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- The Accuracy of Database-Driven Methods -

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Identifying Firms' Tax Loss Carry-Forward Status

– The Accuracy of Database-Driven Methods –

Abstract:

Tax loss carry-forwards (TLCF) are likely to affect the responsiveness of firms to tax incentives. Many empirical studies control for firms' TLCF status by relying on database-driven identification methods, which serve only as a proxy for firms' true TLCF status. If these methods were inaccurate in identifying the TLCF status of firms, studies would not be able to draw any reliable conclusions regarding the impact of TLCF on firm behavior. I am the first to empirically examine the accuracy of database-driven methods in predicting both the availability and the amount of TLCF available at single-firm level. For a panel of listed Italian parent companies, I compare firms' true TLCF status, as determined based on IFRS statement information, to the TLCF status predictions of database-driven identification methods. My results indicate that empirical studies relying on database-driven methods might not be able to properly identify firms' TLCF status. I thus cannot recommend the use of database-driven identification methods in empirical tax research.

Keywords: identification, tax loss carry-forwards, tax loss carry-forward status, loss firms, database-driven methods

JEL Classification: C81, H25, K34

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1 Introduction

Tax loss carry-forwards (TLCF) of firms can be offset against taxable income over several years. They act as a substitute for tax incentives, such as interest deductions or depreciation allowances for example. Due to already being at least partially tax exempt, firms with TLCF benefit less (in terms of immediately reduced tax payments) from such incentives than fully taxable (non-TLCF) firms. For this reason, TLCF firms are expected to be less responsive to tax incentives than non-TLCF firms. Firms' responsiveness to tax incentives is expected to decrease in the amount of TLCF available (Auerbach and Poterba, 1987, DeAngelo and Masulis, 1980).

Many studies empirically examine how TLCF affect the behavior of firms (for example, Dreßler and Overesch, 2013, Dyreng, Hanlon and Maydew, 2010, Mackie-Mason, 1990). Due to fiscal secret, information on firms' TLCF status is difficult to obtain. For this reason, empirical studies commonly apply database-driven methods in order to identify the TLCF status of firms. These database-driven identification methods usually link firms' TLCF status to a measure of loss carry-forwards in terms of commercial law. For example, Overesch and Voeller (2010) assume firms to have TLCF if their earnings before taxes (EBT) were negative in the year before. Bernasconi, Marenzi and Pagani (2005) rely on firms' EBT from two past years in order to predict the amount of TLCF available. Oestreicher, Koch and Vorndamme (2012) determine loss carry-forwards based on a measure of earnings that excludes dividend income.

Database-driven identification methods serve only as a proxy for firms' true TLCF status. For studies to obtain unbiased empirical results regarding the behavior of TLCF and non-TLCF firms, database-driven methods have to be accurate in identifying the TLCF status of firms. If they were not, the responsiveness of TLCF firms to tax incentives would likely be overestimated, whereas the responsiveness of non-TLCF firms would probably be underestimated. I empirically examine the accuracy of database-driven methods in predicting both the availability and the amount of TLCF available. By doing so, I am able to show whether or not database-driven methods allow for a proper identification of firms' TLCF status. Hence, I am able to provide insights into the extent to which empirical studies that rely on database-driven identification methods can derive unbiased results regarding the impact of TLCF on firm behavior. In my study, I assess the accuracy of loss carry-forwards based on IFRS earnings (ILCF), loss carry-forwards based on cashflows (CLCF) and two methods based on industry affiliation. By examining different database-driven identification methods, I am able to show which method (if any) is most accurate in predicting the availability and the amount of TLCF.

As pointed out above, information on firms' true TLCF status is difficult to obtain. Examining the accuracy of database-driven identification methods, however, requires one to know firms' true TLCF status. Only a comparison between firms' true and predicted TLCF status can provide insights into the accuracy of database-driven identification methods. For my study, I rely on hand-collected data from IFRS statements in order to determine the true TLCF status of firms. IAS 12.81 requires that firms disclose information on their TLCF status in the notes on deferred tax assets. This allows me to determine firms' true TLCF status, and to compare it to the TLCF status predictions of database-driven identification methods. All data necessary to determine the TLCF status predictions of database-driven identification methods is obtained from the Amadeus database.

I study the accuracy of database-driven methods in predicting the availability and the amount of TLCF at single-firm level. This seems to be reasonable, given that the impact of TLCF on firm behavior is usually examined at single-firm level. My analyses are based on 325 firm-year observations of listed Italian parent companies between 2010 and 2012. Unlike many other European countries, Italy requires that listed firms publish not only their consolidated but also their unconsolidated financial statements in accordance with the IFRS. By giving me the opportunity to determine firms' true TLCF status using IAS 12.81 information from unconsolidated IFRS statements, employing a panel of listed Italian parent companies ensures that I am able to examine the accuracy of database-driven methods at single-firm level.

To my knowledge, only Kinney and Swanson (1993), Mills, Newberry and Novack (2003) and Niemann and Rechbauer (2013) have investigated the accuracy of database-driven identification methods so far. All three studies examine the accuracy of database-driven methods at group level. Kinney and Swanson (1993) and Mills et al. (2003) investigate the accuracy of Compustat's data item # 52, each based on a sample of U.S. firms. Depending on firms' reporting behavior, data item #52 captures either the amount of TLCF available or firms' loss carry-forwards in terms of commercial law.[1] Niemann and Rechbauer (2013) study the accuracy of different measures representing loss carry-forwards in terms of commercial law. Their analysis is based on a sample of Austrian firms. All three studies conclude that database-driven methods do not allow for a proper identification of firms' TLCF status at group level. By providing first evidence on the

[1] Compustat's data item # 52 is commonly used by empirical tax research in the U.S. in order to identify the TLCF status of firms. Examples include the investigations of Dyreng et al. (2010), Mackie-Mason (1990) or Rego and Wilson (2012).

accuracy of database-driven methods at single-firm level, my study significantly enhances this stream of literature.

I find that no database-driven method performs better in identifying the availability of TLCF than ILCF based on firms' EBT, the method most commonly applied in empirical tax research. Increasing the time horizon employed in order to determine TLCF status predictions does not help to improve the method's accuracy. My findings, however, also suggest that no database-driven method performs well in identifying the availability of TLCF. At best, database-driven methods can correctly predict the (non-)availability of TLCF for only about 80% of the firm-year observations in my sample. This means that TLCF status predictions are wrong for about every fifth firm. ILCF based on firms' earnings before interest and taxes (EBIT) can be regarded as being most accurate in predicting the amount of TLCF available. I find that the method's accuracy can be improved by extending the time horizon employed in order to determine TLCF amount predictions. In general, I find that database-driven methods perform poorly in predicting the amount of TLCF available. The highest observed fraction of prediction errors that are small (and not large) in magnitude corresponds to only about 20%.[2] Hence, it is highly likely (if not sure) that predicted TLCF amounts deviate sharply from firms' true TLCF amount.

My findings have important implications for empirical tax research. They suggest that database-driven methods do not allow for a proper identification of firms' TLCF status at single-firm level. As a result, empirical studies might not be able to derive any reliable results regarding the impact of TLCF on firm behavior. Given my results, I cannot recommend the use of database-driven identification methods. Empirical tax research should therefore consider different approaches in order to identify the TLCF status of firms. In some countries (for example, Norway or the U.S.), tax authorities seem to be willing to provide information on firms' TLCF status (Aarbu and Mackie-Mason, 2003, Cooper and Knittel, 2010). Investigating firm behavior in such countries could thus be a way to avoid any issues related to the proper identification of firms' TLCF status. Exploiting financial statement information on TLCF or conducting a survey could also be a possibility to obtain reliable TLCF status information. The usefulness of the latter two approaches, however, is limited because a hand-collection of data is needed. Moreover, surveys on firms' TLCF status might suffer from the fact that firms are not willing to

[2] For my analyses, I assume that deviations from firms' true TLCF amount are small if the magnitude of a logarithmic prediction error does not exceed a threshold level of 0.1. In such a case, a firm's true TLCF amount is either not more than 1.11 times or not more than 0.9 times as large as the TLCF amount predicted.

respond, or do not answer truthfully.

The remainder of this paper is organized as follows. Section 2 outlines the institutional setting of my study. Section 3 explains how I assess the accuracy of database-driven identification methods. Moreover, it provides insights into how I determine firms' true TLCF status and the TLCF status predictions of database-driven identification methods. Information on the sample employed is given in Section 4. Section 5 discusses the results derived, and Section 6 concludes.

2 Institutional Setting

Italian firms are subject to a flat corporate income tax rate of 27.5% (33% until 2007). Firms with certain activities in the fields of energy production and supply will be subject to an increased corporate income tax rate of 34% if revenue exceeds a level of three million euros and taxable income exceeds a level of 300 thousand euros. The increased rate was introduced in 2009 at a level of 33% and subsequently changed to 38% (2011-2013) and 34%, respectively. There is no minimum tax for listed firms.

