RATING SHOPPING AND RATING INFLATION: EMPIRICAL EVIDENCE FROM ISRAEL

Inna Bakalyar and K. Galil

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Monaster Center for
Economic Research
Ben-Gurion University of the Negev
P.O. Box 653
Beer Sheva, Israel

Fax: 972-8-6472941
Tel: 972-8-6472286

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Inna Bakalyar[1]

Koresh Galil [2]

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[1] Ben-Gurion University of the Negev, Department of Economics, P.O. Box 65, Beer-Sheva 84105, Israel, email: innabaka@bgu.ac.il; Tel: +972-54-5711124
[2] Corresponding author: Ben-Gurion University of the Negev, Department of Economics, P.O. Box 65, Beer-Sheva 84105, Israel, email: galilk@bgu.ac.il ; Tel: +972-54-4565570

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Inna Bakalyar[3]

Koresh Galil [4]

Abstract

The collapse of structured bond ratings during the 2007-2008 financial crisis called attention to the possibility of rating inflation due to lowered rating standards and rating shopping. Nevertheless, little empirical evidence has been offered for this prospect. The Israeli corporate credit rating market serves as solid ground for investigating this matter. In this study, we use data on corporate bond ratings assigned by two local rating agencies affiliated with S&P and Moody's during the period 2004-2009. We show that while one agency (Midroog) systematically assigned higher ratings, the ratings of the other agency (S&P-Maalot) were inflated due to rating shopping. These conclusions are based on several findings: the presence of selection bias in dual ratings, the superior accounting features of firms rated by S&P-Maalot relative to those similarly rated by Midroog, and the greater tendency of single ratings by S&P-Maalot to be downgraded. We confirm the predictions of recent theoretical studies that rating inflation may occur even when the value of the rating agencies derives from their reputation.

[3] Ben-Gurion University of the Negev, Department of Economics, P.O. Box 65, Beer-Sheva 84105, Israel, email: innabaka@bgu.ac.il; Tel: +972-54-5711124

[4] Corresponding author: Ben-Gurion University of the Negev, Department of Economics, P.O. Box 65, Beer-Sheva 84105, Israel, email: galilk@bgu.ac.il ; Tel: +972-54-4565570

Introduction

Ratings of structured bonds significantly deteriorated during the 2007-2008 crisis, much more than those of corporate bonds (Benmelech and Dlugosz, 2009). Rating agencies have been criticized in the past for lagging behind markets or for malfunctioning in specific crises.[5] [6] This time, however, the criticism took a new direction, with rating agencies now accused of using two harmful strategies that inflated ratings: deliberately lowering rating standards and allowing rating shopping.

The accommodation of these strategies within the perception of rating agencies as certifiers that extract value from reputation is not straightforward. Since the crisis, many theoretical studies have attempted to suggest models that accommodate strategic rating inflation, among them Skreta and Veldkamp (2009), Sangiorgi, Sokobin and Spatt (2009), Bar-Issac and Shapiro (2010), Bolton, Freixas and Shapiro (2010), Opp, Opp and Harris (2010), and Fulghieri, Strobl and Xia (2010). These studies pointed to the elements that foster strategic lowering of rating standards and the conditions that facilitate rating shopping. Rating shopping is seen as more prevalent in complex and opaque securities (where there is a greater tendency for disagreement among rating agencies), when rating agencies do not adopt a policy of unsolicited ratings, when shadow rating (indication on possible rating) is relatively cheap, and when investors or regulators ignore the distortions of rating inflation. Among the conditions that encourage the lowering of rating standards are boom periods in the bond market and the ignorance of investors or regulators regarding shifting standards.

In contrast to this large and growing body theoretical literature, empirical evidence is still limited. Previous literature has already pointed to possible rating scale differences among rating agencies. Not only did Cantor and Packer (1997) confirm that both Fitch and Duff & Phelps showed higher ratings in 1993, they also examined whether this was due to rating shopping (selection bias, as termed by the authors) or to a shift in the rating scale. Using Heckman's two-stage estimation regression, they were unable to confirm the presence of selection bias and thus concluded that both Fitch and Duff & Phelps simply used a higher scale. Benmelech and Dlugosz (2009)

[5] Allegations of ratings lagging behind markets nurtured a huge body of literature that examined the information value of rating announcements. A brief summary of many of these studies appears, for example, in Galil & Soffer (2011).
[6] Such financial crises include among others the East Asia financial crisis (1997) and the Enron (2001) and Worldcom (2002) bankruptcies.

documented rating shopping by originators of structured bonds. They showed that bonds that were rated by only one rating agency were downgraded more than those rated by multiple agencies. Becker and Milbourn (2010) showed that the increasing competition in the rating market due to Fitch's greater market share reduced the rating quality and rating standards of the two major agencies (S&P and Moody's). Xia (2010) empirically showed that an issuer-pay model rating agency assigned higher ratings than an investor-pay model agency.

In this paper, we use data from the Israeli corporate bond market during the period 2004-2009 to examine the presence of rating shopping and rating inflation. The conditions in this market during the sample period were consistent with many of the elements necessary for rating shopping and rating inflation. For example, it is clear that this period can be considered a boom period. The market value of corporate bonds traded on the Tel-Aviv Stock Exchange (TASE) grew from 21.5 billion NIS (approximately 6 billion USD) at the end of 2003 to 262 billion NIS (approximately 73 billion USD) at the end of 2009.[7] This growth was accompanied by growing competition between two local rating agencies: S&P-Maalot, which has been in operation since 1991, and Midroog, which was established only at the end of 2003. While these agencies were in one way or another affiliated with the two major global agencies (S&P and Moody's), they did not fully adopt their standards. On the one hand they adopted the issuer-pay model, while on the other hand they relinquished the unsolicited rating policy. They also allowed issuers to withdraw from the rating process prior to final approval of the shadow rating and payment of a significant part of the rating fee.

Simple rating comparisons support this impression. As of September 2009, 267 corporate firms issued public debt, of which 137 obtained at least one credit rating. Interestingly, 19 of the 30 firms that were rated by both agencies were rated higher by Midroog, while only two were rated higher by S&P-Maalot. The higher average rating from Midroog leads to our main research question: are ratings in Israel inflated due to rating shopping and the lowering of rating standards?[8]

We consider the research question in three ways. First, in accordance with Cantor and Packer (1997), we test whether the average higher Midroog rating for the 30 firms rated by both agencies is due to differences in rating scale or to selection bias. We use Heckman's two-stage estimation process. In the first stage we estimate a model for the decision to purchase two ratings rather than

[7] Bank of Israel, Annual Report, 2010.

[8] It should be noted that rating inflation may also be caused by market timing. However, our relatively short sample period does not allow us to address this possibility.

one, and in the second stage we estimate a model for the differences in rating. By introducing the inverse Mills ratio (calculated from first-stage estimates), not only are we able to condition for possible self-selection but also to estimate its effect. Interestingly we find that Midroog ratings were indeed on a higher scale. And more interestingly we discover that S&P-Maalot ratings were inflated due to rating shopping.

A second method we use relies on estimation of ratings by using accounting data. We consider firms that remained with a single rating and test whether the waived ratings would be on average lower than the actual ratings. The answer is positive for those that stayed with the S&P-Maalot ratings only and negative for those that stayed with Midroog only. This result is consistent with inflation of S&P-Maalot ratings due to shopping.

Our third method is similar to that of Benmelech and Dlugosz (2009). This method relies on the following notion. Rating shoppers take advantage of errors in risk assessments by rating agencies. In time, new information corrects these previous errors, and therefore ratings that were inflated due to rating shopping should have a greater tendency to be downgraded. And indeed, we discover that firms rated exclusively by S&P-Maalot had a greater tendency to be downgraded than those rated by both rating agencies. Midroog ratings do not exhibit similar behavior.

This study contributes to the literature by providing empirical evidence for rating shopping and shifted scales in an environment in which rating agencies extract their value from reputation. It appears that the need for maintaining a good reputation does not discourage rating agencies from undesirable strategic behavior. Nevertheless, the resulting distortion appears to be relatively small. While the Israeli rating industry has too many features that encourage rating shopping and shifted scales, the resulting rating inflation is approximately one notch only. This may be a fair price for maintaining a competitive rating industry.

The remainder of the paper is organized as follows. In Section 1 we describe the credit rating market in Israel. Section 2 summarizes the relevant literature. Section 3 describes the data. Section 4 outlines our methodology. The results are presented in Section 5, and Section 6 concludes.

1. Credit rating market in Israel

There are two rating agencies in Israel, S&P-Maalot and Midroog. Both are relatively young in comparison to the leading and world renowned rating agencies, Standard & Poor’s and Moody’s.

