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Empirical Research on Corporate Credit-Ratings: A Literature Review

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Alexander B. Matthies†

Abstract

We report on the current state and important older findings of empirical studies on corporate credit ratings and their relationship to ratings of other entities. Specifically, we consider the results of three lines of research: The correlation of credit ratings and corporate default, the influence of ratings on capital markets, and the determinants of credit ratings and rating changes.

Results from each individual line are important and relevant for the construction and interpretation of studies in the other two fields, e.g. the choice of statistical methods. Moreover, design and construct of credit ratings and the credit rating scale are essential to understand empirical findings.

Keywords: Rating agency; Credit Ratings; Through-the-cycle rating methodology; Corporate Governance

JEL classification: G20; G30; G32; G24; G34

1 Introduction

Credit ratings aim to measure the creditworthiness of an entity (e.g. a corporation). They represent an opinion of a rating agency that evaluates the fundamental credit strength of an issuer and his ability to fully and punctually meet his debt obligations (Gonzales et al. (2004), Berblinger (1996) p. 11, and Wappenschmidt (2009)).

Credit ratings are produced by professional rating agencies. In the US and the EU regulatory norms exist that agencies must fulfil. For instance, in the US, agencies must be approved as *nationally recognized statistical rating organizations* (NRSRO) by the securities and exchange commission (SEC) (Hill (2004)). In an economic sense, rating agencies function as financial intermediaries (Ramakrishan & Thakor (1984)) whose existence would not be justifiable under the hypothesis of strictly efficient markets. The market for ratings has an oligopoly structure as the three leading agencies 'Moody's', 'Standard & Poor's' (S&P), and 'Fitch Publishing Company' control around 95% of the market (Asmussen (2005), Wappenschmidt (2009) p. 13).

Ratings exist for a wide variety of issuers such as corporations, countries, and structured finance products. Banks approve loans and credits (Krahnen (2001) p. 1767) on the

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basis of internal ratings. These so called 'shadow ratings' are distinct from the ratings provided by professional rating agencies. The ratings of agencies can be further divided into solicited (commissioned and paid for by the issuer) and unsolicited ratings (Poon (2003), Poon & Firth (2005), Bannier et al. (2010)). Ratings are placed on a discrete ordinal scale, where for example under the S&P scale an AAA (the so called 'triple A') rating is the highest credit rating assigned to issuers with the highest credit-quality and a D rating is the lowest rating assigned to bonds or firms in default.

Corporate, sovereign, and structured finance products have historically behaved differently (Benmelech & Dlugozs (2010)). The current crisis is largely due to bonds of sovereigns and structured finance products. In this context, empirical results of corporate ratings serve as a benchmark to understand those of other entities.

Agencies insist that ratings are opinions and not recommendations to buy, sell, or hold. Nevertheless, financial regulation in the US and the EU is often based on these ratings (Gonzales et al. (2004)). Overall, ratings are a highly aggregated classification of an issuers debt that can inform a third party on the possibility that the issuers will not be able to meet his obligations (default) (Dilly & Mählmann (2010)). On the other hand, issuers can use ratings as a mechanism of corporate governance to signal low investment risk and transparency (Nordberg (2011) p. 60). Ratings can, in this sense, solve principal agent problems (Gonzales et al. (2004)). In return issuers achieve access to the debt market and can reduce capital costs, as a higher rating reduces the yield spread to a risk free investment (Gonzales et al. (2004)). Potential investors and banks can use ratings as benchmarks for comparisons with their own analysis and internal ratings (Erlenmaier (2006) p. 39).

Credit ratings are produced by using public and confidential information. Agencies employ a firm's financial statements, franchise value, management quality, and consider its competitive position under different possible economic scenarios to form their judgement (Gonzales et al. (2004)). They attempt to asses the long term quality of a corporation. They therefore, take a through-the-cycle approach in contrast to a more point-in-time perspective (Amato & Furfine (2004) and Altman & Rijken (2006)). The through-the-cycle approach means that agencies try to form their opinion independently of short term business cycle effects. Point-in-time estimations of default probabilities are based on Merton-type models (based on Merton (1974)) which present more of a short term risk assessments (Gonzales et al. (2004)).

In the wake of numerous false assessments of credit quality in individual cases (e.g. Enron and Lehman Brothers, see Hill (2004), Löffler (2005), Güttler & Wahrenburg (2007), and Gopalan et al. (2009)), possible systematic errors in the market for structured finance products (Benmelech & Dlugosz (2010)), and the current sovereign rating crisis in Europe, the regulation and practices of agencies have come into the focus of public debate. In Europe the possible creation of an European rating agency is being considered. Additionally, agencies face further possible government reglementation and regulation (Stolper (2009)). Yet, ratings remain a voluntary institution of capital markets. Nevertheless, through regulation applicable for banks and fonds, ratings are effectively compulsory as a monitoring mechanisms (mostly in the US) (White (2007), Opp et al. (2010)), and form the basis of risk management (Nickel et al. (2000)) although there is no obligation to publish credit ratings. Therefore, it is striking what influence these privately offered measures, based on a censored calculation, have on capital markets. To illustrate, the downgrade of a corporation can significantly increase its capital costs and influence its stock price (Kisgen & Strahan (2010)).

In the process of globalisation there are increasing ambitions to harmonise accounting standards. As from 2005 all EU corporations are obliged to publish their financial statements under the *international financial accounting standards* (IFRS). Similar steps have also been taken in other industrial and developing countries. These steps are motivated in principle by the conclusion that capital markets are not efficient (Fama (1970)) and therefore regulatory measures ought to be taken to reduce information asymmetries. The IFRS is designed to help approximate the market value of equity and serve the market participants as a basis from which they can estimate the size and uncertainty of future cash flows. Empirical studies that measure the information content of financial statements find that they are a significant factor of capital market dynamics (e.g. Kothari (2001)). In this sense, the assessment of creditworthiness via ratings and the publication of accounting data serve similar purposes. Credit ratings aim to reflect the default probability of a firm in a single item and financial statements should fairly present the economic situation of a firm. Therefore, ratings and financial statements are alternative information instruments for market participants. Yet the obligational character of financial statements and the non obligational character of ratings force one to reflect to what degree ratings are determined by financial statements. Ratings would be redundant if they could be reproduced with financial statements, corporate governance characteristics, and macroeconomic variables.

This paper reviews the empirical studies conducted on credit ratings in the context of international capital markets and their relationship to financial statements. Moreover, we highlight the statistical properties of credit ratings and how these properties are essential to understanding credit ratings. The function and properties of ratings are crucial to formulating and imposing global and concrete regulation on financial markets. Furthermore, market participants need to understand ratings and their relationship to other measures of default in order to apply them.