Listed Italian parent companies have had to prepare their unconsolidated financial statements in accordance with the IFRS since 2006. IFRS rules on income qualification, timing of computation and classification are also fully relevant for corporate income tax purposes. In contrast, IFRS rules on income evaluation and quantification (for example, depreciation allowances, interest deductibility or the recognition of income from capital investments) are relevant only if they are in line with the provisions imposed by the Italian tax authority. As a result, taxable income of listed Italian firms is derived by adjusting firms' IFRS result so that tax provisions that are different from the IFRS are met (Giacometti, 2009). For depreciation allowances, interest expense and income from capital investments, IFRS and corporate income tax provisions are compared in Appendix B.1.

Negative taxable income of Italian firms can be carried forward to subsequent years in order to reduce future taxable income. Tax losses incurred before 2011 can be carried forward for five years with no deduction limit. Tax losses incurred in 2011 or later can be carried forward indefinitely. The TLCF deduction for these losses, however, is limited to an amount of 80% of firms' positive taxable income. The Italian tax authority does not offer any loss carry-back provisions.

Italian firms are also subject to a regional tax on productive activities, which does not offer any loss carry-back or loss carry-forward provisions.

3 Research Design

In this study, I examine the accuracy of ILCF, CLCF and two methods based on industry affiliation. In empirical tax research, loss carry-forwards in terms of commercial law have been used extensively in order to identify firms' TLCF status. Studies like Buettner, Overesch, Schreiber and Wamser (2012), Dreßler and Overesch (2013), Overesch (2009), Overesch and Voeller (2010) and Ruf (2010) assume that firms with loss carry-forwards in terms of commercial law are also exposed to TLCF. Bernasconi et al. (2005) and Oestreicher et al. (2012) use loss carry-forwards in terms of commercial law in order to predict the amount of TLCF available.[3] In contrast, CLCF as well as methods based on industry affiliation have not been used so far. I examine the accuracy of these methods in order to see if there are any database-driven methods, besides those already used in empirical tax research, that are able to reliably identify firms' TLCF status. CLCF might serve as a good alternative to loss carry-forwards in terms of commercial law if book-tax differences are large. With regard to industry affiliation, empirical evidence suggests that TLCF tend to be concentrated among certain industries (Cooper and Knittel, 2010).

My study is based on two analyses. In the first one, I examine the accuracy of database-driven methods in predicting the availability of TLCF. In order to do so, I determine first whether or not a firm is truly exposed to TLCF. Firms' true TLCF status is then compared to the TLCF status predictions of database-driven identification methods. I assume that a correct prediction is made if the (non-)availability of TLCF is correctly predicted. In order to draw conclusions regarding the methods' accuracy, I rely on an approach similar to those applied in prior empirical tax research on database-driven identification methods.[4] For every database-driven method, I determine the percentage of correct TLCF status predictions. If a database-driven identification method, for example, correctly predicted the (non-)availability of TLCF for eight out of ten firm-year observations, its percentage

[3] Other studies that rely on loss carry-forwards in terms of commercial law in order to identify firms' TLCF status include the investigations of Beuselinck and Deloof (2012), Buettner, Overesch, Schreiber and Wamser (2009), Buettner, Overesch and Wamser (2011), Buettner, Overesch and Wamser (2016), Buettner and Wamser (2013), Haring, Niemann and Rünger (2012), Krämer (2015), Lazăr (2014), Merz and Overesch (2016), Overesch and Wamser (2010a), Overesch and Wamser (2010b), Overesch and Wamser (2014), Stöckl and Winner (2013), Wamser (2011) and Wamser (2014). U.S. studies such as Dyreng et al. (2010), Dyreng and Lindsey (2009), Frank and Goyal (2009), Klassen, Lisowski and Mescall (2016), Mackie-Mason (1990) or Rego and Wilson (2012) are also likely to identify firms' true TLCF status based on loss carry-forwards in terms of commercial law. These studies rely on Compustat's data item #52, which captures either the amount of TLCF available or firms' loss carry-forwards in terms of commercial law.

[4] Kinney and Swanson (1993) and Mills et al. (2003), for example, rely on error rates in order to assess the accuracy of database-driven methods. The analyses of Rechbauer and Niemann (2013) are based on the number of correct TLCF status predictions made.

of correct TLCF status predictions would correspond to 80%. The higher a method's percentage of correct TLCF status predictions, the higher I expect its accuracy to be. A method with a percentage of correct predictions of 80%, for example, is thus assumed to be more accurate in predicting the availability of TLCF than a method with a percentage of correct predictions of only 50%.

In my second analysis, I examine the accuracy of database-driven methods in predicting the amount of TLCF available to firms. For this analysis, I consider only firm-year observations that were correctly identified as TLCF firms in the first place. The findings I derive thus depend upon those obtained in my first analysis. In order to assess the methods' accuracy, I derive firms' true TLCF amount and compare it to the methods' TLCF amount predictions. As suggested by Müller (2008), the comparison is carried out via a logarithmic prediction error, which is defined as the difference between the natural logarithm of the TLCF amount predicted and the natural logarithm of firms' true TLCF amount. The logarithmic prediction error is equal to zero if the amount of TLCF available is correctly predicted. It is larger (smaller) than zero if the TLCF amount predicted exceeds (falls below) firms' true TLCF amount. Consider, for example, a firm with TLCF of ten thousand euros. If a database-driven method predicted this firm's TLCF to be equal to fifteen thousand euros, the logarithmic prediction error would correspond to the difference between $ln(15,000)$ and $ln(10,000)$. It would thus be equal to 0.41. The use of a logarithmic prediction error ensures that over- and underestimates of firms' true TLCF amount are treated symmetrically. This would not be the case if, for example, a percentage prediction error were used (Müller, 2008).

As in my first analysis, I apply an approach similar to prior research in order to assess the accuracy of database-driven methods.[5] I find it unlikely that database-driven identification methods are able to predict firms' TLCF amount completely correctly. For this reason, I do not determine the methods' percentage of correct TLCF status predictions in order to draw conclusions regarding their accuracy. I compute the percentage of prediction errors that are small (and not large) in magnitude. If a database-driven method, for example, correctly predicted the TLCF amount for two out of ten firm-year observations, and small logarithmic prediction errors occurred in five cases, the method's percentage of small prediction errors would correspond to 70%. The higher a method's percentage of small prediction errors, the higher I expect its accuracy to be. A method with a percentage of small predictions errors of 70%, for example, is thus assumed to be more accurate

[5] Kinney and Swanson (1993), for example, rely on error rates in order to assess the accuracy of database-driven methods in predicting the amount of TLCF available.

in predicting the amount of TLCF available than a method with a percentage of small prediction errors of only 30%. I assume that the magnitude of a logarithmic prediction error is small if it does not exceed a threshold level of 0.1. This threshold level is relatively close to the optimum error level of zero. If a logarithmic prediction error were exactly equal to 0.1 (−0.1), the TLCF amount predicted would be about 1.11 (0.9) times as large firms' true TLCF amount.

3.1 Derivation of Firms' True TLCF Status

I determine firms' true TLCF status by exploiting the notes to firms' unconsolidated IFRS statements. According to the IFRS, firms are not obliged to disclose their total stock of TLCF. However, IAS 12.81 requires that firms' publish the amount of deferred tax assets on TLCF, which are recognized in the statement of financial position, as well as the amount of TLCF for which no deferred tax assets have been recorded. An approach to determine firms' true TLCF status based on the provisions imposed by IAS 12.81 was developed by Kager, Niemann and Schanz (2011). I follow their approach by applying the formula below:

$$TLCF_{i,t-1} = \frac{DTA_{i,t-1}}{\tau_{i,t-1}} + NDTA_{i,t-1} \tag{1}$$

In Formula 1, $TLCF_{i,t-1}$ is firm i's total stock of TLCF at the end of year $t-1$. It is available for deduction in year t. $DTA_{i,t-1}$ and $NDTA_{i,t-1}$ represent the amount of deferred tax assets on TLCF recognized in year $t-1$, and the stock of TLCF for which no deferred tax assets have been recorded, respectively. $\tau_{i,t-1}$ is the tax rate used to determine $DTA_{i,t-1}$. In my study, $\tau_{i,t-1}$ corresponds to the applicable Italian corporate income tax rate.[6]