Maalot, founded in 1991, was the result of a joint initiative of the Israel Securities Authority and the Ministry of Finance that sought to provide the same services available to investors and debt issuers elsewhere, as well as to foster development of the non-bank credit market in Israel. Maalot was initially owned by nine major Israeli banks and financial institutions. In November 1998, Standard & Poor's Rating Services and Maalot entered into a strategic alliance, agreeing to cooperate on analytical and business development. Since January 2008, S&P-Maalot has been fully owned by Standard & Poor’s and operates under its European branch as S&P-Maalot.

The second rating agency in Israel, Midroog, was launched in December 2003. Midroog was jointly established by Moody’s Investor Services and a group of institutional and private Israeli investors. Moody’s stake in Midroog started at 10%, with an option to gradually increase its shares. In January 2008 Moody’s obtained full control of Midroog by increasing its share to 51%.

By the time Midroog was established, 41 corporate firms had already been rated by S&P-Maalot. As of September 2009, of the 267 firms that issued public debt (a total of about 450 bonds), about 137 (about 290 bonds) obtained at least one credit rating, while only 30 firms (about 83 bonds) asked both rating agencies in Israel for credit ratings.

The credit rating process is similar to that of global rating agencies and consists of several steps. First, the agency gathers all relevant information concerning the firm. The agency meets the firm’s management, investigates its reports and draws a picture of the firm’s business and financial plans, management policies and other factors that can influence its credit rating. Then, a rating committee comprising an odd number of members is convened and recommends a rating together with its primary considerations. This rating, which at this stage is not yet public, is known as a “shadow rating.” This is the point at which the firm is given the option to respond by adding any relevant information or to withdraw from the process. Assuming the firm decides to continue, the rating is officially assigned and published. The last part of the process is known as surveillance. Both S&P-Maalot and Midroog meet annually with the rated firm's management. The agencies monitor internal and external publications and analyze financial reports, changes in the macro-economic environment, regulation changes, etc. As a result of surveillance, the rating may be reexamined. In such a case, the company is listed on the Credit-Watch list, and after a similar process of assigning the initial rating, a decision is made regarding the change in rating, if any.

S&P-Maalot uses S&P rating symbols, and Midroog uses Moody's symbols.[9] These rating scales, however, do not conform to the international rating scale, resulting in an over-rating of Israeli companies. For example, in January 2009 the Israel Electric Corporation was given an AA+ rating by S&P-Maalot, compared to a BBB+ rating by S&P. In accordance with new guidelines by the Ministry of Finance, starting in 2009 Israeli agencies must publish conversion tables to international ratings. According to these tables, the local ratings are 2-3 main grades higher than the international grades. For example, a firm rated A1 on the Midroog local scale would on average be rated Ba2 on the international scale. The rating agencies claim that the credit risk of local firms should be compared to the "ultimate" risk-free asset in Israel: bonds issued by the government of Israel. And since governmental bonds are only rated A1 on the global scale, a local firm rated A1 on the global scale merits a triple-A rating on the local scale.

In practice, Israeli bond issuers are not obligated to acquire credit ratings. While the issuer-pay system also holds in Israel, issuers have the option to withdraw from the rating process prior to approval by the final committee. This rule holds for both rating agencies.

The fact that firms have the option to withdraw from the rating process already raised some criticism when Midroog was first established. Back then, some institutional investors already claimed that the existence of multiple rating agencies would expose the agencies to issuer manipulation. Issuers would ask one agency for indication of a rating and then approach the other, hoping for a higher rating. This potential for rating shopping is still relevant today.

Another criticism directed at rating agencies is that a conflict of interest may occur on two levels. One is a potential conflict of interest between the agency and its shareholders. Midroog, for example, is partially owned by some capital market activists, investment banks and pension funds, raising the question of how the agency can fairly rate its shareholders. The other possible conflict of interest, which is relevant for global agencies as well, derives from the fact that rating agencies charge bond issuers for their services. As of the end of 2003, for example, S&P-Maalot charged between 120K and 150K NIS (roughly 35K to 40K USD) per rating.[10] As of 2009, Midroog charged a one-time fee ranging from 150K to 200K NIS (roughly 40K to 60K USD), in addition to 0.03 percent of the value of the rated issue. Furthermore, the agency charged an annual fee of 60K NIS (roughly 15K USD) for surveillance. If a firm decided to withdraw from

[9] S&P symbols are AAA, AA+, AA, AA-, A+, A, A-, BBB+, BBB, BBB-, BB+, BB, BB-, B+, B, B-, CCC+, CCC, CCC-, CC, C, D, while Moody's symbols are Aaa, Aa1, Aa2, Aa3, A1, A2, A3, Baa1, Baa2, Baa3, Ba1, Ba2, Ba3, B1, B2, B3, Caa1, Caa2, Caa3, Ca, C.

[10] *Globes* newspaper article (Hebrew), "The one going up or the one going down" January 2, 2004.

the rating process (prior to final approval of the shadow rating), it had to pay a reduced fee of about 90K NIS (about 25K USD).[11]

Some critics also claim that rating agencies are not fast enough in predicting credit deterioration and that ratings are not informative due to the agencies' slow response to new information. Previous studies, such as Hand, Holthausen & Leftwich (1992) and Kliger & Sarig (2000), found that stock and bond markets do react to rating announcements.[12] Norden and Weber (2004) and Galil and Soffer (2011) also confirmed the information relevance of rating announcements using CDS prices. Nevertheless, a recent study by Feinstein and Galil (2011) concerning the response of the stock and bond market to rating announcements in Israel found that Israeli ratings have no information value.

Despite this and other criticism, many firms are still interested in being rated by rating agencies. One possible reason is the issuers' interest in crossing some regulatory hurdles. As of September 2009, Israel had rating-based regulations for investments of provident, pension and insurance funds, with the specific percent of a fund's total assets eligible for investment in a single debt issuer depending on the debtor's rating. In 2007, the Ministry of Finance in Israel published a draft of new investment regulations stating that the allowed investment rate in a single debt issuer would be 10% of the fund's total assets and would no longer depend on debtor ratings. When this draft becomes the official new regulation, institutions will have to evaluate the quality of securities they invest in without any regulatory indication. Obviously another reason for acquiring a credit rating is to reduce uncertainty among investors regarding a firm's default risk.

Both regulators and investors need to know how to compare the credit ratings assigned by different rating agencies. Ratings assigned by the two rating agencies are assumed to be equal. This is despite the fact that as of September 2009, 19 out of 30 firms rated by both rating agencies in Israel obtained a higher rating from Midroog, while only two firms got higher rating from S&P-Maalot. This fact leads to our main research question: Are these differences in ratings random, due to different rating scales or due to selection bias (rating shopping)?

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[11] *Haaretz* newspaper article (Hebrew) "Midroog figures are exposed," February 25, 2010.

[12] Reviews of studies on markets response to rating announcements appears in Norden & Weber (2004) and Galil & Soffer (2009).

2. Literature review

In the wake of the recent financial crisis, a line of theoretical studies have tried to explain the failure of ratings in assessing the credit risk embedded in structured assets. Skreta and Veldkamp (2009) developed a model that allows issuers to shop for ratings. Rating disclosure is not mandatory, and issuers can observe multiple ratings and disclose only the one most favorable for them. The researchers showed that a combination of increase in asset complexity and the ability of asset issuers to shop for ratings can produce rating inflation. The more the rating methodology involves variety, the more incentives issuers have to shop for rating. For simple assets, agencies issue nearly identical forecasts. Asset issuers then disclose all ratings because more information reduces investor uncertainty and increases the price investors are willing to pay for the asset. For complex assets, ratings may differ, creating an incentive to shop for the best rating. Although the focus of this study is on structured credit products, the same reasoning can be applied to corporate bonds in Israel. When the rating methodologies of the two rating agencies sufficiently differ from each other, issuers have greater possibilities of choosing the best one.

Sangiorgi, Sokobin and Spatt (2009) also claimed that in the case of considerable heterogeneity in views, the issuer selects the ratings that are the most positive. They showed that higher costs for obtaining indicative ratings and regulatory mandates to charge fees for obtaining these ratings reduce the extent to which such ratings are obtained, thus decreasing the average published ratings.

Bolton, Freixas and Shapiro (2010) also developed a theoretical model that explains fundamental distortions in equilibrium with respect to ratings. They showed that competition among rating agencies facilitates rating shopping among issuers and reduces market efficiency. Rating agencies also tend to inflate ratings during boom times, when investors are more trusting and the risk of reputation damage is lower. Bar-Isaac and Shapiro (2010) provided a model in which rating accuracy changes over the business cycle. Their model predicts that during boom periods rating agencies inflate ratings in order to exploit their reputation value, while during recessionary periods they increase rating accuracy to augment their reputation. Their results also held in a competitive rating market.

