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COMBINING INFORMATION TO BETTER ASSESS THE CREDIT RISK OF SMALL FIRMS AND MEDIUM-SIZED ENTERPRISES

BY DR. DOUGLAS W. DWYER

Lenders are increasingly tasked with making good lending decisions quickly. Such decisions require the ability to combine different types of information. Lenders typically rely on purely financial information to assess the credit risk of medium-sized enterprises. For small businesses, however, they consider more behavioral factors such as usage of credit lines, history of late payments, and the age of a relationship. Going forward, lenders will be able to access current financial information as well as behavioral information for both small firms and medium-sized enterprises. In order to quickly act on such information, firms will need to be able to combine such information into a unified risk assessment. In this article, we discuss the issues associated with acquiring such information and transforming it into a business decision. We also present a unified modeling approach for combining the information into a credit risk assessment for both small firms and medium-sized enterprises.

Introduction

A good origination process allows a lender to make loans faster, increase market share, and lower operational costs. A good risk model lowers charge-offs and provisions – especially during business downturns. To remain competitive, lenders to small firms and medium-sized enterprises will need to have both.

A lender can evaluate the risk of a borrower based on the borrower's behavior. Does the entity have a history of late payments? How long has it been a borrower? Does it have lines of credit? If so, is it maxing out these lines? If you visit the enterprise, is it what it claims to be? We think of answers to such questions as behavioral information.

Additionally, the lender can analyze the borrower's finances. Does the value of the borrower's assets exceed its liabilities? Is revenue sufficient to meet non-discretionary obligations? Is its

> A lender that assesses both behavioral information and financial information is able to make better decisions than a lender that does not.

financial performance stable over time? Is it improving? We think of answers to these questions as financial information.

If a lender uses the first type of information alone, then it will understate the risk of borrowers with positive behavioral information and poor financials.

Likewise, if a lender uses only the second type of information, it will understate the risk of borrowers with poor behavioral information but good financials.

A lender that assesses both types of information will be able to make better decisions than a lender that does not. This requires information collection as well as a model that can combine both types of information into a summary risk measure, as shown in Figure 1. In this article, we explore modeling options. Where to draw the line between a small firm and a medium-sized enterprise is subject to robust debate. For this article, we will look at two slices of our Credit Research Database (CRD). The first slice, the small firm sample, is made up of firms with less than $1 million in assets. The mediumsized enterprise sample comprises firms with $10 million to $50 million in assets. We will show that one unified model framework that combines both financial and behavioral information can accurately predict the default rate in both samples.

Conventional Approach

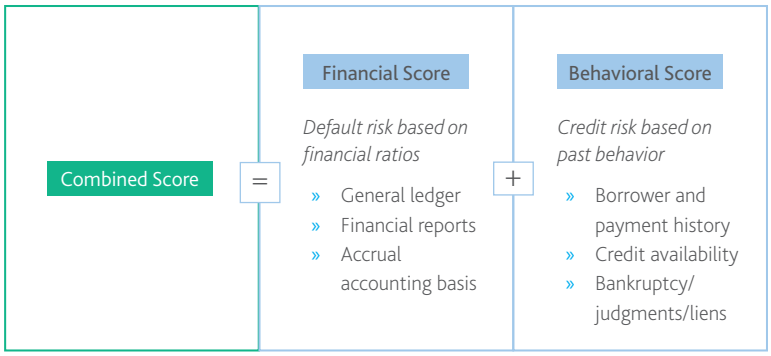
The conventional approach holds that financial information is more important for medium-sized enterprises than for small businesses. Small businesses often do not have audited financial statements and may use cash accounting. Consequently, lenders are uncertain of the reliability of such information. Further, the financials of the owner and the businesses are likely comingled to a certain degree. In this segment, banks rely more on tax returns, collateral information, personal and business credit reports, borrowing activity, and credit utilization than on financial statement information.