Applying Formula 1 yields reliable TLCF estimates if firms fully follow the provisions imposed by IAS 12.81. If firms do not, it is not possible to exactly determine their true TLCF status in the way described above. There are some empirical studies that examine the reporting behavior of firms regarding IAS 12.81. Kager and Niemann (2013), for example, study the disclosure behavior of listed Austrian, German and Dutch firms between 2004 and 2007. They find that firms often do not publish the amount of TLCF for which no deferred tax assets have been recorded. Petermann and Schanz (2013) provide similar evidence for a sample of German firms between 2005 and 2010. Based on these

[6] A numerical example, which shows how to apply Formula 1 in order to determine firms' true TLCF status, can be found in Niemann and Rechbauer (2013).

findings, it is not possible to draw any conclusions regarding the reliability of IAS 12.81 information on TLCF. The fact that the amount of TLCF for which no deferred tax assets have been recorded is often not reported does not necessarily mean that firms are not willing to provide any such information and hence, that TLCF estimates based on IAS 12.81 information are biased. Firms might not disclose anything on TLCF for which no deferred tax assets have been recorded because they simply do not have any such TLCF. The results of a survey I conducted among my sample firms indicate that I am able to reliably identify firms' true TLCF status based on IAS 12.81 information. Seven out of 137 firms in my sample (fourteen firm-year observations) took part in the survey, in which they were asked to reveal their true TLCF status during the observation period. For all fourteen firm-year observations (100%), I can correctly predict the (non-)availability of TLCF by relying on Formula 1. For eight out of eleven firm-year observations with TLCF (72.73%), the amount of TLCF determined based on IAS 12.81 information does not deviate by more than 14.5 percentage points from firms' true TLCF amount, as revealed in the survey.[7]

3.2 Derivation of the Methods' TLCF Status Predictions

All data necessary to compute the TLCF status predictions of database-driven identification methods is obtained from the Amadeus database. Due to the fact that I investigate the accuracy of database-driven methods at single-firm level, I rely on unconsolidated data only.

3.2.1 Loss Carry-Forwards based on IFRS Earnings (ILCF)

The Amadeus database does not offer a specific data item that represents loss carry-forwards in terms of commercial law. For this reason, I determine the amount of ILCF available based on IFRS earnings realized in the past. In empirical tax research, different time horizons are employed in order to compute loss carry-forwards in terms of commercial law. Buettner et al. (2012), Dreßler and Overesch (2013), Ruf (2010) and Overesch (2009), for example, consider all earnings relevant for their loss carry-forwards. Bernasconi et al. (2005) derive loss carry-forwards based on earnings from two past years. Haring et al. (2012), Krämer (2015), Overesch and Merz (2016) and Overesch and Voeller (2010) rely on earnings from only one past year. In order to see if the time horizon employed

7 For my analyses, I employ the TLCF amount revealed in the survey if it differs from the amount determined based on IAS 12.81 information.

influences the accuracy of ILCF, I determine loss carry-forwards based on earnings from one, two, three and four past years.[8] For their loss carry-forwards, Oestreicher et al. (2012) rely on a measure of earnings that excludes dividend income. The majority of studies, however, uses firms' EBT in order to construct loss carry-forwards in terms of commercial law (for example, Buettner et al., 2012, Haring et al., 2012, Overesch, 2009). For my analyses, I consider not only firms' EBT but also firms' EBIT and their earnings before interest, taxes, depreciation and amortization (EBITDA). This approach allows me to see if earnings measures that exclude income that is treated differently by corporate tax law and the IFRS perform better in identifying firms' TLCF status than earnings measures that do not. Whereas firms' EBT includes all income possibly subject to book-tax-differences, firms' EBIT (EBITDA) excludes financial income (financial income and depreciation allowances).

In line with prior empirical tax research, I assume that firms with ILCF available at the end of year $t-1$ are also exposed to TLCF, and that the amount of ILCF available can be used to predict the amount of TLCF available. In order to determine the amount of ILCF available at the end of year $t-1$, I assume that firms are not exposed to any loss carry-forwards prior to year $t-n$ (with $n = 1, 2, 3, 4$). The amount of ILCF available at the end of year $t-1$ is then built up recursively, taking the level of earnings realized in each period between years $t-n$ and $t-1$ into account. A mathematical derivation is shown in Appendix B.2.

3.2.2 Loss Carry-Forwards based on Cashflows (CLCF)

The Amadeus database offers also no specific data item for CLCF. Hence, I determine the amount of CLCF available based on cashflows realized in the past. As for ILCF, I consider cashflows from one, two, three and four past years in order to see if the time horizon employed influences the accuracy of CLCF. I assume that firms with CLCF available at the end of year $t-1$ are also exposed to TLCF, and that the amount of CLCF available can be used to predict the amount of TLCF available. In order to determine the amount of CLCF available at the end of year $t-1$, I apply the same principles as for ILCF, using cashflows instead of IFRS earnings.

I measure firms' cashflows by relying on the cashflow data item provided by the Amadeus

[8] In my study, it is not possible to determine ILCF based on earnings from five past years. This is because unconsolidated IFRS data for Italian parent companies is available only from 2006 on, and my first observation year corresponds to 2010. The maximum number of past years I can consider thus corresponds to four.

database. The cashflow data item is defined on an after-tax base and contains extraordinary income. For my analyses, I adjust the data item in two ways. In order to account for the fact that TLCF are defined on a pre-tax basis, I add firms' total tax expense. Moreover, I remove firms' extraordinary income because it likely contains non-cash income.

3.2.3 Industry Affiliation

In order to predict firms' TLCF status based on industry affiliation, I perform a double-hurdle regression analysis. It is based on a probit regression in the first and a truncated normal regression in the second tier. In the probit part of the analysis, I determine whether or not a firm operating in a certain industry is exposed to TLCF. I first regress a dummy variable indicating the availability of TLCF on a set of industry dummies representing four-digit Global Industrial Classification Standard (GICS) codes. A list of the industries employed including their four-digit GICS codes can be found in Appendix B.3. Based on the results obtained, I then predict the probability of being exposed to TLCF for each industry employed. For a firm operating in a certain industry, I assume that TLCF are available if the predicted probability of being exposed to TLCF exceeds a level of 50%. In the truncated normal part of the analysis, I determine the amount of TLCF available to a firm classified as a TLCF firm. I regress the amount of TLCF available on the same set of industry dummies employed in the probit model, using only firm-year observations with TLCF. The results derived allow me to predict the amount of TLCF available to a TLCF firm operating in a certain industry. The results of the double hurdle regression analysis are shown in Appendix B.4.

Industry affiliation does not capture any individual firm characteristics. In order to see if the method's accuracy can be enhanced by considering firm-specific characteristics, I also examine the accuracy of industry affiliation in combination with firm age. This approach seems to be promising since there is empirical evidence suggesting that TLCF tend to be concentrated among younger firms (Cooper and Knittel, 2010). For the method based on industry affiliation and firm age, I derive TLCF status predictions by replicating the double-hurdle regression analysis introduced above with firm age as an additional explanatory variable in both the probit and the truncated normal part of the analysis. Firm age is defined as the difference between the observation year and a firm's date of incorporation. The results of the analysis are shown in Appendix B.5.

4 Data

My study is based on a panel of listed Italian parent companies between 2010 and 2012. I consider firms listed in one, two or all of the three observation years. Insights into the sample selection process are provided in Table 1.

{Insert Table 1 about here.}

The full sample of listed Italian parent companies corresponds to 837 firm-year observations. For my analyses, I do not consider 177 firm-year observations that belong to the financial industry (two-digit GICS code 40). The preliminary sample size is thus equal to 660. For a firm-year observation to be included in my final sample, all data necessary to determine the firm's true TLCF status and every method's TLCF status prediction has to be available. This requirement results in the removal of 335 further observations, reducing the final sample size to 325 firm-year observations from 137 firms.

I am not able to determine the true TLCF status of a firm if an unconsolidated IFRS statement is not available (66 firm-year observations). If an unconsolidated IFRS statement is available, I am not able to determine the true TLCF status of a firm if deferred tax assets on TLCF are disclosed together with deferred tax assets on other temporary differences (64 firm-year observations). Missing tax rate information can also be a problem. Firms which operate in the industries Energy or Utilities may be subject to the general or the increased Italian corporate income tax rate. If such a firm does not disclose the tax rate used to determine the amount of deferred tax assets on TLCF, it is not possible to determine its true TLCF status based on IAS 12.81 information (ten firm-year observations). A method's TLCF status prediction cannot be derived if the Amadeus database reports a missing value for at least one of the data items required to determine the prediction (195 firm-year observations).

In my sample, 186 out of 325 firm-year observations (57.23%) have no TLCF, whereas 139 (42.77%) have TLCF. For firms with TLCF, the amount of TLCF available varies between 34 and 162,049 thousand euros. For 35 out of 139 firm-year observations with TLCF (25%), the amount of TLCF available exceeds a level of 31,367 thousand euros. Thus, only a small number of firms in my sample is exposed to very large TLCF. On average, TLCF amounts correspond to 23,184 thousand euros.