Opp, Opp and Harris (2010) used a rational expectation model to show that when ratings are used extensively for regulatory purposes, rating agencies tend to inflate ratings. As in Skreta and Veldkamp (2009), this result is more likely to occur for complex securities. Fulghieri, Stroble and

Xia (2010) also used a rational expectation model to show how the policy of unsolicited ratings affects rating quality. Their analysis revealed that this policy enables rating agencies to charge higher fees by threatening to punish issuers that refuse to solicit ratings.[13] On the other hand, rating agencies gain increased reputation because of resistance to releasing inflated ratings. Similar to Bar-Issac and Shapiro (2009), they showed that rating standards during boom periods are lower than during recessionary periods.

Contrary to the large and rapidly growing body of theoretical literature on rating inflation due to rating shopping, empirical studies are scarce. Several studies have already documented the differences in the rating standards and rating scales of S&P, Moody's and Fitch. Morgan (2002) and Livingston, Wei and Zhou (2010) showed that Moody's standards are more stringent than those of S&P. Cantor and Packer (1997) empirically examined whether the higher average ratings of Fitch Investor Service and Duff & Phelps Credit Rating Agency (DCR) at the end of 1993 reflected differences in rating scales or the existence of sample selection bias. Sample selection bias could be a result of the fact that Moody's and S&P also assign unsolicited ratings, while the other agencies assign ratings only upon request. Ultimately their study showed that sample selection bias does not explain the average rating differences and that the same letter grades used by different agencies correspond to different levels of default risk, i.e. different rating scales.

Becker and Mibourn (2010) documented inflated ratings due to increased competition in the rating industry. They showed that Fitch's growing market share in the rating industry reduced the quality of ratings assigned by the major players – S&P and Moody's. They documented higher levels of ratings, lower correlation between ratings and yield to maturity, and lowered ability of ratings to predict default.

An empirical research study by Benmelech and Dlugosz (2009) investigated the recent credit rating crisis of 2007-2008, and in particular described the collapse of the credit ratings of ABS CDOs. The authors provided convincing evidence that rating shopping may have played a role in this crisis. As opposed to the study by Cantor and Packer (1997), Benmelech and Dlugosz found evidence of rating shopping. They showed that tranches rated solely by one rating agency were more likely to be downgraded. This finding is consistent with issuers' shopping for the highest ratings available. They also found evidence that S&P's ratings were somewhat inflated.

[13] Bannier, Behr, and Güttler (2010) empirical results support the prediction of lower unsolicited ratings. This punishment appears effective as predicted by Xia (2010). Behr and Güttler (2008) discovered that stock markets react to unsolicited rating announcement despite of the fact that they are solely based on public information.

Xia (2010) empirically addressed a different aspect of rating inflation – the issuer-pay system. The author compared ratings provided by an issuer-pay model agency to those provided by an investor-pay model agency. The results indicate that the issuer pay-mode provided higher ratings, while this difference was not adjusted either by the regulators or by the investors.

3. Data

The sample in this study comprises 137 corporate firms with outstanding public debt, rated by at least one of the rating agencies in September 2009. S&P-Maalot exclusively assigned ratings to 65 of these firms, compared to 42 rated exclusively by Midroog. Thirty firms were rated both by S&P-Maalot and Midroog. The analysis was based on ratings and financial data stitched together from several data sources.

Historical credit rating data for the period 2004-2008 were gathered from rating agencies' websites and from the Tel-Aviv Stock Exchange (TASE) website. TASE provides a special updated online internet-based system that summarizes all announcements released by the companies themselves and by others, including rating-related announcements such as changes in rating and placement on the watch list. All financial and accounting data for the period 2004-2008 was taken from the Super-Analyst database, which is updated daily and includes financial information about all public companies traded on the TASE.

Table 1 shows the distribution of the assigned ratings between the two rating agencies by industry as of September 2009. The table shows that even though during a period of almost seven years Midroog managed to penetrate the Israeli credit rating market quite well, S&P-Maalot still has a greater number of rated firms. Furthermore, a large proportion of the firms rated by the two agencies come from the real estate industry. This may be due to this industry's greater reliance on debt and to its flourishing activity during our sample period and prior to the crisis.

Table 2 shows the distribution of firms across rating classes for January 1 of each calendar year. Overall, it appears that prior to the crisis of 2007-2008, firms purchasing ratings were graded A-/A3 and above. And during the crisis, we see a downward shift in the distribution. Prior to Midroog's entrance to the market, S&P-Maalot rated 41 issuers. This number grew rapidly so that at the beginning of 2009 S&P-Maalot had already rated 95 issuers. Midroog began operations in 2004, and by the beginning of 2009 it had already rated 72 issuers. Figure 1 also shows the rapid evolution of the number of rated firms during the sample period. In the beginning, most of the firms that purchased a Midroog rating did so in addition to the S&P-Maalot rating (5 out of 8 in

2004, 7 out of 13 in 2005, and 6 out of 11 in 2006). However, in 2007 most of the growth in the number of rated firms came from new issuers. Between January 1, 2006 and January 1, 2008, the number of rated firms almost doubled.

There was only one case of default of a rated firm during the sample period (TMI Limited). This firm obtained its initial rating from S&P-Maalot in July 2007 and defaulted in December 2008. Due to its short rating history and lack of data, it was excluded from our analysis. Other than that, nine issuers defaulted during the period 2009-2010 (seven in 2009 and two in 2010). Four were exclusively rated by S&P-Maalot, three exclusively rated by Midroog and two by both.

Table 3 summarizes the ratings of the firms rated by both agencies at two points: as of September 2009 and at the first time the firm was assigned a second rating. It also shows the rating differences for firms that were rated for the first time in 2004 or after. It turns out that the Midroog ratings were higher on average than those of S&P-Maalot. When a firm was rated for the first time by a second rating agency, in 43% of the cases Midroog gave a higher rating than S&P-Maalot, with an average rating difference of 0.43 notches in favor of Midroog. In September 2009, even more firms (63%) were rated higher by Midroog, and the average rating difference grew as well, to 0.73 notches. Eighteen of the firms rated by both agencies were rated for the first time in 2004 or after, so they had the option of choosing between S&P-Maalot and Midroog. It is easy to see that no matter which agency was the first to assign a rating to a firm, the rating assigned by Midroog was either equal to or higher than the rating assigned by S&P-Maalot. This supports the hypothesis that Midroog employs a higher rating scale than does S&P-Maalot.

4. Methodology

If we disregard the possibility of rating shopping, the two main factors that should explain a firm’s tendency to purchase ratings are costs and information production. Ratings are expensive, but they reduce uncertainty concerning the quality of a firm’s credit quality. Therefore, larger firms and firms that rely more heavily on bond markets should tend to purchase ratings and even multiple ratings. Firms with a higher level of information asymmetry should also benefit more from information revealed through ratings and therefore should tend to purchase multiple ratings.

Table 3 shows that on average Midroog assigned higher ratings than S&P-Maalot when a firm was rated by both. This cannot be explained by the cost and by information production factors.

We propose and test two explanations: self–selection (rating shopping) and differences in rating scales. Hence, our first research hypothesis is:

H1: The rating scale used by Midroog is higher than the scale used by S&P-Maalot.

This means that the Midroog and S&P-Maalot scales are not parallel. For example, a firm rated A1 by Midroog would get a shadow rating lower than A+ from S&P-Maalot.

Sample selection bias could also explain the systematic difference between the two rating agencies. When the difference between the two possible ratings is large, the firm may choose to publish only the higher one. This leads to the second hypothesis:

H2: When shadow ratings significantly differ from each other, firms will tend to keep only the higher rating.

The alternative hypothesis to H1 is that Midroog does not on average issue higher ratings than S&P-Maalot. The alternative hypothesis to H2 is that when the shadow ratings differ significantly from each other, firms will not tend to keep only the higher rating.

Three methods are used to check these hypotheses. The first method resembles that of Cantor and Packer (1997) and involves estimating the factors that determine rating differences and controlling for selection bias using the Heckman (1979) correction. For this purpose, we assign a numerical value to every sub-category rating: Aaa = 1, Aa1 = 2 and so on for Midroog's ratings, and AAA=1, AA+=2 and so on for S&P-Maalot's ratings.

The Heckman correction is a statistical two-step approach that allows us to correct bias that may occur when a sample is not selected randomly. To explain the differences in rating for firms rated by both rating agencies, we estimate the following equation:

$$(1) \qquad r_i = \mathbf{x'}_i \cdot \beta + \varepsilon_i$$

where r_i is the rating difference between two ratings assigned to firm i, $\mathbf{x'}_i$ is a vector of observable information on firm i, β is a vector of coefficients and ε_i is a random variable with zero expectation over the entire population of firms, P, representing all the unobservable information relevant to the rating process. The problem is that data r_i is available only for the firms that were in fact rated by two rating agencies, and if this sub-sample, S, is not selected randomly, the estimation will be biased. The hypothetical regression of the population is:

$$(2) \quad E(r_i \mid i \in P) = E(x'_i \, \beta \mid i \in P)$$

The regression of the sub-sample is:

$$(3)\ E(r_i \mid i \in S) = E(x'_i\,\beta \mid i \in S) + E(\varepsilon_i \mid i \in S)$$

To solve this problem, we first use PROBIT regression to estimate the following equation:

$$(4) \qquad z_i = \mathbf{w'}_i\gamma + u_i$$

where z_i represents a firm's i incentive to acquire a second rating. In this setting $\mathbf{w'}_i$ is the firm's i characteristics, γ is a vector of coefficients and u_i is a random error with mean zero, variance σ_u and covariance with ε, $\sigma_{\varepsilon,u}$.