Firms that are large enough to be considered medium-sized enterprises will typically use accrual accounting and have audited financial statements. In this segment, banks use quantitative models to assess default risk based on financial statements. The assessment is supported by an analysis of business plans and pro-forma financial statements. Banks also look at financial information of the guarantee (if any), and information on customers and suppliers. Business credit reports are used to validate information collected directly from the borrower.

Information technology will improve the accuracy and transparency of small businesses' finances. Businesses are increasingly using online software to maintain their general ledger, which documents every transaction of a firm. Having the general ledger online allows a computer to produce an on-the-fly financial statement that can then be used to evaluate the risk of a borrower. A lender can require a borrower to generate a financial statement via software that accesses the borrower's general ledger. As these financials can be based on accrual accounting, they may avoid the distortions that cash accounting creates in the statements of many small businesses.

Due to improving IT systems, the risk assessment process of small businesses will be able to include techniques that have traditionally been applied to medium-sized enterprises. Omitting this information can result in underestimated loss rates.

Figure 1 Combining different types of information



Source: Moody's Analytics

Implications of Ignoring Information

We illustrate the implications of ignoring information using a pair of 2x2 diagrams. One can sort each borrower into one of the four quadrants according to the combination of their financial score and their behavioral score. The top right quadrant reflects poor financial and behavioral scores, while the lower left reflects good behavioral and financial scores. Firms with bad financial scores but good behavioral go into the upper left quadrant, and firms with good financials but bad behavioral fall into the lower right quadrant. We choose the quadrants so that half the sample is classified as having good financials and the other as having bad financials, and likewise for behaviorals. Consequently, each cell has about 25% of the sample.[1] Of course, one would expect default rates to be highest in the upper right-hand corner and lowest in the lower left-hand corner. The lower right and upper left corners would be in between.

As we have actual data, we can measure the default rates of each quadrant and color code them in proportion to the default rates. To do so, we need both a behavioral score and a financial score.

Our financial score is based on the RiskCalc model and uses financial statement information; the specific line items are available in a bank's FR Y-14Q reporting form. The financial score summarizes all financial information into one number representing the default risk of the firm. We utilize the RiskCalc CCA v4.0 credit measure for this purpose and focus on the small firm sample.

Our behavioral score is based on loan accounting system data; comparable information can be found in a bank's FR Y-14Q. With a bank's loan accounting system, we can track how long a business has been a borrower from a bank, whether it has a history of making timely payments, and whether it is fully utilizing its lines of credit. We have built a model that measures the business's credit risk given this information. Using these scores, we assign small businesses to each quadrant. More details on the data used for this article are in the appendix to this article.

Figure 2 shows two such grids. In both grids, the triangle on the upper left of each cell represents the actual default rate. In the upper right-hand cell of both grids, the actual default rate is 5.24%, which is color-coded, accordingly, in dark red. In the lower left-hand corner of each grid, the actual default rate is 0.43%, which is color-coded, accordingly, in a light pink to indicate low risk. The triangle in the lower right of each cell represents the predicted default rate according to the model.