5 Results

5.1 Availability of TLCF

Table 2 shows the results derived regarding the accuracy of database-driven methods in predicting the availability of TLCF.

{Insert Table 2 about here.}

The percentage of correct TLCF status predictions varies between 59.38% and 79.08%. It is highest for the ILCF based on firms' EBT from four past years and lowest for the method based on industry affiliation and firm age. Pairwise χ^2-tests of independency show that there is no significant difference in the accuracy of ILCF and CLCF. CLCF thus cannot be seen as a more accurate alternative to ILCF. The methods based on industry affiliation perform significantly worse than ILCF or CLCF in predicting the availability of TLCF. As a result, I cannot recommend the use of industry affiliation in order to identify the availability of TLCF. The latter finding is in contrast to what was suggested by prior literature. It indicates that there is hardly any concentration of firms with or without TLCF among certain industries.

Pairwise χ^2-tests show that the time horizon employed has no effect on the accuracy of ILCF. This indicates that extending the time horizon employed in order to determine ILCF does not help to improve the method's accuracy. Tests further reveal that there is no significant difference in the accuracy of ILCF based on firms' EBIT and ILCF based on firms' EBT. Hence, excluding firms' financial income does not help to improve the accuracy of ILCF. I do find a significant difference in the accuracy of ILCF based on firms' EBITDA and ILCF based on firms' EBT. The former perform significantly worse than the latter in predicting the availability of TLCF if $n \geq 2$. Excluding both firms' financial income and their depreciation allowances thus deteriorates the accuracy of ILCF.

The time horizon employed does also not significantly affect the accuracy of CLCF. Pairwise χ^2-tests further reveal that there is no significant difference in the accuracy of industry affiliation alone, and the combination of industry affiliation and firm age. This indicates that firm age cannot be regarded as an accurate measure to identify the availability of TLCF. The latter finding is in contrast to what was suggested by prior literature. It suggests that there is hardly any concentration of TLCF or non-TLCF firms among firms of a certain age. The results of the pairwise χ^2-tests can be found in Appendix B.6.

Overall, my findings indicate that no database-driven method performs better in identifying the availability of TLCF than ILCF based on firms' EBT. Hence, the method most commonly used in empirical tax research is in fact the one being most accurate in identifying the TLCF status of firms. Importantly, the accuracy of ILCF based on firms' EBT cannot be improved by extending the time horizon employed in order to determine the method's TLCF status predictions. This means that studies that consider all earnings relevant for their ILCF might not perform better in identifying the availability of TLCF than studies that do not. Table 2, however, also reveals that no database-driven methods performs well in identifying the availability of TLCF. At best, database-driven methods can correctly identify the (non-)availability of TLCF for only about 80% of all firm-year observations in my sample. This means that wrong TLCF status predictions occur in about every fifth case.[9]

My findings have important implications for empirical tax research. They indicate that database-driven methods are not able to properly identify the availability of TLCF at single-firm level. Empirical studies that rely on database-driven driven identification methods might thus not be able to derive any reliable results regarding the impact of TLCF on firm behavior. It is highly likely that these studies overestimate the responsiveness of TLCF firms to tax incentives. They might underestimate the responsiveness of non-TLCF firms. Given my results, I cannot recommend the use of database-driven methods in order to identify the availability of TLCF at single-firm level.

5.2 Amount of TLCF

Table 3 shows the results derived regarding the accuracy of database-driven methods in predicting the amount of TLCF available to firms.

{Insert Table 3 about here.}

The percentage of small prediction errors varies between 0% (only large logarithmic prediction errors) and 19.64%. It is highest for the methods based on industry affiliation and lowest for CLCF based on cashflows from one past year. Pairwise χ^2- and exact Fisher tests show that there is no significant difference in the accuracy of ILCF based on

[9] In additional analyses (results not reported here), I find that the inability of database-driven methods to correctly predict the availability of TLCF is not determined by certain firm characteristics, such firm size or age for example. For single methods, I find a weak impact of industry affiliation.

firms' EBT or EBITDA and CLCF. CLCF perform significantly worse than ILCF based on firms' EBIT if $n = 1$. This suggests that CLCF cannot be seen as a more accurate alternative to ILCF. The methods based on industry affiliation perform significantly better in predicting the amount of TLCF available to firms than ILCF based on firms' EBT. They outperform ILCF based on firms' EBIT or EBITDA if $n \leq 2$. Tests further reveal that the accuracy of the methods based on industry affiliation is significantly higher than the accuracy of CLCF if $n \neq 3$. Industry affiliation might thus prove to be useful in identifying the amount of TLCF available to firms. One has to keep in mind, however, that the methods based on industry affiliation were not accurate in identifying the availability of TLCF in the first place.[10] The latter finding indicates that firms operating within the same industry are exposed to similar TLCF amounts.

Pairwise χ^2- and exact Fisher tests show that the time horizon employed has no significant effect on the accuracy of ILCF based on firms' EBT. It does, however, significantly affect the accuracy of ILCF based on firms' EBIT or EBITDA. For ILCF based on firms' EBIT, tests show that the percentage of small prediction errors significantly increases if earnings from three to four instead of only one past year are used. ILCF based on firms' EBITDA from four past years perform significantly better than ILCF based on firms' EBITDA from only one past year. This indicates that the accuracy of ILCF can be improved by extending the time horizon employed. Pairwise χ^2- and exact Fisher-tests further reveal that ILCF based on firms' EBIT perform significantly better in predicting the amount of TLCF available than ILCF based on firms' EBT if $n \geq 3$. Hence, excluding firms' financial income helps to improve the accuracy of ILCF. In contrast, I find no significant difference in the accuracy of ILCF based on firms' EBT and ILCF based on firms' EBITDA. This suggests that excluding both firms' financial income and their depreciation allowances does not help to improve the accuracy of ILCF.

The accuracy of CLCF significantly increases if cashflows from three to four instead of only one past year are used. Extending the time horizon employed thus helps to improve the method's accuracy. Pairwise χ^2- and exact Fisher tests further reveal that there is no significant difference in the accuracy of industry affiliation alone, and the combination of industry affiliation and firm age. Hence, including firm age does not help to improve the method's accuracy. The results of the χ^2- and exact Fisher tests are shown in Appendix B.7.

[10] Table 2 shows that the methods based on industry affiliation can correctly predict the (non-)availability of TLCF for only about 60% of all the firm-year observations in my sample.

My findings indicate that the method most commonly used in empirical tax research, an ILCF based on firms' EBT, is not the one being most accurate in predicting the amount of TLCF available to firms. Given its performance in identifying the availability of TLCF, an ILCF based on firms' EBIT performs best in predicting firms' TLCF amounts.[11] It is important to note that the method's accuracy can be improved by extending the time horizon employed to determine TLCF amount predictions. Studies that consider all earnings relevant for their ILCF might thus perform better in predicting firms' TLCF amount than studies that do not. In general, database-driven methods perform poorly in predicting the amount of TLCF available to firms. The highest observed fraction of prediction errors that are small in magnitude corresponds to 20% only. This means that it is highly likely (if not sure) that TLCF amount predictions deviate sharply from firms' true TLCF amount.[12]

My findings indicate that database-driven methods are not able to properly identify the amount of TLCF available at single-firm level. Empirical studies that make use of database-driven identification methods might thus not be able to derive any reliable results regarding the impact of TLCF on firm behavior. If the amount of TLCF available to TLCF firms is overestimated, biased results will indicate that firms are more responsive to tax incentives than expected. If it is underestimated, firms will be less responsive to tax incentives than expected. Given my results, I strongly recommend not to use database-driven methods in order to identify the amount of TLCF available at single-firm level.

6 Summary and Outlook

In empirical studies on tax incentives and firm behavior, it is important to control for firms' TLCF status. TLCF can be offset against taxable income over several years. Hence, TLCF are likely to affect the responsiveness of firms to tax incentives. Information on firms' TLCF status, however, is difficult to obtain. As a result, empirical studies usually rely on database-driven identification methods, which serve as a proxy for firms' true TLCF status. In this paper, I provide empirical evidence on the accuracy of database-driven methods in identifying the availability and the amount of TLCF at single-firm level.

[11] Table 2 shows that an ILCF based on firms' EBIT can correctly predict the (non-)availability of TLCF for 71.69% to 73.85% of all the firm-year observations in my sample.

[12] In additional analyses (results not reported here), I find that the inability of database-driven methods to correctly predict the amount of TLCF available to firms is not determined by certain firm characteristics, such firm size, age or industry affiliation.

The methods I examine are ILCF, CLCF and two methods based on industry affiliation.