Without loss of generality we assume that r_i exists if and only if $z_i > 0$; therefore we can rewrite equation (3) as follows:

$$(5)\ E(r_i \mid i \in S) = E(r_i \mid u_i > -w'_i\,\gamma) = E(x'_i\,\beta \mid i \in S) + E(\varepsilon_i \mid u_i > -w'_i\,\gamma)$$

If ε_i and u_i are jointly normally distributed, then we can rewrite equation (5) as follows:

$$(6)\ E(r_i \mid w_i, u_i > -w'_i\,\gamma) = x'_i\,\beta + \rho\sigma_\varepsilon\lambda_i = x'_i\,\beta + \beta_\lambda\lambda_i$$

where λ_i is the inverse Mills ratio $\varphi(\mathbf{v})/\Phi(\mathbf{v})$ evaluated at $\mathbf{w'}_i\gamma/\sigma_u$ and ρ is the correlation coefficient between ε and u.

The inverse Mills ratio is a measure of the extent to which a firm in the sub-sample is rated by the second agency. After equation (6) is estimated using OLS regression, if the coefficient of λ is positive it would mean that ρ is positive, implying that firms rated by the second agency are more likely to have positive values of u.

In H2 we conjecture that firms prefer to keep only the higher rating when the shadow ratings differ too greatly from one another. This implies that the differences between ratings of the firms who choose to have two ratings are small. Therefore, we would expect the mean of the error term in equation (6) (the coefficient of λ) to be negative.

Cantor and Packer (1997) considered S&P and Moody's ratings to be mandatory and tested whether the positive difference between a third rating and the mandatory rating is due to self-selection or scale differences. In our case, obtaining ratings from either of the rating agencies is not mandatory. Hence we interchangeably considered S&P-Maalot and Midroog ratings as mandatory. This means that to estimate equation (4) we first use all firms rated by S&P-Maalot and estimate the determinants of the decision to purchase a second rating from Midroog. Then we use all firms rated by both agencies to estimate equation (1). Then we repeat the same process by estimating equation (4) using all firms rated by Midroog and firms rated by both agencies to estimate equation (1).

For the second stage estimation, we use the firm's rating at the point when the second rating was initiated. However, for the first-stage estimation such a point does not necessarily exist, since most firms are rated by one rating agency only. Therefore, for this stage we use ratings from January 2007 and accounting data from December 2006. Using ratings prior to January 2007 reduces the size of our sample. Using ratings dated after January 2007 is inappropriate since rating corrections during 2008-2009 could possibly reduce the rating shopping effect.

The second method used is to compare the actual rating by one rating agency to a shadow rating by another agency, estimated as in Kaplan and Urwitz (1979). First, a model for predicting Midroog's rating is estimated using rating data and characteristics of the rated firms. For this purpose we assign a numerical value to every rating category (Aaa = 1, Aa = 2 and so on) and then use it as the dependent variable in OLS and ordered LOGIT regressions. We also run these regressions using a sub-category rating evaluation (Aaa = 1, Aa1 = 2, Aa2 = 3 and so on). After obtaining estimations of the parameters, we build forecasts of the ratings that could have been assigned to the firms that were rated only by S&P-Maalot. These forecasts represent the shadow ratings that these firms chose not to disclose. We test rating shopping by comparing the actual S&P-Maalot rating with the shadow Midroog rating. If firms conceal the Midroog rating when it is lower than the S&P-Maalot rating, we should expect Midroog's shadow rating to be lower on average than the actual S&P-Maalot rating. We then repeat the same procedure by estimating the S&P-Maalot shadow rating and comparing it with the actual Midroog rating.

The best approach would be as follows: for each single rating initiated by one agency, predict a shadow rating by another agency using a database of single ratings issued exactly at the same time. Such an approach, however, would need a large sample of first issues by one agency each time a single rating was initiated by another agency. This is beyond the scope of our sample. The sample of single ratings in January 2007 is relatively large and precedes the rating corrections that occurred during 2008-2009. Hence, to apply this method we use ratings from January 2007 and accounting data from December 2006.

The last method we use is to estimate the determinants of rating changes. For this purpose we create panel data about annual rating changes by Midroog and S&P-Maalot for the period 2004-2009. We run an ordered LOGIT regression estimating the following:

$$(7)\ down\_or\_up_{it}* = x'_{it}\,\beta + \varepsilon_{it}$$

where $down\_or\_up_{it}$ is the dependent variable and has three possible outcomes: 1 – the rating was downgraded (when $down\_or\_up^{*}_{it} \geq c_H$), 0 – no change in rating (when

$c_H > down\_or\_up^*_{it} \geq c_L$) and -1 – the rating was upgraded (when $c_L > down\_or\_up^*_{it}$). c_H, c_L and β are parameters. x'_{it} is a vector of independent variables that may influence rating changes: financial data at the beginning of each year starting from 2004 for S&P-Maalot (2005 for Midroog), rating at the beginning of each year, and a dummy variable indicating whether the firm has been rated by the other agency at the same time. Dummy variables indicating the relevant year (time effect) are also taken into account. This method is reminiscent of the method used in Benmelech and Dlugosz (2009). However, Benmelech and Dlugosz estimated the probability of a downgrade as of January 2008 relative to the issuance rating, and in our research we track rating changes at the beginning of each year during the period 2004-2009. Furthermore, this method allows a downward bias in rating changes, i.e., the higher tendency for downgrades than for upgrades. In fact, our analysis tests the hypothesis that this downward bias is at least partially related to rating shopping.

Based on the estimation outcome of equation (7), we can discover when changes take place, whether they occur when a firm has only one rating or when it has two ratings, and in what direction they occur, upwards or downwards. Since we assume that a firm chooses to obtain only one rating when it is biased upwards, we expect to see more downgrades in this case.

5. Results

5.1. Heckman correction

As previously described in the methodology section, a firm's incentive to purchase a second rating is first estimated. Several variables that may have an impact on a firm's desire to purchase a second rating are taken into consideration. The financial variables *Leverage (Total debt/ Total assets), Coverage (EBIT/Interest expenditures)* and *Profitability (Net Income/Total assets)* may indicate the risk associated with the firm. Since it is in the firm's interest to reduce the uncertainty of this risk, it is more likely to obtain a second rating.[14] We conjecture that the higher the firm's risk, the higher the asymmetry in information between investors and managers and hence the higher the firm's demand for ratings. Therefore we would expect the probability of having a second rating to grow with higher values of *Leverage* and *Profitability* and lower values of *Coverage*. Firm size (*Assets* represented here by the natural logarithm of the firm's total assets) is also a factor in obtaining an additional rating. Large firms also usually have large amounts of

[14] Higher *Profitability* may be associated with risk, since according to financial theory, profitability compensates for systematic risk.

money to purchase ratings. Thus we expect the probability of obtaining a second rating to grow as the value of the *Assets* variable increases. Another variable included in the S&P-Maalot estimation is an indicator whether a firm was rated for the first time after Midroog was established in 2003. Such a firm could have chosen the favorable single rating from the outset, while firms rated for the first time before 2004 would tend to take the Moody's-Midrooog rating only as a second rating. The rating considered to be the "mandatory" one serves as one of the explanatory variables as well. That is, a firm's rating (S&P-Maalot or Midroog) may also be an indicator of a firm's desire to purchase an additional rating. Since higher values of the variable represent lower actual ratings, implying that the firm is more risky, we expect the probability of obtaining a second rating to grow with higher values of the "existing" rating. In addition to the above, industry dummies are included.

We can see that the coefficient on *Leverage* in both regressions is negative, and in the case of S&P-Maalot even statistically significant at the 10% significance level, indicating that the probability of obtaining a second rating decreases with *Leverage*, which is contrary to our expectation. The coefficient on *Profitability* is negative in the S&P-Maalot regression and positive in the Midroog regression, though neither is statistically significant. The coefficient on *Coverage* is negative in both regressions and consistent with our expectation, though it also is not statistically significant. The coefficient on *Assets* is positive in all regressions, as expected, and is statistically significant at the 5% significance level. This implies that larger firms have greater resources to bear the burden of the costs of dual ratings. This variable also identifies the estimation in the first step from the second step. As is shown later (Tables 5 and 6), the effect of size on ratings by the two rating agencies is similar, while here we find that size affects the decision about the number of ratings. Since results concerning *Leverage*, *Coverage* and *Profitability* are not consistent with our expectations, we also run the first step with specifications excluding these variables (regressions III, IV, VII and VIII).

