3889	-
Status 2014 Def. 2b (1=act.)	0.8596	0.3504	0.8393	0.3672	-

Notes: Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. H_0: means are equal for both groups.

Table 15: Information criteria for parametric models fitted with different distributions (NB=3)

Without covariates in addition to aid		Exponential	Log Logistic	Log Norm.	Weibull	Gompertz
AIC	Def. 1a	305.16	284.53	**281.29**	285.58	291.74
	Def. 2a	275.56	265.71	**262.50**	266.54	271.59
	Def. 1b	306.83	289.79	**286.39**	290.43	296.70
	Def. 2b	273.37	262.21	**259.22**	262.92	268.06
BIC	Def. 1a	357.84	342.47	**339.23**	343.53	349.69
	Def. 2a	280.84	276.28	**273.07**	277.12	282.16
	Def. 1b	312.08	300.28	**296.88**	300.92	307.19
	Def. 2b	278.63	272.73	**269.75**	273.44	278.56

With additional covariates		Exponential	Log Logistic	Log Normal	Weibull	Gompertz
AIC	Def. 1a	309.54	294.33	**290.65**	295.22	301.47
	Def. 2a	272.02	258.75	**255.00**	260.36	265.48
	Def. 1b	302.35	279.69	**276.69**	280.44	286.22
	Def. 2b	269.46	254.52	**250.97**	256.02	261.03
BIC	Def. 1a	314.81	304.87	**301.18**	305.76	312.01
	Def. 2a	324.87	316.88	**313.13**	318.50	323.61
	Def. 1b	354.78	337.36	**334.36**	338.11	343.89
	Def. 2b	322.07	312.39	**308.84**	313.89	318.89

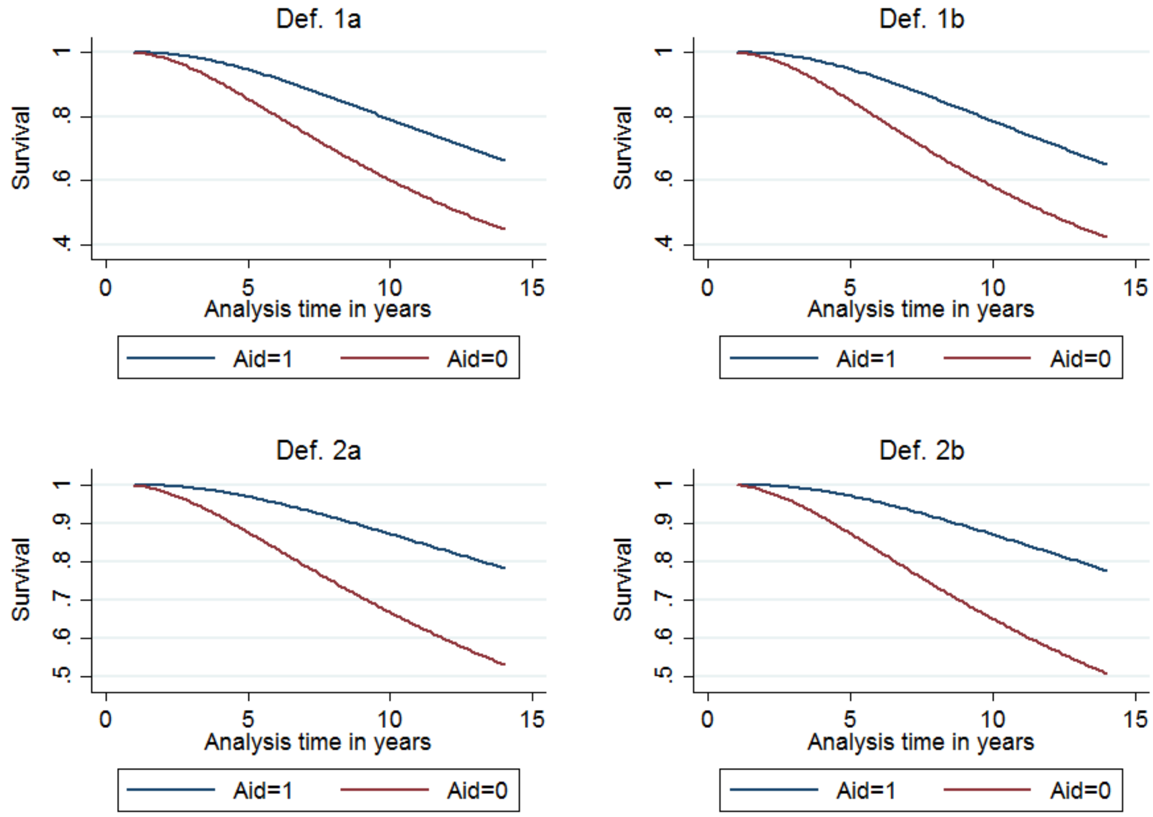

Figure 3: Parametric survival curves (NB=3)