My findings are highly relevant for empirical tax research. They provide insights into whether or not database-driven methods allow for a proper identification of firms' TLCF status. If database-driven methods were inaccurate in identifying firms' TLCF status, any results derived in empirical studies regarding the behavior of TLCF and non-TLCF firms would likely be distorted. My findings thus also provide insights into the extent to which empirical studies can derive unbiased results regarding the impact of TLCF. Due to the fact that I examine the accuracy of different database-driven methods, I can further show which method (if any) is most accurate in identifying the TLCF status of firms. Moreover, by providing first evidence on the accuracy of database-driven methods at single-firm level, my study significantly enhances existing literature in this area of tax research.

My investigation is based on 325 firm-year observations of listed Italian parent companies between 2010 and 2012. In order to assess the accuracy of database-driven identification methods, I compare firms' true TLCF status to the TLCF status predictions of database-driven methods. In order to derive firms' true TLCF status, I rely on IAS 12.81 information on TLCF published in firms' unconsolidated IFRS statements. All data necessary to determine TLCF status predictions is obtained from the Amadeus database.

I find that database-driven identification methods do not perform well in identifying the availability of TLCF at single-firm level. At best, database-driven methods can correctly predict the (non-)availability of TLCF in only about 80% of all cases. For every fifth firm, TLCF status predictions are wrong. Database-driven methods perform poorly in predicting the amount of TLCF available at single-firm level. The highest observed fraction of prediction errors that are small (and not large) in magnitude corresponds to about 20% only. Hence, it is highly likely (if not sure) that TLCF amount predictions deviate sharply from firms' true TLCF amount.

My findings imply that database-driven identification methods do not allow for a proper identification of firms' TLCF status at single-firm level. Hence, studies that use database-driven methods in order to identify the TLCF status of firms, might not be able to draw any reliable conclusions regarding the behavior of TLCF and non-TLCF firms. Given my results, I cannot recommend the use of database-driven identification methods. Empirical tax research should consider more reliable approaches in order to obtain information on firms' TLCF status. Possibilities include investigating firm behavior in countries that provide information on firms' TLCF status, exploiting financial statement information on TLCF or conducting a survey.

This paper offers some directions for further research. My findings indicate that any results derived regarding the behavior of TLCF and non-TLCF firms are likely to be biased if empirical studies rely on database-driven identification methods. It would be interesting to know the extent of this bias. If the extent of the bias caused by the methods' inability to properly identify the TLCF status of firms was fairly small, database-driven identification would still be an option for empirical tax research. Future research could examine the nature of this bias by investigating the impact of TLCF in two distinct scenarios: one in which database-driven methods are used in order to identify firms' TLCF status, and one in which reliable TLCF status information is used instead. I also recommend to replicate previous studies in empirical tax research (for example, Bernasconi et al., 2005, Buettner et al., 2012, Dreßler and Overesch, 2013, Haring et al., 2012, Oestreicher et al., 2012, Overesch, 2009, Overesch and Voeller, 2010, Ruf, 2010) using reliable TLCF status information instead of database-driven methods. If database-driven identification methods do not substantially distort the results derived, this could be a way to show that prior conclusions drawn in empirical tax research are still valid.

My study is a first attempt to close the gap in empirical tax research regarding the accuracy of database-driven methods in identifying the TLCF status of firms at single-firm level. The findings derived are likely to be influenced by the Italian institutional setting. It would be interesting to know to what extent my results hold if firms located in countries with an institutional setting different from that of Italy were examined. Empirical tax research commonly uses loss carry-forwards in terms of commercial law as a proxy for firms' TLCF status. In this paper, I examine the accuracy of loss carry-forwards based on IFRS earnings (ILCF). It would be interesting to know to what extent my results hold if firms located in countries with accounting standards different from the IFRS were examined. The results of the survey conducted suggest that I am able to accurately determine firms' true TLCF status based on IFRS statement information. Nevertheless, if I was able to base my analyses on firm-specific TLCF status information provided by the Italian tax authority, the reliability of the results derived would certainly be enhanced.

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A Tables

Table 1: Sample Selection Process

This table provides insights into the sample selection process. N corresponds to the number of firm-year observations.

		N
	full sample of listed Italian parent companies	837
–	firms operating in the financial industry	– 177
	preliminary sample size	660
–	unconsolidated IFRS statement is not available	– 66
–	insufficient IFRS statement information on TLCF	– 74
–	missing data in the Amadeus database	– 195
	final sample size	325

Table 2: Availability of TLCF - Results

This table shows the results derived regarding the accuracy of database-driven methods in predicting the availability of TLCF. A method's percentage of correct predictions corresponds to the percentage of firm-year observations for which the (non-)availability of TLCF is correctly predicted. The higher a method's percentage of correct predictions, the higher I expect its accuracy to be. The findings are based on a total of 325 firm-year observations of listed Italian parent companies between 2010 and 2012.

Method	Percentage of Correct Predictions
ILCF ($n = 1$, EBT)	73.85%
ILCF ($n = 2$, EBT)	76.31%
ILCF ($n = 3$, EBT)	78.15%
ILCF ($n = 4$, EBT)	79.08%
ILCF ($n = 1$, EBIT)	71.69%
ILCF ($n = 2$, EBIT)	72.62%
ILCF ($n = 3$, EBIT)	72.62%
ILCF ($n = 4$, EBIT)	73.85%
ILCF ($n = 1$, EBITDA)	68.62%
ILCF ($n = 2$, EBITDA)	69.85%
ILCF ($n = 3$, EBITDA)	70.15%
ILCF ($n = 4$, EBITDA)	70.15%
CLCF ($n = 1$)	71.08%
CLCF ($n = 2$)	72.31%
CLCF ($n = 3$)	73.85%
CLCF ($n = 4$)	74.77%
Industry	60.92%
Industry/Age	59.38%

Table 3: Amount of TLCF - Results

This table shows the results derived regarding the accuracy of database-driven methods in predicting the amount of TLCF available. A method's percentage of small prediction errors corresponds to the percentage of firm-year observations for which logarithmic prediction errors are small (and not large) in magnitude. A logarithmic prediction error is defined as the difference between the natural logarithm of the TLCF amount predicted and the natural logarithm of firms' true TLCF amount. It is assumed to be small if it does not exceed a threshold level of 0.1. The higher a method's percentage of small prediction errors, the higher I expect its accuracy to be. For every method, results are based on firm-year observations between 2010 and 2012 that are correctly classified as TLCF firms in the first place. N corresponds to the number of firm-year observations.

Method	N	Percentage of Small Prediction Errors
ILCF ($n = 1$, EBT)	96	3.13%
ILCF ($n = 2$, EBT)	107	6.54%
ILCF ($n = 3$, EBT)	113	7.96%
ILCF ($n = 4$, EBT)	116	7.76%
ILCF ($n = 1$, EBIT)	102	5.88%
ILCF ($n = 2$, EBIT)	109	10.09%
ILCF ($n = 3$, EBIT)	112	16.96%
ILCF ($n = 4$, EBIT)	117	15.38%
ILCF ($n = 1$, EBITDA)	79	3.80%
ILCF ($n = 2$, EBITDA)	85	3.53%
ILCF ($n = 3$, EBITDA)	87	10.34%
ILCF ($n = 4$, EBITDA)	87	12.64%
CLCF ($n = 1$)	75	0.00%
CLCF ($n = 2$)	82	4.88%
CLCF ($n = 3$)	87	10.34%
CLCF ($n = 4$)	90	8.89%
Industry	56	19.64%
Industry/Age	56	19.64%

B Appendix

B.1 Comparison of Selected IFRS and Corporate Income Tax Provisions in Italy

Table B.1: Comparison of Selected IFRS and Corporate Income Tax Provisions in Italy

This table compares IFRS and corporate income tax provisions in Italy for depreciation allowances, interest expense and income from capital investments.

Provision	IFRS	Italian Corporate Income Tax Law
depreciation allowances	various methods	since 2008: straight-line basis previously: possibility to double depreciation allowances in the first three years of an asset's life, increase in the amount of depreciation allowances in case of intensive utilization
interest expense	fully deductible	since 2008: interest barrier, net interest expense can be deducted up to an amount of 30% of firms' EBITDA, interest and EBITDA carry-forwards possible previously: thin-capitalization rule based on a safe debt-to-equity ratio of 4:1, equity pro rata rules
income from capital investments	fully recognized	since 2008: 95% of income is tax-exempt previously: tax-exempt proportion of income varied between 84% and 100%

B.2 ILCF - Mathematical Derivation

Based on IFRS earnings from n past years, the amount of ILCF available at the end of year $t-1$ can be derived as follows:

For $j = n$:

$$ILCF_{i,t-j} = \begin{cases} |EARN_{i,t-j}| & \text{if } EARN_{i,t-j} < 0 \\ 0 & \text{otherwise} \end{cases} \tag{B.1}$$

For $j = n-1, .., 1$ (given that $n > 1$):

$$ILCF_{i,t-j} = \max\{ILCF_{i,t-j-1} - EARN_{i,t-j}; 0\} \tag{B.2}$$

where $ILCF_{i,t-j}$ ($ILCF_{i,t-j-1}$) is the stock of ILCF of firm i at the end of year $t-j$ ($t-j-1$), and $EARN_{i,t-j}$ is the amount of IFRS earnings realized in year $t-j$.