The coefficient on the rating variable is positive and significant in the S&P-Maalot regression. As expected, firms do seek an additional rating from Midroog when the one they obtained from S&P-Maalot is relatively low. On the other hand, the coefficient on the same variable in the Midroog regression is not low in absolute terms and is statistically insignificant. In conclusion, firms that are more likely to seek an additional rating are mainly the larger firms that usually have more outstanding debt and more available funds. There is also some evidence that firms with low ratings are likely to obtain a second rating.

The bottom half of Table 4 shows the results of the second stage analysis. For each agency, two specifications are built. One includes only a constant term that accounts for possible differences in rating scales and the inverse Mills ratio which represents the effect of sample selection. In addition to the constant term and the inverse Mills ratio, the second specification includes dummies to take into consideration the effects of rating different industries. In all these regressions, the explained variable is S&P-Maalot rating minus Midroog rating. Since the numerical representation of ratings increases with lower credit quality, this difference represents the number of notches by which the Midroog shadow rating exceeds the S&P-Maalot rating.

Adding the industry dummies significantly improves the explanatory power of the regression in both agency cases. The results show that the constant term in all four regressions is positive and significant at the 5% significance level. This means that on average Midroog assigns higher ratings than S&P-Maalot, even after controlling for possible self-selection. This result confirms our first hypothesis (H1) and is similar to the results of Cantor and Packer (1997), which indicated that the optional agencies, DCR and Fitch, had higher rating scales than Moody's and S&P. The estimated coefficients of the industry dummies are all negative and statistically significant (except in regression IV). The coefficient of ‘real estate’ is significant at the 10% significance level, and the coefficient of ‘finance’ is significant at the 5% significance level. The implication of this result is that Midroog's shifted scale is nonexistent for financials and smaller for real estate companies.

The estimated coefficient of the inverse Mills ratio in the S&P-Maalot regression is negative and significant at the 5% significance level when controlling for industrial classification. The coefficients of the Mills ratio in the Midroog equations are small and insignificant. These results suggest that, as outlined in the methodology section, sample selection exists for the S&P-Maalot ratings only. The firms that chose the S&P-Maalot rating only are those that would have received a lower rating from Midroog. These results differ from those of Cantor and Packer (1997), which could not reject the hypothesis that there is no selection bias in the optional ratings. In our case the hypothesis itself differs slightly. We hypothesize that when the shadow ratings given by S&P-Maalot and Midroog differ too greatly from one another, firms will tend to keep only the higher rating, and in fact we found evidence of this.

A possible explanation of the differences in the results is the difference in starting points. In the US, both S&P and Moody’s employ the unsolicited rating policy and therefore assign ratings to virtually all large issues. This creates a situation in which every firm has two ratings or two ‘points of view’ regarding its credit worthiness from the outset. In this case, another rating is added, for example, to provide more information to the market so as to serve as a tiebreaker when the two main rating agencies highly disagree between themselves. This is true especially if the third rating agency specializes in rating firms from a particular industry. In Israel, however, there are only two rating agencies, and these have not adopted the unsolicited rating policy. Hence, each firm must decide whether to consult one of the agencies or both of them. This creates more incentive to choose only the agency that assigns the higher rating.

It should be noted that the relatively small size of the sample should have lowered the statistical significance of the results. It appears that rating inflation is large enough so that its presence would be detected despite the small size of the sample. Moreover, the statistical results also conform to the expected. Nevertheless, in the next subsections we verify our conclusions by two additional types of analysis: rating comparison and analysis of rating changes.

5.2. Rating comparison

Tables 5b and 6b show the results of building a forecast for the shadow rating given by one of the agencies (the one not chosen by the firm) and comparing it to the published rating given by the other. Tables 5a and 6a present the regressions upon which these forecasts are built. It should be noted that the signs of all coefficients are as expected. Parts A and B of Tables 5b and 6b show the results of the OLS regressions, using sub-category ratings and main category ratings, respectively. Parts C and D similarly show the ordered LOGIT regression results. The first row of each part shows the results of building a forecast of the shadow rating, and the second row shows the results of using the estimated coefficients to build a forecast for the actual ratings used in the estimation process.

Figure 2 illustrates the results of Table 5b. We can see that according to our model, a higher percentage of firms rated by S&P-Maalot would have a lower Midroog rating than a higher Midroog rating. For example, our model for sub-category ratings projected that 50% of the firms rated by S&P-Maalot only would receive a lower Midroog rating, compared to only 21% that would receive a higher Midroog rating. In the case of sub-category ratings these results are significant at the 5% significance level, and in the case of main category ratings the results are significant at the 10% significance level. Applying the same procedure on the firms rated by Midroog only, i.e., estimating a rating function based on S&P-Maalot ratings and forecasting for the firms rated solely by Midroog, we get somewhat insignificant results. In this configuration, the results are similar to the previous case when the sub-category ratings are used. For instance, more firms (38%) would have been assigned a lower rating by S&P-Maalot than firms that would have been assigned a higher rating (31%). However, these results are statistically insignificant. When the main category ratings are used, the results are reversed and are statistically significant at the 10% level but are economically insignificant. Figure 3 illustrates these results.

These results are consistent with our previous findings that Midroog ratings are inflated due to a shifted rating scale and that S&P-Maalot ratings are inflated due to rating shopping. Since there is a selection bias in the S&P-Maalot ratings, we obtain an upward biased prediction of S&P-Maalot shadow ratings for those rated by Midroog only. Therefore, the fact that the S&P-Maalot shadow ratings are not significantly lower than the Midroog ratings possibly indicates that the level of inflation in the two rating systems is approximately similar.

Examining the results for the estimation sample, we find no significant biases in predicted ratings. For example, in preditions of Midroog sub-category ratings using ordered LOGIT regression, 24% of predicted ratings are higher than actual and 24% lower. The optimal test would be to compare predicted and actual ratings for a control sample that is not used in the estimation process. This cannot be done in this study because of the small size of the population. Nevertheless, a bias that is already in the estimation sample would make our analysis absolutely irrelevant.

In general, the results of this method further confirm the results of the first method and support the hypothesis that firms tend to stay with the higher rating – the S&P-Maalot rating – when the Midroog rating would be lower.

5.3. Rating changes

The last method of analyzing rating changes offers further evidence in support of our previous results. Table 7 shows the number of downgrades and upgrades in our sample for firms rated by a single rating agency or by both. Out of 361 annual observations of S&P-Maalot ratings, 42 were followed by downgrades and 25 by upgrades. Out of 175 annual observations on Moody's ratings, 18 were followed by downgrades and four by upgrades. It appears that the downgrade bias (downgrades exceeding upgrades) is present in both rating samples, something that may indicate rating inflation due to market timing. It also appears that the number of rating changes for Midroog is relatively small and may affect our statistical inference. Most rating changes in our sample period occurred during 2008, which was the year of crisis. It also appears that the ratio of downgrades to upgrades was higher for firms rated by a single rating agency than for those rated by both agencies. The percentage of downgrades out of total rating changes by S&P-Maalot stands at 76 for those rated solely by S&P-Maalot, compared to only 47 for those rated by both agencies. The same pattern also appears among firms rated by Midroog – 100 percent for those rated solely by Midroog compared to 64 percent for those rated by both agencies.

Table 8 presents the results of ordered LOGIT regressions for S&P-Maalot rating changes and for Midroog rating changes. The panel data for each regression includes all annual observations of firms rated by the specific rating agency. The dependent variable is a categorical variable that equals 1 if the firm was downgraded in that year, -1 if it was upgraded, and 0 otherwise. The dependent variables are rating (of beginning of the year), *Second* rating (a dummy variable that indicates if the firm had dual ratings at the beginning of the year), financial ratios (*Leverage* and *Profitability*), *Assets* (natural logarithm of total assets) and dummy variables for calendar years (time effect).

Both regressions are statistically significant at the 5% significance level, as are most of the independent variable coefficients. The variable of interest in these regressions is the *Second rating* variable. The coefficient of this variable is negative in both regressions, as expected, and significant at the 5% significance level in the S&P-Maalot regression. This means that when a firm is rated only by S&P-Maalot, it has a higher tendency to be downgraded. These results again support our hypothesis that firms prefer to obtain only one rating, the higher one, when the two options presented to them are sufficiently different. This could be due to differences in rating scales or random self-selection. It appears that Midroog has a higher rating scale. Hence, firms rated by Midroog have higher average ratings. The higher Midroog ratings are consistent with the Midroog scale. Hence, self-selection is insignificant, and firms with single ratings do not suffer less from downgrades. However, since the S&P-Maalot ratings are lower on average, there is higher tendency toward random self-selection among firms rated by S&P-Maalot only. The higher ratings for those that choose to be rated by S&P-Maalot due to random errors are not consistent with S&P-Maalot's rating scale. Hence, firms exclusively rated by S&P-Maalot tend to experience more downgrades.