Empirical studies on credit ratings can be roughly divided into three lines of research (Blume et al. (1998)). The first two measure the information content of credit ratings in different ways. The first line analyses whether credit ratings measure what they claim to measure, i.e. an issuers creditworthiness. More specifically, the relationship of ratings and corporate default is measured (Zhou (2001) and Jorion & Zhang (2007)). The second line measures the information content of ratings on capital markets. Here, capital market reactions around rating changes are analysed to see if ratings contain additional information (for a review see Gonzales et al. (2004)). The third line of research investigates the determinants of credit ratings. Here ratings as independent variables are modeled on a number of financial data (e.g. Ederington (1985)), corporate governance characteristics (Bhojraj & Sengupta (2003)), and macroeconomic factors (e.g. Amato & Furfine (2004)). These studies show that ratings can be replicated to a certain degree solely using publicly available data. Further studies in this context analyse the stability of credit ratings with respect to their 'through–the–cycle' approach (Altman & Rijken (2006)) and the determining factors of rating changes and transition probabilities (e.g. Lando & Skødeberg (2002) and Koopman et al. (2008)).

This paper continues as follows: in Section 2 we review the results of studies that investigate the relationship of ratings and default frequencies. The main finding is that ratings correlate on average negatively with future default rates, e.g. a firm with the highest rating AAA is less likely to default in the future than one with a B rating. In Section 3 we present the major findings of studies investigating the information content of ratings on capital markets. The results show that the characteristic and structure of the rating scale is crucial. Specifically, market reactions are asymmetrical, i.e. prices react differently to downgrades than to upgrades. Section 4 provides a review of empirical studies measuring the determinants of credit ratings. Ratings depend on financial ratios, firm size, corporate governance mechanisms, and macroeconomic variables. Section 5 surveys the statistical methods used in the studies presented in Section 4 to estimate and predict credit ratings. As in Section 3 we find that the character of the rating scale is an important feature in method selection. Section 6 reviews studies that analyse the empirical properties of rating transitions. We find that transitions, like capital market reactions, have asymmetrical features. Section 7 concludes.

2 Credit ratings and defaults

The informativeness of credit ratings can be basically measured in two ways. First, one can relate ratings within the same class to the frequency of default. The second is to investigate the information content of changes in credit ratings on the adjustment process of prices and returns of bonds and stocks (Jorion & Zhang (2007)). The results of the latter line of inquiry are discussed later in Section 3. We first analyse the results of the former line.

Historic default frequencies can be used as estimates for default probabilities of individual rating categories. Agencies do not assign a specific default probability to individual rating categories but define them as with regard to credit quality.

2.1 One year default rates

Rating agencies like Moody's and Standard & Poor's provide regular studies that relate their credit rating to the frequency of default in fixed cohorts. Zhou (2001) provides an extensive study of yearly default rates for Moody's rating from 1971 to 2000. Furthermore, studies estimating transition matrices (explained in detail below in Section 6) calculate transition frequencies to default for all S&P rating categories (e.g. Nickel et al. (2000) and Lando & Skødeberg (2002)), which are used as proxies for default probabilities.

Rating scales are not cardinal but ordinal, i.e. the difference in credit quality between an AAA rated firm and an AA rated firm is not the same as between an AA and an A rated firm. The difference in quality increases with each category down the scale. This feature is reflected in the measured default frequencies of the individual categories. For example, over an 18 year period from 1971 to 1988 there are no one year defaults in the Aaa and Aa categories (Zhou (2001)).

Rösch (2005) compares default risk forecasts of different rating philosophies. Specifically, the point-in-time and through-the-cycle approaches (more on that in Section 4.3). The through-the-cycle approach gives a certain amount of independence from the business cycle. Yet defaults are an objective event and therefore independent of the rating approach and thus default rates vary across the business cycle (Nickel et al. (2000)). Moreover, macroeconomic and sectorial shocks cause default rates to vary across bond market sectors for long time spans (Cantor & Falkenstein (2001)). Specifically, Cantor & Falkenstein (2001) find that discrepant default rates in different sectors and geographic regions are often caused by shocks in small samples.

Short-term interval horizons can cause estimated default probabilities to increase non-uniformly. In contrast, longer horizons produce smoother patterns (Jorion & Zhang

(2007)). Furthermore, one year default rates correlate with the business cycle (Nickel et al. (2000) and Zhou (2001)) and may therefore be an inaccurate estimate of a categories default probability.

2.2 Multi year default rates

Multi year default rates correlate less with the business cycle and are therefore more likely to reflect the agencies 'through–the–cycle' approach. In order to present the default frequency of a particular rating class Jorion & Zhang (2007) and Zhou (2001) analyse multi year default rates for S&P and Moody's respectively.

Table 1 presents the average 8 year (Moody's) and 10 year (S&P) cumulative default rates from 1983 to 1998 (Moody's) and 1981 to 2002 (S&P). The default rates for S&P ratings increase smoother than those of Moody's. This discrepancy could be caused by the lower horizon in the Moody's set or it might indicate that S&P ratings are more accurate than Moody's. Nevertheless there are common striking features worth noting. The statistics highlight a crucial feature of credit ratings. Different downgrades can correspond to different changes in default probability. For example, default rates for AA- and Aa3 are about 1%, below 5% for A- and A3, and around 10% for BBB- and Baa3. This means, for instance, under the S&P scale a downgrade from AAA to A- over 6 notches presents a smaller change in default probability than a downgrade from BBB- to BB+ over 1 notch. The ordinality of the rating scale is an essential characteristic and a key component in understanding empirical observations of ratings and how to apply them, and crucial in evaluating credit rating related research.

Rating	Default frequency	
	S&P	Moody's
AAA/Aaa	0.005	0.005
AA+/Aa1	0.004	0.004
AA/Aa2	0.007	0.009
AA-/Aa3	0.012	0.006
A+/A1	0.016	0.011
A/A2	0.017	0.014
A-/A3	0.023	0.010
BBB+/Baa1	0.047	0.024
BBB/Baa2	0.055	0.024
BBB-/Baa3	0.109	0.054
BB+/Ba1	0.140	0.143
BB/Ba2	0.187	0.138
BB-/Ba3	0.265	0.324
B+/B1	0.315	0.397
B/B2	0.396	0.343
B-/B3	0.492	0.483
CCC	0.572	–
Time period	1981 – 2002	1983 – 1998

Table 1: Default frequencies of rating categories of Moody's and Standard & Poor's (Sources Jorion & Zhang (2007) and Zouh (2001)).