Table 16: Mean value of Altman z-scores per year, Def. 1(·), NB=1

Time					Number of firms from N					Number of firms from A				
Cat.	Year	$\overline{Z_N}$	$\overline{Z_A}$	p-val.	in $\overline{Z_N}$	died	acq	miss	total	in $\overline{Z_A}$	died	acq	miss	total
1	0	1.39	1.36	0.7609	56	0	0	0	56	56	0	0	0	56
	1	1.42	1.36	0.6297	50	5	0	1	56	50	0	0	6	56
2	2	1.57	1.47	0.4758	46	7	1	2	56	49	1	0	6	56
	3	1.45	1.48	0.8644	40	7	2	4	53	42	3	0	8	53
	4	1.48	1.47	0.9450	31	8	2	2	43	36	4	0	3	43
3	5	1.46	1.63	0.3910	26	9	2	1	38	32	3	0	3	38
	6	1.58	1.63	0.8579	19	9	2	1	31	24	2	0	5	31
	7	1.47	1.70	0.3809	15	9	2	0	26	20	4	0	2	26
4	8	1.57	1.58	0.9752	7	9	1	3	20	12	2	0	6	20
	9	1.60	2.14	0.3287	5	8	2	1	16	7	3	0	6	16
	10	2.00	2.38	.	1	9	2	1	13	8	2	0	3	13

Table 17: Mean value of Altman z-scores per year, Def. 2(·), NB=1

Time					Number of firms from N					Number of firms from A				
Cat	Year	$\overline{Z_N}$	$\overline{Z_A}$	p-val	in $\overline{Z_N}$	died	acq	miss	total	in $\overline{Z_A}$	died	acq	miss	total
1	0	1.39	1.36	0.7609	56	0	0	0	56	56	0	0	0	56
	1	1.42	1.36	0.6297	50	5	0	1	56	50	0	0	6	56
2	2	1.57	1.47	0.4758	46	6	1	3	56	49	1	0	6	56
	3	1.45	1.48	0.8644	40	6	2	5	53	42	1	0	10	53
	4	1.48	1.47	0.9450	31	7	2	3	43	36	2	0	5	43
3	5	1.46	1.63	0.3910	26	8	2	2	38	32	1	0	5	38
	6	1.58	1.63	0.8579	19	8	2	2	31	24	1	0	6	31
	7	1.47	1.70	0.3809	15	9	2	0	26	20	3	0	3	26
4	8	1.57	1.58	0.9752	7	9	1	3	20	12	1	0	7	20
	9	1.60	2.14	0.3287	5	8	2	1	16	7	2	0	7	16
	10	2.00	2.38	.	1	7	2	3	13	8	2	0	3	13

Table 18: Mean value of Altman z-scores per year, Def. 2(·), NB=3

Time					Number of firms from N					Number of firms from A				
Cat	Year	$\overline{Z_N}$	$\overline{Z_A}$	p-val.	in $\overline{Z_N}$	died	acq	miss	Total	in $\overline{Z_A}$	died	acq	miss	total
1	0	1.49	1.36	0.1544	168	0	0	0	168	56	0	0	0	56
	1	1.52	1.36	0.1254	154	11	0	3	168	50	0	0	6	56
2	2	1.59	1.47	0.2561	143	17	1	7	168	49	1	0	6	56
	3	1.62	1.48	0.2682	116	22	2	19	159	42	1	0	10	53
	4	1.68	1.47	0.1395	94	24	3	8	129	36	2	0	5	43
3	5	1.65	1.63	0.8836	77	24	5	8	114	32	1	0	5	38
	6	1.51	1.63	0.5580	51	27	5	10	93	24	1	0	6	31
	7	1.67	1.70	0.8774	39	24	6	9	78	20	3	0	3	26
4	8	1.75	1.58	0.5692	20	23	5	12	60	12	1	0	7	20
	9	1.83	2.14	0.4721	12	21	5	10	48	7	2	0	7	16
	10	2.20	2.38	0.6550	5	18	5	11	39	8	2	0	3	13