6. Summary and conclusions

Israel represents an interesting example of the difficulties of setting up a new bond rating system in a small country. The bond rating process in Israel appears to suffer from a number of problems including a small number of bond issues, small size of individual bonds issues, short life of the bond rating agencies, and the lack of arm's-length relationships between the bond rating agencies and the issuers and the buyers of public bond issues.

In this study we test the existence of rating shopping in the Israeli corporate market. To ensure that our results are not affected by the relatively small size of the sample, we use three different statistical methods and show that ratings are inflated because of dual distortions. It appears that the new rating agency (Midroog) has adopted a rating scale that is approximately one notch higher than that of the veteran agency (S&P-Maalot). On the other hand, S&P-Maalot's ratings are inflated due to rating shopping. These conclusions are reflected in several findings. First, using a Heckman two-stage estimation we showe that the higher Midroog rating for firms with dual ratings is statistically significant after controlling for selection bias. The same analysis also reveals that the selection bias is negative and statistically significant only when considering firms that adopted S&P-Maalot’s ratings. That means that issuers that obtained relatively high ratings from S&P-Maalot tended to conceal the possible (shadow) rating suggested by Midroog.

Estimation of shadow ratings using accounting data supports the abovementioned conclusions. Estimation of Midroog rating for firms that chose to be rated by S&P-Maalot only reveals that the shadow rating would be lower than the actual S&P rating. However, the parallel comparison (S&P-Maalot shadow rating vs. actual Midroog rating) does not yield similar results. Consistent with the hypothesis, Midroog ratings are inflated because of lower standards, while S&P-Maalot ratings are inflated because of rating shopping.

The final analysis shows that firms rated only by S&P-Maalot tended to be downgraded more than firms rated by both rating agencies. This could be a result of rating shopping. Firms that take advantage of a positive deviation of rating from the real value should experience additional downgrades. Since the inflated ratings of Midroog are due to lower standards and not due to rating shopping, they should not experience higher rates of downgrades (compared to those with dual ratings).

In conclusion, corporate bond ratings in Israel are inflated due to distortions in the rating market system. This has several implications for the Israeli rating market, some of which have already been implemented elsewhere. First, regulation should take into account the possibility of shifted rating scales. This could be achieved by compelling rating agencies to adjust their average actual and shadow ratings to an average rating provided by a third-party scoring model. An alternative would be to reduce regulatory reliance on corporate ratings. Second, the possibility of rating shopping must be reduced. One way to achieve this would be by forcing an unsolicited rating policy on the rating agencies. The other would be to eliminate the reduced fee currently charged for shadow ratings.

This study has also broader implications. Its results are consistent with the predictions of many theoretical papers that consider rating shopping. The Israeli corporate bonds market and rating industry are marked by the attributes indicated in the literature as stimulants for rating shopping and rating inflation. Among these are a competitive rating industry, an issuer-pay model, an economic boom period, particularly in the corporate bonds market, the absence of an unsolicited rating policy and regulatory reliance on ratings. While some of these features are unavoidable, some could be restricted to reduce rating distortions. As predicted by theoretical literature, rating shopping and rating inflation may occur even when the value of the rating agencies derives from their reputation.

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Tables

Table 1

Sample distribution across rating agencies and industries

This table shows the distribution of the sample firms across rating agencies and industries.

Industry	S&P-Maalot only	Midroog only	Both	Total
Finance	11	3	6	20
Real Estate	25	20	11	56
Other	29	19	13	61
Total	65	42	30	137

Table 2

Sample distribution across ratings

This table shows the distribution of ratings by each rating agency during the sample period (2004-2009) for January 1st of each calendar year.

Panel a: S&P-Maalot ratings

Rating	2004	2005	2006	2007	2008	2009
AAA	1	1	1	2	2	2
AA+	4	3	4	3	3	4
AA	8	11	14	15	18	12
AA-	8	9	8	13	11	8
A+	7	8	10	12	16	18
A	6	11	11	12	20	21
A-	5	4	5	7	14	16
BBB+	1	2	2	2	4	8
BBB	0	0	0	0	1	3
BBB-	1	0	0	0	0	1
BB	0	0	0	0	0	1
CC	0	0	0	0	0	1
Total	41	49	55	66	89	95

Panel b: Midroog ratings

	2005	2006	2007	2008	2009
Aaa	0	0	0	1	1
Aa1	2	3	3	3	3
Aa2	2	6	6	7	4
Aa3	1	3	5	6	5
A1	1	2	6	10	17
A2	1	3	6	12	12
A3	1	4	6	11	19
Baa1	0	0	0	4	5
Baa2	0	0	0	2	5
Ba1	0	0	0	0	1
Total	8	21	32	56	72

Table 3

Ratings summary of dual rated firms

This table shows the differences between Midroog and S&P-Maalot ratings for firms rated by both rating agencies.

Panel a – Rating differences of mutually rated firms in September 2009 and at the first time a second rating was assigned to a firm.

Midroog relative to S&P-Maalot	Initial second rating	September 2009
Higher	43% (13)	63%(19)
Equal	57%(17)	30% (9)
Lower	0%	7% (2)
Average rating difference	0.43	0.73

Panel b – Rating differences of mutually rated firms which were rated for the first time in 2004 or after.

<table>
<tr><td colspan="2">First rated by S&P-Maalot, then by Midroog</td><td colspan="2">First rated by Midroog, then by S&P-Maalot</td></tr>
<tr><td colspan="2">72% (13)</td><td colspan="2">28% (5)</td></tr>
<tr><td>Rated higher by S&P-Maalot</td><td>Rated higher by Midroog</td><td>Rated higher by S&P-Maalot</td><td>Rated higher by Midroog</td></tr>
<tr><td>0%</td><td>54% (7)</td><td>0%</td><td>20% (1)</td></tr>
</table>

Table 4

Heckman correction results for the decision for dual ratings

This table shows the results for the two-step Heckman regression. The 1st stage measures the extent to which a firm has a second rating, using rating data as of January 2007 and accounting data as of December 2006. The 2nd stage explains the rating differences between S&P-Maalot and Midroog at the point when a firm was rated for the first time by a second agency.

	S&P-Maalot				Midroog			
	(I)	**(II)**	**(III)**	**(IV)**	**(V)**	**(VI)**	**(VII)**	**(VIII)**
1st stage	Dependent variable: z=1 if rated by both, 0 otherwise							
Constant	-11.711** (-3.51)		-9.056** (-3.42)		-17.135** (-2.99)		-16.918** (-3.52)	
Leverage	-0.065* (-1.82)		-		-0.031 (-0.47)		-	
Coverage	-0.004 (-0.30)		-		-0.119 (-1.52)		-	
Profitability	-0.697 (-0.16)		-		10.639 (1.43)		-	
Assets	0.654** (3.64)		0.493** (3.50)		1.189** (3.48)		1.184** (4.03)	
Real estate	-0.019 (-0.05)		-0.066 (-0.20)		-0.122 (-0.22)		0.171 (0.32)	
Finance	-0.425 (-0.80)		-0.616 (-1.33)		-0.028 (-0.02)		0.248 (0.24)	
First rated after '03	0.141 (0.40)		0.053 (0.16)		-		-	
S&P-Maalot's rating	0.342** (2.11)		0.247* 1.87		-		-	
Midroog's rating	-		-		0.002 (0.01)		-0.055 (-0.26)	
Number of obs.	**86**				**66**		**66**	
2nd stage	Dependent variable: S&P-Maalot rating minus Midroog rating							
Constant	0.834** (2.84)	1.057** (3.72)	1.038** (3.00)	1.217** (3.61)	0.404** (3.41)	0.620** (4.51)	0.418** (3.67)	0.614** (4.40)
Real estate	-	-0.358* (-1.80)	-	-0.337 (-1.54)	-	-0.341* (-1.87)	-	-0.344* (-1.78)
Finance	-	-0.609** (-1.97)	-	-0.394 (-1.40)	-	-0.619** (-2.16)	-	-0.414* (-1.69)
Inverse mills ratio	-0.461* (-1.60)	-0.471** (-1.81)	-0.650** (-1.99)	-0.633** (-2.07)	0.009 (0.05)	-0.014 (-0.08)	-0.012 (-0.07)	0.004 (0.175)
Number of obs.	**28**		**29**		**28**		**29**	

* 10% significance level

** 5% significance level

(a) *z* values are in parentheses.

(b) The alternative hypothesis for inverse mills ratio is that it is greater or equal to zero

(c) The following variables are 0/1 dummies which take the value of 1 as follows:

Real estate – if a firm belongs to the real estate industry.