In total, one year default rates correlate with the business cycle, whereas multi year default rates reflect more the through-the-cycle approach of rating agencies. Both statistics nevertheless stress the ordinal character of the rating scale.

3 Capital market reactions

Ratings have an effect on capital markets, influencing them directly and/or indirectly through rating based regulation. The direct effect of ratings on yields implies that ratings contain information that is publicly unavailable, and that markets are therefore not efficient. In this sense, empirical studies on market dynamics test the theoretical concept of market efficiency. Further determinants of bond prices are taxation, systematic risk, volatility, supply and demand, and liquidity (Gonzales et al. (2004)).

3.1 Information content

The effect of credit ratings on capital markets has been analysed over a long time in highly aggregated studies. Empirically, the influence of ratings has been measured on the price or return of bonds (Katz (1974), Ederington et al. (1987), Goh & Ederington (1999)), stocks (Pinches & Singelton (1978), Holthausen & Leftwich (1986), Followill & Martell (1997), Jorion et al. (2005), Jorion & Zhang (2007)), and more recently credit default swaps (Micu et al. (2004), Carthart et al. (2010)). The focus in these research papers is on the big rating agencies and on the US in geographic terms. A few individual studies have also analysed the European market (Gropp & Richards (2001), Cesare (2006)) and single countries, e.g. the UK (Barron et al. (1997) and Batchelor & Manzoni (2006)), Germany (Steiner & Heinke (2001)), and Spain (Abad–Romero & Robles–Fernández (2006) and (2007)).

Specifically, Katz (1974) finds that investors react to ratings as they react to new information. He performs an event study to test the efficiency of the bond market by analysing the price adjustment of bonds around rating changes. The expected yields of bonds are forecasted for their old and new rating classes. Katz finds no anticipation of the rating change prior to the announcement, implying that bond holders rely on the judgement of rating agencies and that the bond market is inefficient.

These results would justify the existence of rating agencies as financial intermediaries. Ederington et al. (1987) show that investors use ratings and accounting data to form their decisions. Furthermore, they find that ratings provide information beyond that of accounting statistics. Corporations often acquire two ratings. This is a way in which the rating market is informally regulated, the so called 'two rating regime' (White (2004)). Kish et al. (1999) test if markets value ratings of S&P and Moody's differently. They find diverging effects but can not show that one rating agency is more informative than the other.

Beyond the bond market ratings also lead to price adjustment processes on other markets underscoring their importance for market participants. Pinches & Singelton (1978) analyse the movement of stock prices around rating changes. They conclude that agencies lag behind the market which implies that ratings add no additional information to stock markets. Rating agencies actions are not limited to rating changes, but also include placements on watch lists and review announcements. Holthausen & Leftwich (1986) measure an effect on the stock market when S&P places a firm on its credit watch list. Similarly, Followill & Martell (1997) show that after announcements have an effect on the stock market, the effect of the actual rating change is negligible. The additional informational content of ratings depends also on how much more information agencies have than most market participants. Jorion et al. (2005) show that since the passing of the Fair Disclosure regulation in 2000 in the US, which gives agencies access to confidential information, ratings have a stronger effect on stock markets than before.

The choice of investing in either equity or debt is a central issue in corporate governance (Shleifer & Vishny (1997)). Barron et al. (1997) argues that, due to wealth redistribution effects from bond holders to stock holders, rating downgrades could increase stock returns in some cases. In this case, losses on the bond market would not lead to losses on stock markets. Abdad-Romero & Roles-Fernández (2006) and (2007) argue that because stock prices on Spanish markets react negatively to both downgrades and upgrades there could be a wealth redistribution effect in the opposite direction from stock holders to bond holders. Alternatively, the discrepant market reactions might also be influenced by other factors. For instance, Gropp & Richards (2001) find no announcement effects for rating changes of European banks on the bond market but strong effects on the stock market. They suggest that this could be due to insufficient liquidity on the bond market.

Micu et al. (2004) find that rating changes cause dynamics on CDS markets. Cesare (2006) measures if market based indicators can predict rating changes. Consistent with other studies, he finds that ratings still add information to the market although measures based on bond prices, stock prices, and CDS anticipate downgrades. Specifically, CDS are good indicators for negative and stock for positive events. Rating changes of one firm can also influence other firms in the same sector. Cathcart et al. (2010) show that stock and CDS returns correlate through industry effects.

Apart from the big rating agencies, there are many rating agencies that operate mostly in specific sectors or regions. Li et al. (2006) compare the influence of two local Japanese agencies with that of Moody's and S&P on Japanese stock markets. They find that the influence of Moody's and S&P is greater.

The lagging of actual rating changes to movements on markets and market based measures highlights the through-the-cycle approach of agencies. This gap to point-in-time approaches could be closed by the use of outlooks and reviews (watch lists) (Altman & Rijken (2007)). Furthermore, the results of experimental analysis by Ferri & Morone (2008) suggest that agencies can prevent herding behaviour and increase price convergence.

Overall, rating agencies seem to provide additional information to market participants. At least market participants, either through free will or forced by regulation, will act on ratings. This does not definitely answer if markets are not efficient, but at least market participants act as if they are not.

3.2 Asymmetrical effects

Market reactions are asymmetrical, especially those of stock prices. Specifically, markets react stronger to downgrades than to upgrades (Gonzales et al. (2004)). Downgrades have an empirically significant impact on stock prices in all studies, unlike upgrades that have no effect in most studies, e.g. Holthausen & Leftwich (1986) and Dichev & Pitroski (2001). This would imply that downgrades contain valuable information but upgrades do not.

Jorion & Zhang (2007) provide a theoretical basis for different price effects as a non-linear function of the rating prior to the announcement of the rating change. Here the change in default probability and the change in stock price are linked using a structural Merton-type model. Prior studies implicitly assumed an equal change in default probability for all rating changes, which is false (see Section 2). Jorion & Zhang (2007) show that, after including the prior rating to forecast price reactions, upgrades also have a significant effect on stock prices. Yet this effect is still smaller than that of downgrades.

This discrepancy in the effects of downgrades and upgrades might be due to several causes. It might be that rating agencies spend more resources to detect credit deterioration and firms are more willing to make positive information public (Jorion & Zhang (2007)). Downgrades may therefore — in contrast to upgrades — contain additional information that is not publicly available (Gonzales et al. (2004)). It could also be possible that stock markets overreact to downgrades (Dichev & Pitroski (2001)). A further reason may be the way in which rating agencies operate. As Altman & Rijken (2006) note, one of the consequences of the 'through-the-cycle' method of rating agencies is that agencies adjust their ratings upwards slower than their downgrades compared to more 'point-in-time' Merton-type methods. Another reason might be the observed correlation of ratings and the business cycle (Amato & Furfine (2004)). Bar-Isaac & Sharpio (2010) provide a theoretical model for the quality of ratings. It suggests that the quality of ratings decreases in boom phases of the business cycle. As upgrades are more likely to occur during economic expansions, the quality and therefore the information content of upgrades would be lower. Upgrades would then, on average, have a smaller impact on market reactions.