B.3 Industry Affiliation - Industries Employed

Table B.2: Industries Employed

This table shows the industries employed for the analyses in this study including their four-digit GICS codes.

Industry	Four-Digit GICS Code
Energy	1010
Materials	1510
Industrials Other	2000
Capital Goods	2010
Consumer Discretionary Other	2500
Consumer Durables & Apparel	2520
Media	2540
Consumer Staples	3000
Health Care	3500
Information Technology	4500
Telecommunication Services	5010
Utilities	5510

B.4 Industry Affiliation - TLCF Status Predictions

Table B.3: Industry Affiliation - Double Hurdle Regression Results

This table shows double hurdle regression results for the method based on industry affiliation. The results of the probit regression are based on the following model: $AVB_{i,t} = \alpha + \sum_{j=1}^{k-1} \beta_j \; INDUSTRY_{i,j} + \epsilon_{i,t}$. $AVB_{i,t}$ is equal to one if $TLCF_{i,t-1} > 0$ and zero otherwise. $TLCF_{i,t-1}$ ist the amount of TLCF available to firm i at the end of year $t-1$. $\sum_{j=1}^{k-1} \beta_j \; INDUSTRY_{i,j}$ is a set of industry dummies representing k four-digit GICS codes. Industry Information Technology serves as the reference category. Industry Other summarizes industries Energy and Telecommunication Services. $\epsilon_{i,t}$ represents the error term. The results of the truncated normal regression are based on the following model: $AMT_{i,t} = \alpha + \sum_{j=1}^{k-1} \beta_j \; INDUSTRY_{i,j} + \epsilon_{i,t}$. For an observation to be included in the truncated normal regression, $TLCF_{i,t-1}$ has to be greater than zero. $AMT_{i,t}$ corresponds to $TLCF_{i,t-1}$. σ represents the standard deviation of the error term. In both regressions, standard errors (shown in parentheses) are clustered at firm-level. *, ** and *** correspond to significance levels of 10%, 5% and 1%, respectively. N corresponds to the number of firm-year observations.

Variable	Probit Model	Truncated Normal Model
Other	−0.103	59,262
	(0.596)	(168,915)
Materials	−0.103	239,886
	(0.473)	(306,488)
Industrials Other	−0.035	−777,852
	(0.508)	(1,118,744)
Capital Goods	−0.647 *	−265,676
	(0.386)	(410,292)
Consumer Discretionary Other	−0.410	109,146
	(0.469)	(322,237)
Consumer Durables & Apparel	−0.345	100,765
	(0.406)	(173,452)
Media	−0.398	220,250
	(0.437)	(279,283)
Consumer Staples	−1.075 **	−1,374,116
	(0.457)	(2,106,350)
Health Care	−0.254	213,435
	(0.501)	(281,111)
Utilities	−0.912 *	−366,535
	(0.546)	(506,381)
Constant	0.199	−334,567
	(0.295)	(536,429)
σ		83,077
		(58,935)
N	325	139
Wald statistic	9.71	0.93
Pseudo R^2	0.042	

Table B.4: Industry Affiliation - Predicted Probability of Being Exposed to TLCF

This table shows the predicted probability of being exposed to TLCF for a firm operating in a certain industry. The following formula, taken from Burke (2009), is applied in order to compute the probability of being exposed to TLCF: $\Phi(\widehat{\alpha} + \sum_{j=1}^{k-1} \widehat{\beta_j}\ INDUSTRY_{i,j})$. $\sum_{j=1}^{k-1} \widehat{\beta_j}\ INDUSTRY_{i,j}$ represents the set of industry dummies specified in Table B.3. $\widehat{\alpha}$ and $\sum_{j=1}^{k-1} \widehat{\beta_j}$ are the coefficient estimates on the intercept and the industry dummies, as determined in the probit regression shown in Table B.3. Φ ist the standard normal cumulative distribution function.

Industry	Predicted TLCF Probability
Other	0.538
Materials	0.538
Industrials Other	0.565
Capital Goods	0.327
Consumer Discretionary Other	0.417
Consumer Durables & Apparel	0.442
Media	0.421
Consumer Staples	0.190
Health Care	0.478
Information Technology	0.579
Utilities	0.238

Table B.5: Industry Affiliation - Predicted TLCF Amount

This table shows the predicted TLCF amount (in thousand euros) for a firm with TLCF operating in a certain industry. The following formula, taken from Burke (2009), is applied in order to compute the amount of TLCF a available: $\widehat{\alpha} + \sum_{j=1}^{k-1} \widehat{\beta_j}\ INDUSTRY_{i,j} + \widehat{\sigma} \cdot \frac{\phi\left(\frac{\widehat{\alpha}+\sum_{j=1}^{k-1} \widehat{\beta_j}\ INDUSTRY_{i,j}}{\widehat{\sigma}}\right)}{\Phi\left(\frac{\widehat{\alpha}+\sum_{j=1}^{k-1} \widehat{\beta_j}\ INDUSTRY_{i,j}}{\widehat{\sigma}}\right)}$. $\sum_{j=1}^{k-1} \widehat{\beta_j}\ INDUSTRY_{i,j}$ represents the set of industry dummies specified in Table B.3. $\widehat{\alpha}$ and $\sum_{j=1}^{k-1} \widehat{\beta_j}$ are the coefficient estimates on the intercept and the industry dummies, as determined in the truncated normal regression shown in Table B.3. $\widehat{\sigma}$ represents the standard deviation of the error term. ϕ and Φ correspond to the standard normal density function and the standard normal cumulative distribution function, respectively.

Industry	Predicted TLCF Amount
Other	21,800
Materials	41,408
Industrials Other	6,137
Capital Goods	11,094
Consumer Discretionary Other	25,313
Consumer Durables & Apparel	24,654
Media	38,039
Consumer Staples	4,020
Health Care	36,971
Information Technology	18,638
Utilities	9,585

B.5 Industry Affiliation and Firm Age - TLCF Status Predictions

Table B.6: Industry Affiliation and Firm Age - Double Hurdle Regression Results

This table shows double hurdle regression results for the method based on industry affiliation and firm age. The results of the probit regression are based on the following model: $AVB_{i,t} = \alpha + \sum_{j=1}^{k-1} \beta_j \ INDUSTRY_{i,j} + \gamma \ AGE_{i,t} + \epsilon_{i,t}$. $AGE_{i,t}$ represents firm age. $AVB_{i,t}$, $\sum_{j=1}^{k-1} \beta_j \ INDUSTRY_{i,j}$ and $\epsilon_{i,t}$ are defined as in Table B.3. The results of the truncated normal regression are based on the following model: $AMT_{i,t} = \alpha + \sum_{j=1}^{k-1} \beta_j \ INDUSTRY_{i,j} + \gamma \ AGE_{i,t} + \epsilon_{i,t}$. For an observation to be included in the truncated normal regression, $TLCF_{i,t-1}$ has to be greater than zero. $AMT_{i,t}$ and σ are defined as in Table B.3. In both regressions, standard errors (shown in parentheses) are clustered at firm-level. *, ** and *** correspond to significance levels of 10%, 5% and 1%, respectively. N corresponds to the number of firm-year observations.

Variable	Probit Model	Truncated Normal Model
$AGE_{i,t}$	0.002	452
	(0.004)	(1,952)
Other	−0.143	39,660
	(0.596)	(182,130)
Materials	−0.210	211,757
	(0.527)	(232,464)
Industrials Other	−0.050	−772,650
	(0.511)	(1,073,730)
Capital Goods	−0.680 *	−267,180
	(0.395)	(404,075)
Consumer Discretionary Other	−0.436	97,251
	(0.473)	(281,562)
Consumer Durables & Apparel	−0.377	92,296
	(0.413)	(158,598)
Media	−0.415	212,924
	(0.438)	(250,526)
Consumer Staples	−1.103 **	−1,369,560
	(0.460)	(2,043,199)
Health Care	−0.261	214,291
	(0.505)	(276,285)
Utilities	−0.917	−367,963
	(0.546)	(497,350)
Constant	0.167	−338,185
	(0.306)	(532,861)
σ		82,551
		(56,092)
N	325	139
Wald statistic	9.91	1.18
Pseudo R^2	0.043	

Table B.7: Industry Affiliation and Firm Age - Predicted Probability of Being Exposed to TLCF

This table shows the predicted probability of being exposed to TLCF for a firm of a certain age operating in a certain industry. Predicted probabilities are computed using the formula shown in Table B.4 adjusted for firm age. $AGE_{i,t}$ is defined as in Table B.6. Φ represents the standard normal cumulative distribution function.