Finance – if a firm belongs to the finance industry.

First rated after '03 – if was rated for the first time by one of the rating agencies in 2004 or later.

(d) The other variables are defined as follows:

Leverage – Total debt/Equity on December 31st, 2006.

Coverage – EBIT/Interest expenditures on December 31st, 2006.

Profitability – Net profit/Total assets on December 31st, 2006.

Assets – natural logarithm of the firm's total assets on December 31st, 2006.

S&P-Maalot's rating – firm's rating on January 1st, 2007 as assigned by S&P-Maalot.

Midroog's rating – firm's rating on January 1st, 2007 as assigned by Midroog.

Tables 5a
Explanation of Midroog ratings

This table shows the results of estimating a rating model, where the explained variable is the Midroog rating as of January 1 2007 or the first rating if the firm began being rated by Midroog in 2007. The explanatory variables are accounting data as of December 2006. Columns A and B present the results of the OLS regressions; columns C and D present the results of the Ordered Logit regressions

Midroog	A: OLS - sub categories	B: OLS - main categories	C: Ordered Logit - sub categories	D: Ordered Logit - main categories
Dependent variable: Midroog's rating, January 2007				
constant	14.202** (7.27)	5.778** (7.23)	-	-
Leverage	0.077* (1.83)	0.039** (2.28)	0.265** (2.08)	0.105 (1.38)
Profitability	-7.914** (-2.05)	-1.875 (-1.19)	-13.481 (-1.33)	-20.697** (-2.43)
Assets	-0.617** (-4.16)	-0.218** (-3.59)	-1.449** (-2.73)	-1.223** (-3.57)
Real estate	0.786** (2.62)	0.124 (1.01)	0.983 (1.14)	1.718** (2.77)
Market value/10^8	-11.7* (-1.93)	-2.51 (-1.01)	-15.9 (-0.65)	-2.45* (-1.65)
Sales/10^8	5.35 (1.11)	2.47 (1.25)	18.4 (1.49)	11.9 (1.12)
Number of obs: 54				

* 10% significance level
** 5% significance level

(a) t/*z* values are in parentheses.
(b) See table 3 for variables definitions.
(c) Sub categories - AAA/Aaa = 1, AA+/Aa1 = 2, AA/Aa2 = 3 and etc.
(d) Main categories – AAA/Aaa = 1, AA+/Aa1 = AA/Aa2 = AA-/Aa3 = 2, A+/A1 = A/A2 = A-/A3 = 3 and etc.
(e) Leverage is Total debt/Total Assets, Profitability is Net income/Total assets, Assets is the natural logarithm of Total assets, Real estate is a dummy variable for real-estate companies.

Table 5b

Results of comparison between actual S&P-Maalot ratings and shadow Midroog ratings for firms rated only by S&P-Maalot

Rows numbered 1 show the prediction of our model of Midroog's ratings for firms rated only by S&P-Maalot relative to the known S&P-Maalot rating. Rows numbered 2 shows the prediction of our model of Midroog's ratings for firms rated by Midroog (estimation sample) relative to the actual Midroog rating.

		Out of sample (firms rated by S&P-Maalot but not rated by Midroog)		Regression sample (firms rated by Midroog)	
	Midroog	**% of predicted Midroog ratings higher than S&P-Maalot's**	**% of predicted Midroog ratings lower than S&P-Maalot's**	**% of predicted Midroog ratings higher than actual Midroog ratings**	**% of predicted Midroog ratings lower than actual Midroog ratings**
A		**OLS - sub categories**			
1	Rated only by S&P-Maalot (48)	21% (10)**	50% (24)**		
2	Rated by Midroog (including rated by both) (54)			31% (17)	24% (13)
B		**OLS - general categories**			
1	Rated only by S&P-Maalot (48)	8% (4)*	23% (11)*		
2	Rated by Midroog (including rated by both) (54)			13% (7)	7% (4)
C		**Ordered LOGIT - sub categories**			
1	Rated only by S&P-Maalot (48)	21% (10)**	42% (20)**		
2	Rated by Midroog (including rated by both) (54)			24% (13)	24% (13)
D		**Ordered LOGIT - general categories**			
1	Rated only by S&P-Maalot (48)	8% (4)*	23% (11)*		
2	Rated by Midroog (including rated by both) (54)			13% (7)	7% (4)

* 10% significance level using Wilcoxon sign test
** 5% significance level using Wilcoxon sign test
The numbers in parentheses are actual number of firms

Table 6a
Explanation of S&P-Maalot ratings

This table shows the results of estimation of a rating model, where the explained variable is S&P-Maalot rating as of January 1 2007, or the first rating if the firm began being rated by S&P-Maalot in 2007. The explanatory variables are accounting data as of December 2006. Columns A and B present the results of the OLS regressions; columns C and D present the results of the Ordered LOGIT regressions.

	A: OLS - sub categories	B: OLS – main categories	C: Ordered LOGIT - sub categories	D: Ordered LOGIT - main categories
Dependent variable: S&P-Maalot's rating, January 2007				
Constant	16.175**	6.285**	-	-
	(14.68)	(14.45)		
Leverage	0.078**	0.022**	0.128**	0.164**
	(3.14)	(2.23)	(2.06)	(3.43)
Profitability	-8.164**	-2.08**	-10.994	-14.803**
	(-3.14)	(-2.03)	(-1.61)	(-3.12)
Assets	-0.747**	-0.245**	-1.432**	-1.363**
	(-10.19)	(-8.46)	(-5.3)	(-7.38)
Real estate	0.299	0.116**	0.63	0.528
	(1.28)	(14.45)	(1.14)	(1.3)
Number of obs: 87				

* 10% significance level
** 5% significance level

(a) t/*z* values are in parentheses.
(b) See table 3 for variables definitions.
(c) Sub categories - AAA/Aaa = 1, AA+/Aa1 = 2, AA/Aa2 = 3 and etc.
(d) Main categories – AAA/Aaa = 1, AA+/Aa1 = AA/Aa2 = AA-/Aa3 = 2, A+/A1 = A/A2 = A-/A3 = 3 and etc.
(e) Leverage is Total debt/Total Assets, Profitability is Net income/Total assets, Assets is the natural logarithm of Total assets, Real estate is a dummy variable for real-estate companies.

Table 6b
Results of comparison between actual Midroog ratings and shadow S&P-Maalot ratings for firms rated by Midroog only

Rows numbered 1 show the prediction of our model of S&P-Maalot ratings for the firms rated by Midroog only relative to the known Midroog rating. Rows numbered 2 shows the prediction of our model of S&P-Maalot ratings for firms rated by S&P-Maalot (regression sample) relative to the actual S&P-Maalot rating.

		Out of sample (firms rated by Midroog but not rated by S&P-Maalot)		**Regression sample (firms rated by S&P-Maalot)**	
	S&P-Maalot	**% of predicted S&P-Maalot ratings higher than Midroog's**	**% of predicted S&P-Maalot ratings lower than Midroog's**	**% of predicted Midroog ratings higher than actual Midroog ratings**	**% of predicted Midroog ratings lower than actual Midroog ratings**
A		**OLS - sub categories**			
1	Rated only by Midroog (39)	31% (12)	38% (15)		
2	Rated by S&P-Maalot (including rated by both) (87)			25% (22)	26% (23)
B		**OLS - general categories**			
1	Rated only by Midroog (39)	15% (6)*	8% (3)*		
2	Rated by S&P-Maalot (including rated by both) (87)			11% (10)	9% (8)
C		**Ordered LOGIT - sub categories**			
1	Rated only by Midroog (39)	28% (11)	36% (14)		
2	Rated by S&P-Maalot (including rated by both) (87)			25% (22)	22% (19)
D		**Ordered LOGIT- general categories**			
1	Rated only by Midroog (39)	15% (6)*	8% (3)*		
2	Rated by S&P-Maalot (including rated by both) (87)			11% (10)	9% (8)

* 10% significance level using Wilcoxon sign test
** 5% significance level using Wilcoxon sign test
The numbers in parentheses are actual number of firms

Table 7

Annual rating changes during the period 2004-2009

This table presents rating changes documented at the end of each year relative to the previous year ending during 2003-2009 for S&P-Maalot and 2004-2009 for Midroog. The table also shows the number (and percentage) of rating changes documented in 2008.