In a similar line of research empirical studies test the information content of financial statements. Financial statements can cause similar effects on capital markets as ratings do (for an empirical review see Mölls & Strauß (2007)). In the next section, we discuss that financial statements are basic determinants of corporate credit ratings. Therefore accounting data and credit ratings can be seen as alternative and even competing mechanisms to reduce information asymmetries on capital markets.

To conclude, it is found that capital markets react to credit rating changes, implying that markets are not efficient. Moreover, reactions are asymmetrical, i.e. stronger for downgrades than for upgrades. This finding holds even after allowing for the actual change in default probability that differs over rating classes due to the ordinal structure of the rating scale.

4 Determinants of credit ratings

The determinants of credit ratings fall into three main categories. The first are financial ratios and financial data. These variables proxy firm specific factors such as leverage, liquidity, and firm size (e.g. Ederington (1985), Kamstra et al. (2001), and Blume et al. (1998)). The second category are corporate governance mechanisms. Here, factors such as ownership structure and board independence are measured (Bhojraj & Sengupta (2003) and Ashbaugh-Skaife et al.(2006)). The third group comprises macroeconomic factors that could influence credit ratings like GDP growth measures (e.g. Amato & Furfine (2004)).

4.1 Financial statements and financial ratios

Financial ratios are easily obtainable from financial statements and are therefore publicly available information that determine corporate credit ratings. They are also traditionally applied in default prediction studies (e.g. Altman (1968)), which are similar to rating prediction and estimation studies. The ratios represent factors such as leverage, liquidity, interest coverage, and profitability that determine a firm's creditworthiness. Similarly, the firm's size also contributes to its default probability and creditworthiness.

4.1.1 Financial ratios and default probability

Altman (1968) uses five ratios, similar to those used in rating studies, to predict bankruptcy: *working capital/total assets*, *retained earnings/total assets*, *earnings before interest and taxes/total assets*, *market value of equity/book value of total assets*, and *sales/total assets*. He highlights their possible impact on default probability, and therefore on ratings too. The *working capital total assets ratio* is a measure of net liquid assets of the firm relative to its capitalisation. A firm that experiences operational losses will have shrinking current assets in relation to its total assets. Without liquidity it will not be able to continue operations, or repay its debt. Therefore, this ratio should be positively related to credit ratings, i.e. the higher the ratio is *ceteris paribus* the better the firm's rating.

The *retained earnings total assets ratio* is a measure of cumulative profitability over time, implicitly this also measures the age of a firm. Younger firms are more likely to fail than older firms and usually have a low retained earnings total assets ratio. The retained earnings can be used in less profitable times and may ensure continued operations. The ratio should therefore be positively correlated to credit ratings.

The *earnings before interests and taxes total assets ratio* is a measure of the productivity of the firm's assets. A firm's existence, including its creditworthiness, is based on the earning power of its assets. The productivity of a firm should therefore be positively related to credit ratings.

The *market value of equity to book value of total debt ratio* measures how much the firm's assets may decline in value before its liabilities exceed its assets and the firm could become insolvent. The ratio is therefore positively related to credit ratings.

The *sales total assets ratio* measures the sales generating ability of the firm's assets, and thereby the capability of the management to deal in competitive situations. A good management should decrease the probability of default and therefore be positively related to credit ratings.

Altman (1968) finds statistically significant effects for all these variables in a default prediction exercise. Kim & Sohn (2008) employ these ratios to predict rating transitions, and also find a significant effect.

4.1.2 Determinants of ratings

The ratios of Altman (1968) are significant determinants of corporate bankruptcy. Similar ratios and financial variables are employed to estimate and forecast ratings. Specifically, Kaplan & Urwitz (1979) use interest coverage, the long term debt to total assets ratio, the long term debt to net worth ratio, the net income to total assets ratio, the coefficient of variation of total assets, the coefficient of variation of net income, and total assets. Ederington (1985) uses interest coverage, the long term debt to capital ratio, and total assets. Kamstra et al. (2001) use net income plus interest expenses divided by interest expenses to represent interest coverage, a debt ratio measured by total debt divided by total assets, profitability captured by the net income total assets ratio, and firm size measured as book value of firm assets.

The financial ratios employed in these studies usually have a statistically significant intuitive effect. Specifically, in Kamstra et al. (2001) the debt ratio is negatively related and return on assets is positively related to credit ratings. The firm's size equally significantly improves ratings, i.e. on average larger firms will have better ratings. In contrast, they are unable to find a statistically significant effect of the interest coverage, implying that it does not determine credit ratings.

The stability of the determinant's effects does change over the time span of the relationship between firms and the rating agency. Mählmann (2011) shows that corporate ratings improve the longer the relationship lasts although the default rates do not decrease.

4.1.3 Nonlinear effects and multicollinearity

Blume et al. (1998) provide a more comprehensive study by estimating ratings in a panel regression from 1978 to 1995. They examine whether the observed decline in the quality of US corporate debt is due to more stringent rating standards. They employ ratios for pre-tax interest coverage, operating income to sales, long term debt to assets, total debt to assets, and total assets.

The findings are that the long term ratio is significantly related to credit ratings whereas the total debt ratio is insignificant. This is puzzling as the total debt ratio should be negatively related to credit ratings. An answer may lie in the high correlation of these two variables. More specifically, the insignificance might be due to multicollinearity as Amato & Furfine (2004) point out.

Motivated by the strong skewness in the distribution of interest coverage (a much smaller average than median), Blume et al. (1998) allow for a nonlinear effect for interest coverage. They show that interest coverage has a significantly positive effect for small values and an insignificant one for larger values. This result explains the empirical findings of Kamstra et al. (2001). Amato & Furfine (2004) confirm the basic finding that interest coverage has a nonlinear influence.

Financial ratios are the basic determinants of credit quality. Studies that omit these variables are almost incomplete by definition. The strong significance and effects that are measured emphasise the strong correlation and dependence credit ratings and financial statements have and underscore the observation that credit ratings and financial statements are alternative measures of corporate default.