Industry	Predicted TLCF Probability
Other	$\Phi(+0.023 + 0.002 \cdot AGE_{i,t})$
Materials	$\Phi(-0.044 + 0.002 \cdot AGE_{i,t})$
Industrials Other	$\Phi(+0.117 + 0.002 \cdot AGE_{i,t})$
Capital Goods	$\Phi(-0.513 + 0.002 \cdot AGE_{i,t})$
Consumer Discretionary Other	$\Phi(-0.269 + 0.002 \cdot AGE_{i,t})$
Consumer Durables & Apparel	$\Phi(-0.211 + 0.002 \cdot AGE_{i,t})$
Media	$\Phi(-0.249 + 0.002 \cdot AGE_{i,t})$
Consumer Staples	$\Phi(-0.936 + 0.002 \cdot AGE_{i,t})$
Health Care	$\Phi(-0.095 + 0.002 \cdot AGE_{i,t})$
Information Technology	$\Phi(+0.167 + 0.002 \cdot AGE_{i,t})$
Utilities	$\Phi(-0.751 + 0.002 \cdot AGE_{i,t})$

Table B.8: Industry Affiliation and Firm Age - Predicted TLCF Amount

This table shows the predicted TLCF amount (in thousand euros) for a firm of a certain age with TLCF operating in a certain industry. TLCF amount predictions are computed using the formula shown in Table B.5 adjusted for firm age. $AGE_{i,t}$ is defined as in Table B.6. ϕ and Φ correspond to the standard normal density function and the standard normal cumulative distribution function, respectively.

Industry	Predicted TLCF Amount
Other	$-298,517 - 452 \cdot AGE_{i,t} + 82,551 \cdot \frac{\phi(\frac{-298,517-452 \cdot AGE_{i,t}}{82,551})}{\Phi(\frac{-298,517-452 \cdot AGE_{i,t}}{82,551})}$
Materials	$-126,423 - 452 \cdot AGE_{i,t} + 82,551 \cdot \frac{\phi(\frac{-126,423-452 \cdot AGE_{i,t}}{82,551})}{\Phi(\frac{-126,423-452 \cdot AGE_{i,t}}{82,551})}$
Industrials Other	$-1,110,805 - 452 \cdot AGE_{i,t} + 82,551 \cdot \frac{\phi(\frac{-1,110,805-452 \cdot AGE_{i,t}}{82,551})}{\Phi(\frac{-1,110,805-452 \cdot AGE_{i,t}}{82,551})}$
Capital Goods	$-605,349 - 452 \cdot AGE_{i,t} + 82,551 \cdot \frac{\phi(\frac{-605,349-452 \cdot AGE_{i,t}}{82,551})}{\Phi(\frac{-605,349-452 \cdot AGE_{i,t}}{82,551})}$
Consumer Discretionary Other	$-240,927 - 452 \cdot AGE_{i,t} + 82,551 \cdot \frac{\phi(\frac{-240,927-452 \cdot AGE_{i,t}}{82,551})}{\Phi(\frac{-240,927-452 \cdot AGE_{i,t}}{82,551})}$
Consumer Durables & Apparel	$-245,882 - 452 \cdot AGE_{i,t} + 82,551 \cdot \frac{\phi(\frac{-245,882-452 \cdot AGE_{i,t}}{82,551})}{\Phi(\frac{-245,882-452 \cdot AGE_{i,t}}{82,551})}$
Media	$-125,257 - 452 \cdot AGE_{i,t} + 82,551 \cdot \frac{\phi(\frac{-125,257-452 \cdot AGE_{i,t}}{82,551})}{\Phi(\frac{-125,257-452 \cdot AGE_{i,t}}{82,551})}$
Consumer Staples	$-1,707,699 - 452 \cdot AGE_{i,t} + 82,551 \cdot \frac{\phi(\frac{-1,707,699-452 \cdot AGE_{i,t}}{82,551})}{\Phi(\frac{-1,707,699-452 \cdot AGE_{i,t}}{82,551})}$
Health Care	$-123,890 - 452 \cdot AGE_{i,t} + 82,551 \cdot \frac{\phi(\frac{-123,890-452 \cdot AGE_{i,t}}{82,551})}{\Phi(\frac{-123,890-452 \cdot AGE_{i,t}}{82,551})}$
Information Technology	$-338,175 - 452 \cdot AGE_{i,t} + 82,551 \cdot \frac{\phi(\frac{-338,175-452 \cdot AGE_{i,t}}{82,551})}{\Phi(\frac{-338,175-452 \cdot AGE_{i,t}}{82,551})}$
Utilities	$-706,129 - 452 \cdot AGE_{i,t} + 82,551 \cdot \frac{\phi(\frac{-706,129-452 \cdot AGE_{i,t}}{82,551})}{\Phi(\frac{-706,129-452 \cdot AGE_{i,t}}{82,551})}$

B.6 Availability of TLCF - Statistical Tests

Table B.9: Availability of TLCF - Statistical Tests (I)

This table compares the accuracy of database-driven identification methods in predicting the availability of TLCF. Results are based on pairwise χ^2-tests of independency. Δ (in percentage points) corresponds to the difference in the percentage of correct TLCF status predictions between two methods. A method's percentage of correct predictions corresponds to the percentage of firm-year observations for which the (non-)availability of TLCF is correctly predicted. *, ** and *** correspond to significance levels of 10%, 5% and 1%, respectively.

	ILCF (EBT)		ILCF (EBIT)		ILCF (EBITDA)		CLCF		Industry		Industry/Age	
	Δ	$\chi^2(1)$	Δ	$\chi^2(1)$	Δ	$\chi^2(1)$	Δ	$\chi^2(1)$	Δ	$\chi^2(1)$	Δ	$\chi^2(1)$
(A) $n = 1$:												
ILCF (EBT)			2,15	0,38	5,23	2,17	2,77	0,62	12,92	12,35 ***	14,46	15,28 ***
ILCF (EBIT)	−2, 15	0,38			3,08	0,73	0,62	0,03	10,77	10,90 ***	12,31	10,90 ***
ILCF (EBITDA)	−5, 23	2,17	−3, 08	0,73			−2, 46	0,47	7,69	4,21 **	9,23	6,01 **
CLCF	−2,77	0,62	−0,62	0,03	2,46	0,47			10,15	9,80 ***	11,69	9,80 ***
Industry	−12,92	12,35 ***	−10,77	10,90 ***	−7,69	4,21 **	−10,15	9,80 ***			1,54	0,16
Industry/Age	−14,46	15,28 ***	−12,31	10,90 ***	−9,23	6,01 **	−11,69	9,80 ***	−1,54	0,16		
(B) $n = 2$:												
ILCF (EBT)			3,69	1,17	6,46	3,45 *	4,00	1,36	15,38	17,86 ***	16,92	21,33 ***
ILCF (EBIT)	−3,69	1,17			2,77	0,61	0,31	0,01	11,69	12,68 ***	13,23	12,68 ***
ILCF (EBITDA)	−6,46	3,45 *	−2,77	0,61			−2,46	0,48	8,92	5,72 **	10,46	7,78 ***
CLCF	−4,00	1,36	−0,31	0,01	2,46	0,48			−72,31	12,07 ***	12,92	12,07 ***
Industry	−15,38	17,86 ***	−11,69	12,68 ***	−8,92	5,72 **	−11,38	12,07 ***			1,54	
Industry/Age	−16,92	21,33 ***	−13,23	12,68 ***	−10,46	7,78 ***	−12,92	12,07 ***	−1,54			
(C) $n = 3$:												
ILCF (EBT)			5,54	2,69	8,00	5,43 **	4,31	1,65	17,23	22,78 ***	18,77	26,65 ***
ILCF (EBIT)	−5,54	2,69			2,46	0,48	−1,23	0,13	11,69	12,68 ***	13,23	12,68 ***
ILCF (EBITDA)	−8,00	5,43 **	−2,46	0,48			−3,69	1,10	9,23	6,13 **	10,77	8,26 ***
CLCF	−4,31	1,65	1,23	0,13	3,69	1,10			12,92	15,28 ***	14,46	15,28 ***
Industry	−17,23	22,78 ***	−11,69	12,68 ***	−9,23	6,13 **	−12,92	15,28 ***			1,54	0,16
Industry/Age	−18,77	26,65 ***	−13,23	12,68 ***	−10,77	8,26 ***	−14,46	15,28 ***	−1,54	0,16		
(D) $n = 4$:												
ILCF (EBT)			5,23	2,47	8,92	6,83 ***	4,31	1,70	18,15	25,50 ***	19,69	29,58 ***
ILCF (EBIT)	−5,23	2,47			3,69	1,10	−0,92	0,07	12,92	15,28 ***	14,46	15,28 ***
ILCF (EBITDA)	−8,92	6,83 ***	−3,69	1,10			−4,62	1,73	9,23	6,13 **	10,77	8,26 ***
CLCF	−4,31	1,70	0,92	0,07	4,62	1,73			13,85	17,42 ***	15,38	17,42 ***
Industry	−18,15	25,50 ***	−12,92	15,28 ***	−9,23	6,13 **	−13,85	17,42 ***			1,54	0,16
Industry/Age	−19,69	29,58 ***	−14,46	15,28 ***	−10,77	8,26 ***	−15,38	17,42 ***	−1,54	0,16		