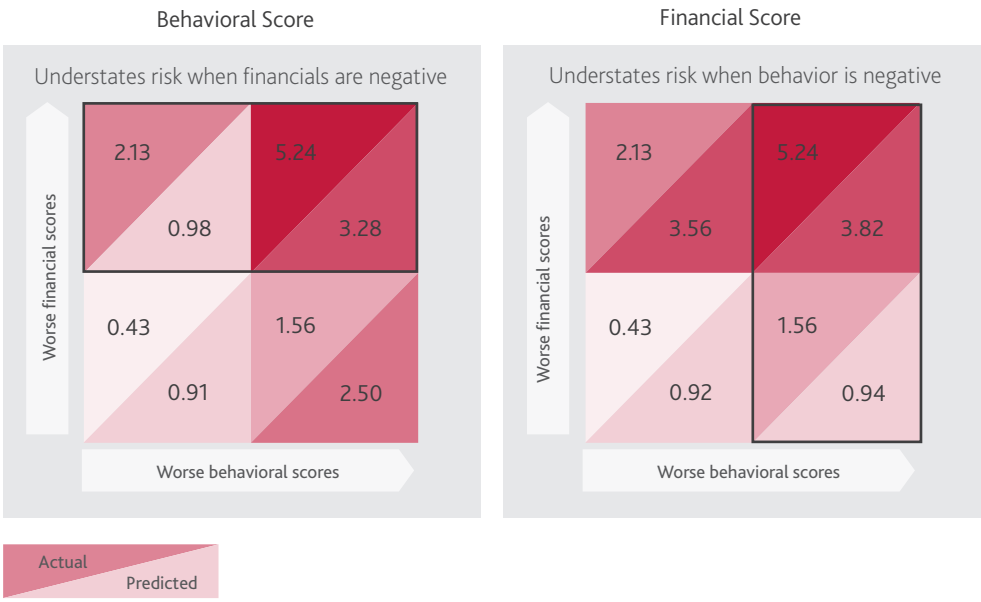
In the first grid, the predicted values are based on the behavioral score alone; in the second, they are based on the financial score alone. In the lower right-hand cell of each grid, the actual default rate is 1.56% indicated in the upper left corner of the cell. The lower right-hand triangle of each cell represents the predicted default rate based on the model. The first grid utilizes behavioral information alone and therefore overestimates the risk of this quadrant (2.50%). The colors of the cell indicate this as the lower right triangle is a darker red than the upper left triangle in the cell. The second grid utilizes financial information alone and therefore underestimates the risk of this cell (0.94%). The colors of the cell indicate this as the upper left triangle is a darker red than the lower right triangle in this cell.

The first grid of this figure illustrates that if one relies on behavioral information alone, one overstates the risk of firms with good financials: In the lower row, the actual versus predicted was 0.43% versus 0.91%, and 1.56% versus 2.50%. Further, one understates the risk of firms with poor financials. In the upper row, the actual versus predicted was 2.98% versus 0.98% and 5.24% versus 3.28%. The second grid of this figure illustrates that if one relies on financial information alone, one overstates the risk of firms with good behaviorals: In the right-hand column, the actual versus predicted was 0.43% versus 0.92% and 2.13% versus 3.56%. Further, one understates the risk of firms with poor behaviorals: In the right-hand column, the actual versus predicted was 1.56% versus 0.94% and 5.24% versus 3.82%.

Figure 3 contrasts the implications of using both types of information to strictly relying on financial information. Note that utilizing both types of information results in a predicted default rate that coincides closely with the actual, as indicated by very similar colors of the triangles within each cell. Where risk is highest (in the upper right quadrant), the combined model predicts 5.58% while financials alone predict 3.82% and behavioral scores predict 3.28%. If a lender relied on a single model, it would make the loan

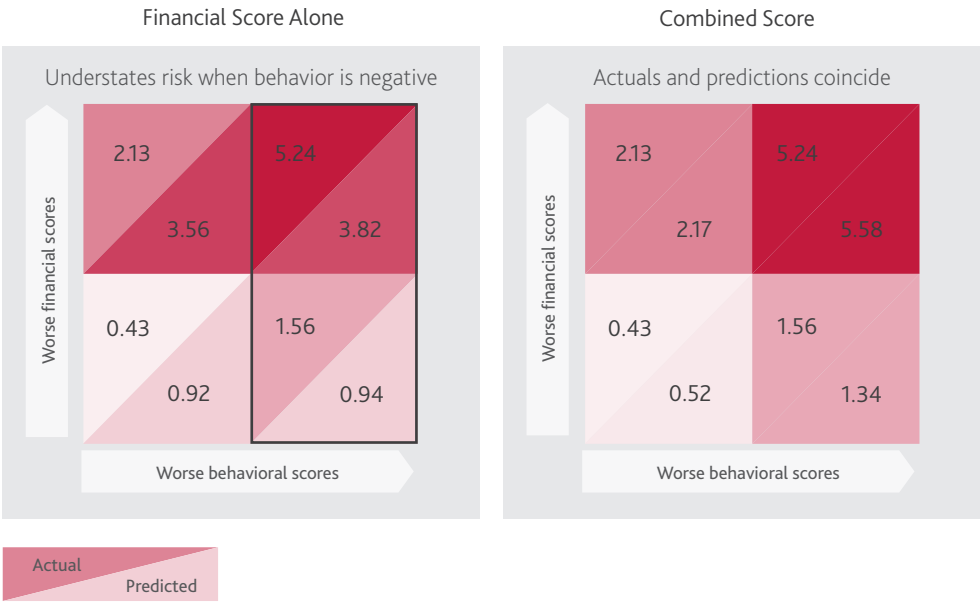
1 Strictly speaking, good behavioral scores are associated with good financial scores, which implies that the cells where the signals from behavioral information and financial information agree are better populated than when the signals disagree. Further, in the small firm sample, 53% of firms have the median or better behavioral score due to the discrete nature of the independent variables in the behavioral model. The breakdown of the small firm sample is as follows: 25% for bad financials and good behaviorals, 25% for bad financials and bad behaviorals, 29% for good financials and good behaviorals, and 21% for good financials and bad behaviorals. The corresponding numbers for the medium-sized enterprise sample are 23%, 27%, 27%, and 23%.