As Kamstra et al. (2001) point out, a problem of financial ratios is that factors such as leadership quality, management ability, and technology changes are not captured or are hard to proxy. Blume et al. (1998) and Amato & Furfine (2004) use β's and standard errors from market models to represent measures of management quality. Large β and standard errors are associated with greater idiosyncratic risk and are therefore negatively related to credit ratings. Yet, as we will see below, this is problematic. Blume et al. (1998) omit measures of corporate governance to determine ratings that are crucial in assessing the credit worthiness of corporations and question the use of market based indicators.

4.2 Corporate governance

Bhojraj & Sengupta (2003) point out that a firm's likelihood of default depends on the availability of credible information to evaluate the default risk and agency costs. Both of these are determined by governance mechanisms. Corporate governance is essentially the system by which firms are controlled and directed. Corporate governance is the focus of much research (Brown et al. (2011)). Here the choice of investing as a bondholder or a stockholder is one of the central issues (Shleifer & Vishny (1997)). The assessment of the rating agency reflects the view of a debt owner.

Some studies measure the influence of corporate governance on firm performance. A summary of the state of corporate governance research is provided by Bebchuck & Weisbach (2010). Bhagat & Bolton (2008) find that governance as measured by the Gompers et al. (2003) index is positively correlated with better operating performance. Moreover, they argue that contrary to previous studies, governance measures are not correlated with future stock market performance, if endogeneity is adequately addressed[1].

The relationship of bond yields and corporate governance measures is highly correlated to that of credit ratings and corporate governance. Bhojraj & Sengupta (2003) show that corporate governance measures that increase ratings also lower bond yields. Nevertheless, Moody's and S&P ratings are not sufficient to explain spot rate curves and pricing relationships completely (Elton et al. (2004)). Liu & Jiraporn (2010) find that higher decision making power of CEO's lowers ratings and increases yield spreads.

To value the efficiency of corporate governance, there are also some corporate governance rating firms that seek to provide assistance to investors. The results of Daines et al. (2010) suggest that these commercially available corporate governance rankings provide no useful information to shareholders.

Under the agency theory framework of Jensen & Meckling (1976), bondholders face two potential conflicts that can reduce the value of their claims by increasing the probability of default. The first is that one between management and all stakeholders (equity and debt), and the second one is that between bondholders (providing debt) and shareholders (providing equity).

4.2.1 The principal agent problem

The separation of ownership and control leads to information asymmetry problems between external stakeholders and managers. Managers that act selfishly can reduce expected cash flows to the firm and its external stakeholders. As the cash flows decline, the default risk increases and therefore effects a credit rating negatively. In this respect governance mechanisms that provide independent and effective monitoring of the management should improve ratings. Ashbaugh-Skaife et al. (2006) refer to this role as the management disciplining hypothesis.

Bhojraj & Sengupta (2003) distinguish two mechanisms through which governance mechanisms effect credit ratings. The first is agency risk. This is the risk that management acting in its self interest would take actions that deviate from firm value maximization, as well as the risk that the manger is incompetent. The second is information risk. This is the risk that managers have private information that would adversely affect the default risk of a loan. Governance mechanisms can reduce both these risks. Specifically with regard

[1] For a more detailed discussion of the importance of endogeneity of governance measures see Brown et al. (2011).

to agency risk, firms with strong governance should receive a higher rating. Similarly mechanisms that induce firms to disclose information in a timely and transparent manner should reduce information risks and therefore improve a firm's rating.

Bhojraj & Sengupta (2003) list three factors to capture these mechanisms; institutional ownership, block holding, and board structure. Institutional owners may actively monitor the management actions and if necessary take the required steps to protect shareholder interests. In this case institutional investors have incentives to monitor and control management under the active monitoring hypothesis. On the other hand it could be argued that institutional investors are limited in their motivation to monitor management. Bad management under this passive monitoring hypothesis would then encourage institutional investors rather to sell their stock than to initiate corrective action. This effect could vary in a cross sectional analysis, as it might depend on the corporate governance codex of the relevant country. Under this hypothesis, the influence of institutional ownership on credit ratings would depend upon the investment strategy, i.e. voice or exit. Yet neither Bhojraj & Sengupta (2003) nor Ashbaugh-Skaife et al. (2006) investigate this effect.

Concentrated ownership could allow block holders (holding more than five percent of shares) to exercise undue influence over management to secure benefits that are detrimental to other providers of capital. This private benefits hypothesis is distinct from the wealth redistribution hypothesis discussed below. Under the private benefits hypothesis block holders are negatively related to ratings. Bhojraj & Sengupta (2003) focus on the conflict between block holders and other stake holders. A contrary effect could be that block holders, similar to institutional investors, monitor management effectively. This is the shared benefits hypothesis, which postulates a positive effect of block holders on ratings.

Corporate boards have the duty of monitoring management performance and protecting shareholder interests. Outside directors bear a reputation cost if a firm's performance is poor. This should motivate them to monitor management more closely and thereby improve ratings. On the other hand, outside directors might be inefficient as they are selected by management, or because board culture might discourage conflict, thereby causing a negative relation to bond ratings.

Bhojraj & Sengupta (2003) use the percentage of stock held by institutional investors and the percentage of outside board directors as proxies for institutional ownership and board independence respectively. They find that both variables effect credit ratings positively. This supports both the monitoring hypothesis and the benefits of an independent board.

To capture block ownership they separately use the percentage of stock held by block holders and the percentage of shares held by institutional investors. Both of these variables have a significantly negative effect which supports the private benefits hypothesis. Yet without a control variable to represent a possible wealth redistribution effect, this result requires further analysis. Bhojraj & Sengupta (2003) argue, based on empirical work, that this effect is irrelevant. If this were the case, then the coefficients of the control variables would be insignificant. Moreover, even if the argument from Bhojraj & Sengupta(2003) were correct and wealth transfer effects are irrelevant to determine the creditworthiness of a firm, rating agencies might still consider them relevant. It might then be similar to an anchor effect where a classification decision is influenced by an irrelevant factor (Tversky & Kahneman (1974)).

A further result of Bhajroi & Sengupta (2003) is that governance mechanisms are more critical for lower rated firms. In the light of the results of Blume et al. (1998), mentioned above, who find that ratios are more important for larger firms, this result should be further investigated. These results are logically compatible, as firm size is a positive determinant of credit ratings. Therefore larger firms on average have better ratings. Yet it is necessary to test if the credit rating in the Bhojraj & Sengupta (2003) analysis can be replaced by the independent variable 'firm size' to discriminate for the importance of corporate governance mechanisms.

4.2.2 Wealth redistribution hypothesis

The conflict between bond holders and stock holders is capsulated in the wealth redistribution hypothesis (Barron et al. (2001)). As shown in Section 3 rating changes can affect bond and stock prices differently. Gompers et al. (2003) find that stronger shareholder rights correlate with higher firm value. Moreover, anti-takeover governance provisions are viewed favorably by bondholders yet not by stockholders (Klack et al. (2005)).