	All changes*	***2008****	***All changes****	***2008****
	All firms rated by S&P-Maalot		**All firms rated by Midroog**	
Downgrades	42 (63%)	22 (52%)	18 (82%)	18 (100%)
Upgrades	25 (37%)	2 (8%)	4 (18%)	2 (50%)
Total Changes	67	24 (36%)	22	20 (91%)
Total obs.	361		175	

	Rated by S&P-Maalot only		**Rated by Midroog only**	
Downgrades	28 (76%)	16 (57%)	11 (100%)	11 (100%)
Upgrades	9 (24%)	0 (0%)	0 (0%)	0
Total Changes	37	16 (43%)	11	11 (100%)
Total obs.	240		91	

	Rated by both			
	Changes by S&P-Maalot		**Changes by Midroog**	
Downgrades	14 (47%)	6 (43%)	7 (64%)	7 (100%)
Upgrades	16 (53%)	2 (13%)	4 (36%)	2 (50%)
Total Changes	30	8 (27%)	11	9 (82%)
Total obs.	121		84	

* The percentage in parentheses in ‘All changes’ column shows percentage of downgrades/upgrades out of total changes in the firm sample. For example, 47% (14) rating downgrades were made by Maalot to firms rated by both rating agencies out of 30 rating changes made (downgrades and upgrades).

** The percentage in parentheses in 2008 column shows the percentage of upgrades/downgrades/ total changes documented in 2008 out of all upgrades/downgrades/ total changes documented during the sample period. For example, 57% (16) out of 28 rating downgrades documented during the sample period for firms rated by S&P-Maalot only, occurred during 2008.

Table 8
Results of the forecast of rating changes

This table shows the results of a panel regression where the dependent variable is annual rating change for a single company. The rating changes for S&P-Maalot are for 2004-2009 and for Midroog-Maalot for 2005-2009.

	S&P-Maalot	Midroog
Dependent variable: Was the rating changed downwards (1), upwards (-1), wasn't changed at all(0)?		
S&P-Maalot's rating	0.532** (3.50)	-
Midroog's rating	-	0.544** (2.66)
Second rating	-0.963** (-2.46)	-0.835 (-1.09)
Leverage	-0.078** (-2.53)	-0.06** (-2.11)
Profitability	-12.07** (-4.05)	-7.414** (-2.10)
Assets	0.484** (3.07)	0.623** (2.49)
2004	0.646 (1.24)	-
2005	-1.779** (-2.61)	-1.773** (-2.95)
2006	-1.452** (2.71)	-2.726** (-2.02)
2007	-0.859* (-1.72)	-1.794** (-2.89)
2008	-1.216** (-2.98)	-2.428** (-3.16)
Number of downgrades.	**42**	**18**
Number of upgrades	**25**	**4**
Number of obs.	**361**	**175**

* 10% significance level

** 5% significance level

(a) *z* values are in parentheses.

(b) The dependent variable has three possible outcomes: it takes the value of -1 when there was an upgrade relatively to the previous year rating, 0 when there was no change in rating and 1 when the rating was downgraded.

(c) The explanatory variables are defined as follows:
S&P-Maalot's rating – firm's rating on December of previous year as assigned by S&P-Maalot.
Midroog's rating – firm's rating o on December of previous year as assigned by Midroog.
Second rating – a dummy variable which take the value of 1 if the firm has additional rating from the second agency.
Leverage – Total debt/Equity on December 31st, 2006.
Coverage – EBIT/Interest expenditures on December 31st, 2006.
Profitability – Net profit/total assets on December 31st, 2006.
Assets – natural logarithm of the firm's total assets on December 31st, 2006.
2004-2008 are dummy variables which take the value of 1 if the data is taken from the relevant year.

Figures

Figure 1 – Firms rated by rating agencies

This figure shows the number of firms rated by each rating agency and by both agencies during the sample period for January 1st of each calendar year.

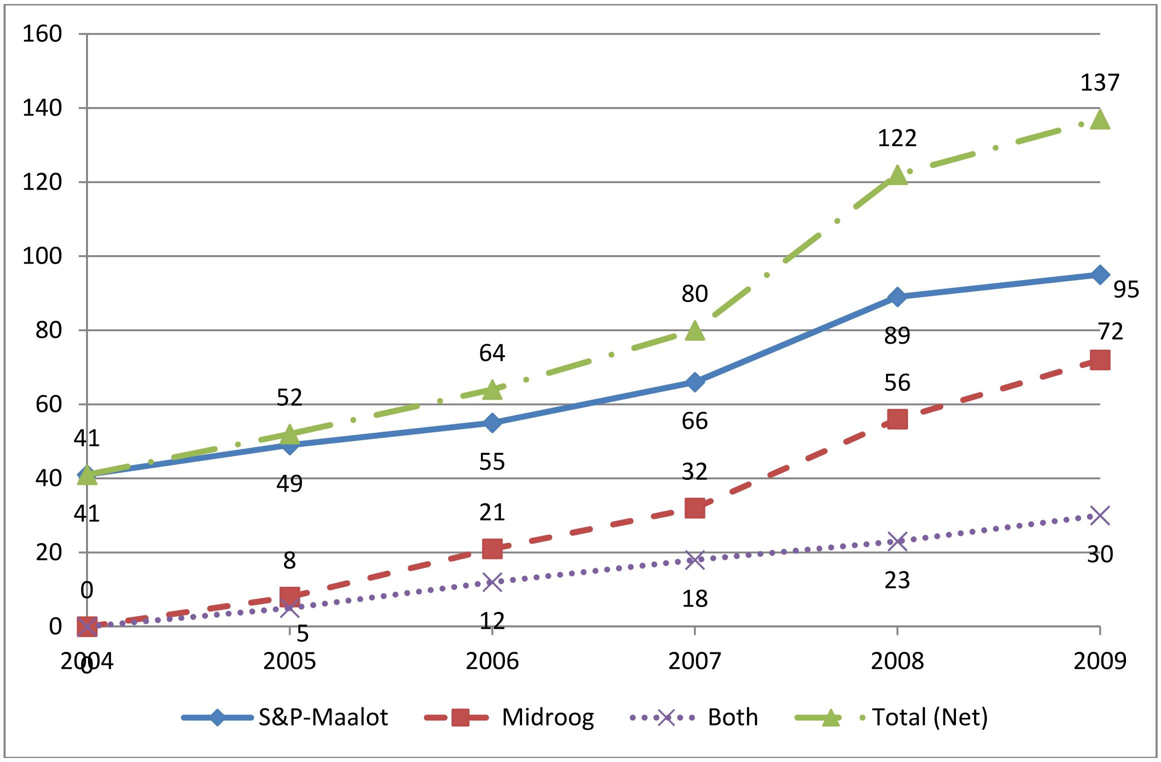

Figure 2 – Predicted Midroog ratings vs. actual S&P-Maalot ratings

This figure compares the predicted Midroog rating with actual S&P-Maalot rating on January 1, 2007. The Midroog ratings are based on regressions using data on firms rated by Midroog in 2007 or earlier (Table 5a).

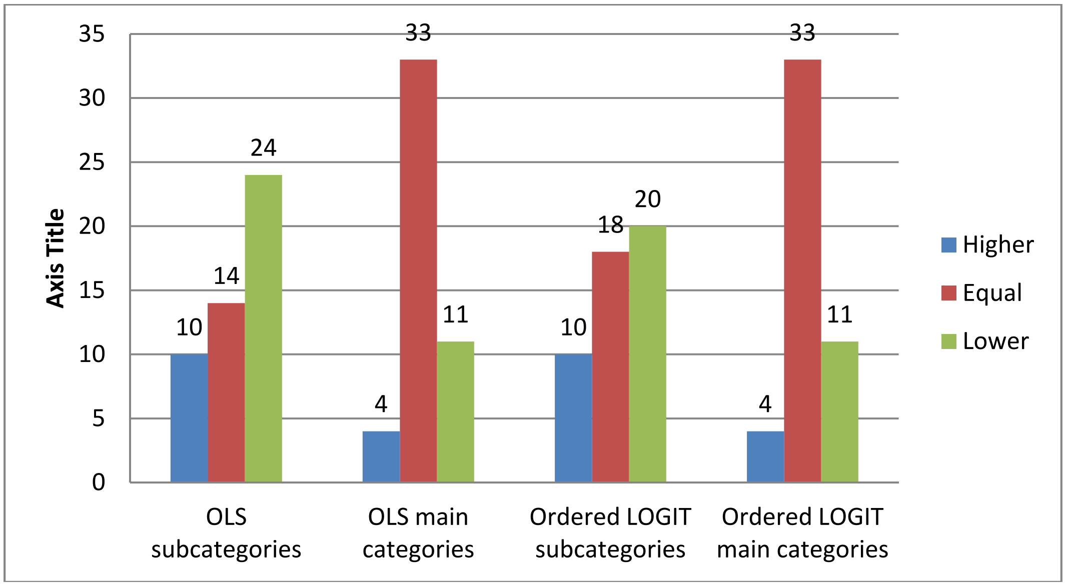

Figure 3 – Predicted S&P-Maalot ratings vs. actual Midroog ratings

This figure compares the predicted S&P rating with actual Midroog ratings on January 1, 2007. The S&P-Maalot ratings are based on regressions using data of firms rated by S&P-Maalot in 2007 or earlier (Table 6a)