Table B.10: Availability of TLCF - Statistical Tests (II)

This table shows how the accuracy of ILCF and CLCF in predicting the availability of TLCF changes if the time horizon employed is increased. Results are based on pairwise χ^2-tests of independency. Δ (in percentage points) corresponds to the difference in the percentage of correct TLCF status predictions if ILCF or CLCF are based on information from only one instead of n (with $2 \leq n \leq 4$) past years. A method's percentage of correct predictions corresponds to the percentage of firm-year observations for which the (non-)availability of TLCF is correctly predicted. *, ** and *** correspond to significance levels of 10%, 5% and 1%, respectively.

	$n = 2$		$n = 3$		$n = 4$	
	Δ	$\chi^2(1)$	Δ	$\chi^2(1)$	Δ	$\chi^2(1)$
(A) ILCF (EBT):						
n=1	−2,46	0,53	−4,31	1,65	−5,23	2,47
(B) ILCF (EBIT):						
n=1	−0,92	0,07	−0,92	0,07	−2,15	0,38
(C) ILCF (EBITDA):						
n=1	−1,23	0,12	−1,54	0,18	−1,54	0,18
(D) CLCF:						
n=1	−1,23	0,12	−2,77	0,62	−3,69	1,12

B.7 Amount of TLCF - Statistical Tests

Table B.11: Amount of TLCF - Statistical Tests (I)

This table compares the accuracy of database-driven identification methods in predicting the amount of TLCF available. Results are based on pairwise χ^2-tests of independency or, alternatively, exact Fisher tests (a). Δ (in percentage points) corresponds to the difference in the percentage of small prediction errors between two methods. A method's percentage of small prediction errors corresponds to the percentage of firm-year observations for which logarithmic prediction errors are small (and not large) in magnitude. A logarithmic prediction error is defined as the difference between the natural logarithm of the TLCF amount predicted and the natural logarithm of firms' true TLCF amount. It is assumed to be small if it does not exceed a threshold level of 0.1. *, ** and *** correspond to significance levels of 10%, 5% and 1%, respectively.

	ILCF (EBT)		ILCF (EBIT)		ILCF (EBITDA)		CLCF		Industry		Industry/Age	
	Δ	$\chi^2(1)$	Δ	$\chi^2(1)$	Δ	$\chi^2(1)$	Δ	$\chi^2(1)$	Δ	$\chi^2(1)$	Δ	$\chi^2(1)$
(A) $n = 1$:												
ILCF (EBT)			−2,76	0,87 ^{a}	−0.67	0.06 ^{a}	3.13	2.39 ^{a}	−16.52	11.54 ***	−16.52	11.54 ***
ILCF (EBIT)	2.76	0.87 ^{a}			2.08	0.41 ^{a}	5.88	4.57 **^{a}	−13.76	7.13 ***	−13.76	7.13 ***
ILCF (EBITDA)	0.67	0.06 ^{a}	−2.08	0.41 ^{a}			3.80	2.90 ^{a}	−15.85	8.85 ***	−15.85	8.85 ***
CLCF	−3.13	2.39 ^{a}	−5.88	4.57 **^{a}	−3.80	2.90 ^{a}			−19.64	16.08 ***	−19.64	16.08 ***
Industry	16.52	11.54 ***	13.76	7.13 ***	15.85	8.85 ***	19.64	16.08 ***			0.00	0.00
Industry/Age	16.52	11.54 ***	13.76	7.13 ***	15.85	8.85 ***	19.64	16.08 ***	0.00	0.00		
(B) $n = 2$:												
ILCF (EBT)			−3.55	13.07 0.89	3.01	0.87 ^{a}	1.66	0.23 ^{a}	−13.10	6.42 **	−13.10	6.42 **
ILCF (EBIT)	3.55	0.89			6.56	3.07 *	5.21	1.76	−9.55	2.92 *	−9.55	2.92 *
ILCF (EBITDA)	−3.01	0.87 ^{a}	−6.56	3.07 *			−1.35	0.19 ^{a}	−16.11	9.80 ***	−16.11	9.80 ***
CLCF	−1.66	0.23 ^{a}	−5.21	1.76	1.35	0.19 ^{a}			−14.76	7.49 ***	−14.76	7.49 ***
Industry	13.10	6.42 **	9.55	2.92 *	16.11	9.80 ***	14.76	7.49 ***			0.00	0.00
Industry/Age	13.10	6.42 **	9.55	2.92 *	16.11	9.80 ***	14.76	7.49 ***	0.00	0.00		
(C) $n = 3$:												
ILCF (EBT)			−9.00	4.18 **	−2.38	0.34	−2.38	0.34	−11.68	4.89 **	−11.68	4.89 **
ILCF (EBIT)	9.00	4.18 **			6.62	1.77	6.62	1.77	−2.68	0.18	−2.68	0.18
ILCF (EBITDA)	2.38	0.34	−6.62	1.77			0.00	0.00	−9.30	2.45	−9.30	2.45
CLCF	2.38	0.34	−6.62	1.77	0.00	0.00			−9.30	2.45	−9.30	2.45
Industry	11.68	4.89 **	2.68	0.18	9.30	2.45	9.30	2.45			0.00	0.00
Industry/Age	11.68	4.89 **	2.68	0.18	9.30	2.45	9.30	2.45	0.00	0.00		
(D) $n = 4$:												
ILCF (EBT)			−7.63	3.31 *	−4.89	1.34	−1.13	0.09	−11.88	5.19 **	−11.88	5.19 **
ILCF (EBIT)	7.63	3.31 *			2.74	0.31	6.50	1.95	−4.26	0.49	−4.26	0.49
ILCF (EBITDA)	4.89	1.34	−2.74	0.31			3.75	0.65	−7.00	1.28	−7.00	1.28
CLCF	1.13	0.09	−6.50	1.95	−3.75	0.65			−10.75	3.53 **	−10.75	3.53 **
Industry	11.88	5.19 **	4.26	0.49	7.00	1.28	10.75	3.53 **			0.00	0.00
Industry/Age	11.88	5.19 **	4.26	0.49	7.00	1.28	10.75	3.53 **	0.00	0.00		

Table B.12: Amount of TLCF - Statistical Tests (II)

This table shows how the accuracy of ILCF and CLCF in predicting the amount of TLCF available changes if the time horizon employed is increased. Results are based on pairwise χ^2-tests of independency or, alternatively, exact Fisher tests (a). Δ (in percentage points) corresponds to the difference in the percentage of small prediction errors if ILCF or CLCF are based on information from only one instead of n (with $2 \leq n \leq 4$) past years. A method's percentage of small prediction errors corresponds to the percentage of firm-year observations for which logarithmic prediction errors are small (and not large) in magnitude. A logarithmic prediction error is defined as the difference between the natural logarithm of the TLCF amount predicted and the natural logarithm of firms' true TLCF amount. It is assumed to be small if it does not exceed a threshold level of 0.1. *, ** and *** correspond to significance levels of 10%, 5% and 1%, respectively.

	$n=2$		$n=3$		$n=4$	
	Δ	$\chi^2(1)$	Δ	$\chi^2(1)$	Δ	$\chi^2(1)$
(A) ILCF (EBT):						
n=1	−3.42	1.26 ^{a}	−4.84	2.25	−4.63	2.11
(B) ILCF (EBIT):						
n=1	−4.21	1.26	−11.08	6.35 **	−9.50	5.04 **
(C) ILCF (EBITDA):						
n=1	0.27	0.01 ^{a}	−6.55	2.65	−6.55	4.20 **
(D) CLCF:						
n=1	−4.88	3.75 ^{a}	−10.34	8.22 ***^{a}	−8.89	7.00 ***^{a}

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