Ashbaugh-Skaife et al. (2006) conduct a more comprehensive analysis and follow the framework of Standard & Poor's (2004) to evaluate a firm's governance structures and practices. Standard & Poor's focuses on four major components of governance: ownership structure and influence, financial shareholder rights and relations, financial transparency, and board structure and process. Moreover, Ashbaugh-Skaife et al. (2006) test for possible wealth redistribution effects which Bhojraj & Sengupta (2003) intentionally ignore. They find that the number of block holders has a negative impact on credit ratings this is consistent with Bhojraj & Sengupta (2003) results but also with the wealth redistribution hypothesis. Furthermore, their measure of shareholder rights — a score counting single shareholder rights — is negatively related to credit ratings. This suggests that greater shareholder rights are negative for credit ratings and supports the wealth redistribution hypothesis.

Ashbaugh-Skaife et al. (2006) further find a positive influence for their measures of financial transparency and board independence and expertise. The results on board structure are also consistent with the results of Bhojraj & Sengupta (2003). In conclusion, Bhojraj & Sengupta (2003) and Ashbaugh-Skaife et al. (2006) provide empirical evidence that corporate default probability depends on governance mechanisms.

4.2.3 Measuring management quality

Blume et al. (1998) and Amato & Furfine (2004) employ the β of market models to proxy for management quality. Moreover, Bhojraj & Sengupta (2003) use cumulative stock returns and the market model β. Cumulative stock returns are almost unique as a determinant of credit ratings. Its use as a control variable may be considered unusual, as Bhojraj & Sengupta (2003) are uncertain about its relationship to credit ratings.

The results of Bhojraj & Sengupta (2003) highlight the unclear influence of β and cumulative stock returns. In a regression without measures of concentrated ownership both variables have an insignificant influence on credit ratings. This is in contrast to Blume et al. (1998) and Amato & Furfine (2004) who find a significantly negative relation for the β. In the regression that includes block ownership the β is significantly negative and in the regression with the percentage of institutional owned shares it is significantly positive (the coefficient of cumulative stock returns shows the exact opposite behaviour).

Variables derived from market models therefore seem inappropriate to capture management quality, as its effect is not understood. The results could also imply that governance mechanisms that monitor management behaviour are more important for credit ratings than measures of management quality.

4.3 Macroeconomic determinants

Rating Agencies declare that they employ a rating through-the-cycle as opposed to a more point-in-time perspective (e.g. Merton-type models (Gonzales et al. (2004))), to avoid short term business cycle effects while assessing the creditworthiness of corporations (Standard & Poor's (2002)). But it is empirically observed that agency ratings and the business cycle do correlate (Amato & Furfine (2004), Kim & Sohn (2008), Feng et al. (2008)).

4.3.1 Observed decline in US debt

Blume et al. (1998) argue that an — at that time — observed increase in downgrades by rating agencies is due to more stringent standards in rating assessment. Specifically they find that in a panel regression intercepts for each year show a constant decline over time. This causes the panel model to underpredict ratings in the future, suggesting that rating standards have become more stringent. Amato & Furfine (2004) can reproduce this result and attribute the observed stronger trend (in comparison to Blume et al. (1998)) to the fact that they also employed speculative grade ratings.

In order to tackle two possible criticisms, Blume et al. (1998) test the robustness of the results. The first for them is their assumption that the slope coefficients remain constant over time. Yet, in year by year regressions, the intercepts still decline over time and the slope coefficients vary little and are similar to those in the panel model. Moreover, they find no trend in the independent variables (except for market value, which increases). The second objection they consider is that there could be crucial omitted variables that caused the decline. They show that firms that had no rating change over time on average improved the factors that determine their credit ratings to counter the objection. Nevertheless, omitted variables might be found in the set of corporate governance variables used by Ashbaugh-Skaife et al. (2006) or the macroeconomic variables employed by Amato & Furfine (2004).

Jorion et al. (2009) suggest that the observations of Blume et al. (1998) are due to a decline in accounting quality. Specifically, accounting information of investment grade firms has reduced in quality over time. In line with these results Helfin et al. (2011) find that higher annual report disclosures improve credit ratings.

4.3.2 Ratings through the cycle

Amato & Furfine (2004) show empirically that the observed decrease in credit quality might be due to macroeconomic effects of the business cycle. Nevertheless they claim to find no evidence that ratings are unduly influenced by the business cycle, and agencies therefore achieve a form of rating stability.

Specifically, they advance the Blume et al. (1998) analysis by performing three further regressions in which they replace the time dummies with a linear trend and alternatively with an indicator for expansion and recession (the NBER recession indicator), and two indicators for the state of the economy (the output growth gap and a discrete measure of the output gap). The linear trend is significant which is consistent with the behaviour of the time variables and therefore with the claim that rating standards have become more stringent. Furthermore, the macroeconomic measures are mostly insignificant which would confirm the agencies' claim that they see through the cycle. Yet, in a further regression with the time series of the financial means, the linear trend is also insignificant. This result somewhat undermines the findings of Blume et al. (1998). Moreover, they find that the predictive power of the time dummy model is similar to that with a linear trend and cyclical variables.

They subject their results to the possible criticism that putting together investment and speculative grade ratings might result in model misspecification, by performing their analysis solely for investment grade firms. Their results imply that investment grade firm's ratings are more cyclical, as the economic indicators have an significant influence. Here, similar to the results of Ashbaugh-Skaife et al. (2006) which imply that ratings determine the importance of governance mechanisms, the rating classification could be replaced with firm size. They then question the implicit assumption that each observation represents an active decision of the rating agency. Alternatively, it could be that due to resource constraints not every rating is accurate in time (compare with the information content of credit ratings). In a regression that solely uses new issues and rating changes, one can be certain that these observations reflect active decisions based on recent research. For this sample, procyclicality is even stronger than for the investment grade ratings. Furthermore, the linear trend changes signs and implies that rating standards have become more lenient rather than more stringent, as Blume et al. (1998) suggest. Yet, as Amato & Furfine (2004) point out, these results are limited to a subset of the ratings universe, and therefore the results could be biased, as there are numerous instances of unchanged ratings where their presence on the agency's watch list decisions suggests an active decision.

Löffler (2004) points out that a through-the-cycle approach requires a separation of permanent and cyclical components of default risk. In a Monte Carlo simulation he shows how this can cause the observed empirical irregularities of agency ratings. He (Löffler (2005)) then goes on to show how the attempt of the agencies to avoid frequent rating reversals can lead to the empirically observed rating stability, serial dependence of rating transitions (Güttler & Raupach (2010)), and the lag of ratings to changes in issuer's default risk.

Changes in ratings can empirically be captured by so-called transition-probability matrices. Feng et al. (2008) use a factor probit model to predict such credit rating matrices in order to show the effect of the economic cycle on corporate ratings. They argue that this effect provides evidence that rating agencies, contrary to their claims, apply the point-in-time perspective. Yet, as Amato & Furfine (2004) point out, the individual business risk factors of corporations can exhibit cyclical behaviour which may cause the cyclical behaviour of corporate ratings.

The practical consequences of rating agencies' through-the-cycle perspective are highlighted by Altman & Rijken (2006), arguing that the objectives of rating stability and default prediction performance can come into conflict. They observe that rating agencies only partly adjust ratings to the actual credit quality, and less so for upgrades than for downgrades. This reduces the rating migration probability — confirming the findings of Amato & Furfine (2004) — and delays rating transitions. Furthermore, compared to their own point-in-time predictions, this causes the rating agencies' one-year-horizon predictions to be less accurate, yet they turn out to be more accurate at larger forecast horizons.

More recently Bar-Isaac & Sharpio (2010) develop a model in which rating quality is dependent on factors affected by the business cycle. These include agencies' income from fees and competition on the labour market for analysts. The model is set out to explain the inaccurate predictions of rating agencies during the 2008 financial crisis, specifically those of structured finance products empirically observed by Benmelech & Dlugosz (2010).

In summary, financial ratios are essential to determine the creditworthiness of corporations. Corporate governance characteristics and macroeconomic variables supply additional relevant information for ratings. In particular, corporate governance mechanisms that can reduce principal agent problems between management and stakeholders and effect wealth redistribution from bondholders to shareholders are important. Agencies attempt to filter out macroeconomic effects by a through-the-cycle approach that seeks to be independent of the business cycle. Yet this is difficult as it is often unclear which developments are fundamental and which are short-term. Unfortunately no study up to now has incorporated all three groups of determinants.

5 Statistical methods used to estimate credit ratings

There are a number of statistical applications to estimate and forecast credit ratings. They differ in the underlying assumptions they make. Most studies employ a linear regression, logistic regressions, or discriminate analysis method. These are the standard approaches to estimate ratings. Furthermore, some studies for example use neuronal networks or duration and hazard models to forecast rating transitions.

5.1 Classical methods

The *ordinary least squares (OLS)* and the *ordered probit* model are ordered methods. They include the assumption that ratings are ranked. In contrast, the *unordered logit* and *linear discriminant analysis* are not ranked. Ederington (1985) provides a comprehensive theoretical comparison of these four methods and how they perform for in-sample estimation and for out-of-sample prediction.

The *OLS* regression is an ordered method. An issue arises concerning the definition of the independent variable (ratings) which is addressed by assigning integers to the ordered groups. The problem with this approach is that it defines ratings as an interval scale on which the difference between each two rating classes are the same.

The *ordered probit* model estimates an unobservable continuous variable (e.g. default probability), which falls into intervals that correspond to an observable discrete variable (rating class). Because the intervals can vary in size, the method addresses the scale problem more adequately than the OLS method. A problem of the two ordered methods is that variables may influence credit ratings differently across different rating categories.

The multinomial or *unordered logit* model allows the importance of variables to vary across ratings. Yet, as the name implies, it does not incorporate the ordered character of the ratings. An assumption of this model is that the error terms have a Weibull distribution, unlike an unordered probit model, where the disturbances are assumed to be normally distributed.

A further unordered method is the *multivariate discriminate analysis (MDA)*. It distinguishes itself from the unordered logit model by being a conjoint method. While logit and probit model the rating as an independent variable, MDA considers the distribution parameters of the firm's characteristics to be dependent on the bond ratings. Unordered logit and MDA have different basic assumptions but use the same classification equation.

In an empirical application Ederington (1985) finds that the unordered logit and ordered probit outperform the OLS and MDA methods. Moreover, unordered logit achieves the best fit for in-sample estimation and ordered logit performs best for out-of-sample prediction. Most newer studies that focus on business or economic issues apply the ordered logit method (e.g. Blume et al. (1998), Amato & Furfine (2004), and Ashbaugh-Skaife et al. (2006)). Intuitively it is more appropriate due to its a priori assumptions to model ratings than the other methods listed above. It assumes the ordered structure of the ratings but it can also adjust to the specific features of the rating scale. Nevertheless, it assumes a constant influence of variables across all rating categories. Yet, as seen above in Section 4, the influence of individual factors vary across rating classes, in particular between investment and speculative grades. Furthermore, the ordered probit panel regression assumes an point-in-time perspective instead of the through-the-cycle approach, that is employed by rating agencies (Altman & Rijken (2004)). This is problematic if the probit method is used to forecast rating changes as in Amato & Furfine (2004). In other rating transition studies it is common to use forms of duration or hazard models (Du & Suo (2005) and Koopman et al. (2008)). Yet, due to its economic significance, a large number of studies have employed further methods to predict ratings.

5.2 Learning methods

In principal the classification of a credit rating to a given set of firm specific variables can be regarded as a mere categorisation problem. In this sense, methods can be 'trained' on a sample of ratings and corresponding financial data. These so called learning or artificial intelligence methods can then be used in forecasting exercises. For instance, within neuronal networks learning is defined as the search for the weights to produce the best fit with the given training data (Kwon et al. (1997)). Most of these studies are not discussed within the business or economic research but in the context of the development and application of alternative methods in computer science. These are methods such as the already mentioned neuronal networks (Dutta & Shekhar (1988) and Kwon et al. (1997)), support vector machines (SVM) (Huang et al. (2004), Härdle et al. (2005), Ahn et al. (2005), Cao et al. (2006), Chen & Shih (2006), Lee (2007), and Ye et al. (2008)), fuzzy logic (Shin et al. (2004), Liu & Liu (2005)), and π-grammatical evolution (Brabazon & O'Neill (2008)).

Overall, it is important to consider the a priori knowledge on ratings (ordered and ordinal scale) while selecting a statistical method to estimate or predict ratings. Yet the ordered probit model has two difficulties. One is the variation of influence of determinants over rating classes. The other is its implicit point-in-time perspective approach while forecasting rating transitions. Studies using so-called 'learning methods' are usually not discussed in an economic or business context.

6 Rating transitions

Similar to the estimation of credit ratings is the estimation and prediction of credit rating changes. A general difference in these two approaches is that studies that forecast rating changes usually condition their forecasts on prior rating.

Some studies mentioned above (e.g. Amato & Furfine (2004)) incorporated rating transition predictions based on firm specific factors. Some studies solely rely on a set of more general predictors. Rating transition matrices (or some times migration matrices) are used, that estimate transition probabilities. Further studies investigate the empirical properties of transition probabilities and what determines them.

6.1 Rating transition matrices

Transition matrices are at the centre of modern risk management, as transition probabilities are a crucial component of many credit risk models (Lando & Skødeberg (2002)). Risk is measured using the distribution of rating transitions for the firms (bonds) in a given portfolio.

In Nickel et al. (2002) the assumption is made that a constant transition probability p_{ij} exists that reflects the likelihood in a given time period (usually a year) that a rating from class i will change to class j. They can, in the simplest way, be estimated by dividing the number of firms (or bonds) that change from i in time period t to j in $t+1$ with the total number of firms in class i in at t. This is an unconditional estimation, where the transition matrix is made up by the p_{ij}. A common property of transition matrices is that they are diagonally dominated, i.e. most ratings do not change and those that do, do so only over one or a few notches (Nickel et al. (2000), Lando & Skødeberg (2002), Kim & Sohn (2008)).

Nickel et al. (2000) estimate conditional and unconditional transition matrices based on S&P's ratings from 1970 to 1997. They find that the precision of probability estimation for lower rated bonds is reduced, as there are fewer speculative bonds and higher volatility in the unconditional transition matrix. Estimating conditioned transition matrices they further find that transition probabilities are determined by the state of the business cycle, the regional origin of the issuer, and the issuers industry.

Transition matrices are widely used in rating studies (e.g. Lando & Skødeberg (2002), Kim & Sohn (2008), and Koopman et al. (2008)). Nickel et al. (2000) implicitly assume that rating transitions probabilities are produced by a Markov–process, i.e. all ratings in a category have the same up and downgrade probabilities.

6.2 Duration and momentum effects

In order to produce more efficient estimates of transition matrices, Lando & Skødeberg (2002), Du & Suo (2005), and Koopman et al. (2008) employ continuous-time estimations of transition probabilities. That is, instead of yearly transition rates they consider monthly (Lando & Skødeberg (2002) and Du & Suo (2005)) and even daily (Koopman et al. (2008)) observations. Lando & Skødeberg (2002) motivate this procedure by the fact that observations for large transitions are rare or do not occur at all. For example, AAA to D transitions are not observed in one year, but a bond or firm can still in the time of one year be downgraded from AAA to A and from A to D. In contrast to discrete-time methods, continuous-time methods capture effects like this one. Moreover, they test credit rating transitions for so called non-Markov effects, in particular duration and momentum. In a Markov-chain a transition probability depends solely on the current state an object is in and not on how it reached it or how long it has been in that state. In terms of rating transitions that would mean that the probability of, for instance, an AA rated bond to be downgraded does not depend on how long it has been rated AA (duration) or if it reached its state through a down- or upgrade (momentum).

Lando & Skødeberg (2002) and Du & Suo (2005) find empirical evidence for both momentum and duration effects. Specifically, Lando & Skødeberg (2002) find a strong downgrade momentum and only significant upgrade momentum for lower rated bonds. This means that a previous downgrade increases the probability to be downgraded again, but the equivalent for upgrades only holds for lower rated bonds. Furthermore, with respect to duration, the longer a firm occupies a rating class the less likely it will be up- or downgraded.

The asymmetric effect measured for momentum fits together with the results of Jorion & Zhang (2007) with regard to the information content of credit ratings (see Section 3). Part of the price adjustment process around rating changes might include the expectations of market participants of further reclassifications. Furthermore, the reluctancy of agencies to issue an upgrade shortly after a downgrade (Altman & Rijken (2006)) and the higher possibility of a further downgrade might contribute to the observed asymmetric price adjustments that are empirically observed.

In total, rating transition probabilities are often estimated using rating transition matrices. These differ over the business cycle, industries, and the regional origin of the issuer. Rating transitions furthermore exhibit non-Markov effects, i.e. they do not solely depend on the current state of the rating.

7 Conclusion

This paper reviews the empirical work conducted on credit ratings in the context of international capital markets. We highlight three lines of research within this field and how they interact with each other. Furthermore, we show how the implications of each individual line are crucial to understand the results in other fields.

The first line of research explores the information content of credit ratings and their relationship to corporate default. The results highlight the ordinal character of the rating scale. Differences in rating classes do not correspond to equivalent differences in default probability. This has important implications for the two second lines of research, the information content of ratings with regard to capital market reactions and the determinants of credit ratings.

The relevance of credit ratings changes for capital markets, i.e. the efficient market hypothesis, can only be measured effectively if they are conditioned on the respective change in default probability. Moreover, market reactions around rating changes are asymmetrical. Specifically, markets react stronger to downgrades than to upgrades (even after incorporating the corresponding default probability). This discrepancy might have multiple reasons. It might be caused by the way rating agencies operate or specific features of the market for ratings. On the other hand it might be caused by the behaviour of corporations and how they release relevant information. One important feature of the agencies' approach that might cause the asymmetrical information content of credit ratings is the so called through-the-cycle method. Rating agencies try to estimate the long term creditworthiness of a corporation independent of short-term business cycle effects. Nevertheless, ratings do correlate with the business cycle. Therefore macroeconomic variables along with financial ratios and corporate governance characteristics are determinants of credit ratings.

The third line of research highlights the relationship of financial statements and credit ratings. Financial statements form the core element of determining credit ratings. Moreover, corporate governance mechanisms that can reduce principal agent problems between management and stakeholders and effect possible wealth redistribution from bondholders to shareholders are relevant to determine the creditworthiness of a corporation. The issue of choosing a statistical method again depends on the ordered and ordinal structure of the rating scale. Most recent studies therefore employ an ordered probit approach. It is ordered like the rating scale and can incorporate its ordinal character. Yet there are two potential deficiencies. First, the method does not allow for the varying influence of variables over different classes of ratings. This is problematic as the influence of corporate governance mechanisms and macroeconomic variables depends on the rating class. Second, in particular with respect to predicting rating changes, a panel regression assumes a point-in-time approach instead of the rating agencies' through-the-cycle method. Therefore employing the probit panel approach to credit rating change predictions might produce inaccurate results.

Studies to estimate and predict credit rating transitions probabilities and rating transitions employ rating transition matrices and duration methods. They find that rating probabilities depend on the state of the business cycle, its industry, and on the regional origin of the issuer. Moreover, rating transitions depend on the length a rating has spent in one rating class and how it reached that class (via up- or downgrade). More specifically, a firm that has recently been downgraded is more likely to be downgraded again. This finding might again be caused by the agencies' rating procedures.

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