Figure 2 Implications of using behavioral scores or financial scores in isolation for small firms



Source: Moody's Analytics

Figure 3 Combined score accurately predicts the default rate in all four quadrants for small firms



Source: Moody's Analytics

with partial information, perhaps charging these borrowers 4% above the funding costs. If the lender had the full information, however, it would likely turn down the potential borrower. By turning down such loans, a lender avoids a 5.58% loss rate on approximately 25% of its portfolio. Therefore, the net benefit of these rejections to the lender would be approximately 0.40% on

the portfolio as a whole.[2]

Overstating the risk of firms that are safe has its own costs as well. For the firms with both good financial and behavioral scores, their risk is overstated by a factor of two. This elevated estimate of risk may lead the lender to ask for more collateral or more yield than is required. Further, lenders may perform more due diligence than is required, which slows down the origination process. Consequently, they may lose business to another lender who is able to process the deal faster and offer more attractive terms.

So far, we have looked at the implications of combining behavioral information and financials for small firms. We will now look at the implications of combining these information types for both small firms and medium-sized enterprises.

Dynamic Weights

Behavioral information is useful for understanding the credit risk of a small business, but is it as useful for medium-sized enterprises? Conventional wisdom would say no – for medium-sized enterprises, the financial statement information is much better, so credit assessments can rely more on the financial statements. One can address the question empirically by constructing a model that measures the relative importance of financial information and behavioral information by firm size.

Using our sample of firms with up to $50 million in assets, one can estimate a model in which the relative importance of financial factors increases with the size of the firm using the equation that follows. The basic idea is to let the weight on financial statement information be a linear function of the size of the firm (measured by log of assets):

$$pd(B,F) = G(\gamma_o+\gamma_o(w_{Size}F+(1-w_{Size})B))$$

Where

- B is the behavioral score
- F is the financial score
- pd(B,F) is the probability of default for the given behavioral and financial scores
- γ_0 and γ_1 are parameters to be estimated that determine the level and the variability of the PD, respectively
- w_{Size} is the weight on the financial factors, determined by:
- $w_{Size} = \alpha_0+\alpha_1\log(Size)$
- Size is measured as the log of total assets and α_0 and α_1 are parameters to be estimated
- G is a link function that transforms the combined score into a probability of default; in this article, we use a probit function

If the behavioral information is more important for smaller firms, we should see a positive coefficient on α_1. Figure 4 shows that the weight on the financial statement information increases with firm size. For a medium-sized enterprise with $50 million in assets, the weight on financial information comes out to 65%. This weight is consistent with conventional wisdom, in that many scorecards that we see used in practice use a weight in this range for the financial index. For a small firm with total assets of $200,000, the weight comes to about 51%. Consistent with conventional wisdom, the weight on financials is lower for small firms than for medium-sized enterprises. What is perhaps surprising is that the weight on financials is about 51% for the smallest firms. Many credit analysts would have expected it to be lower.

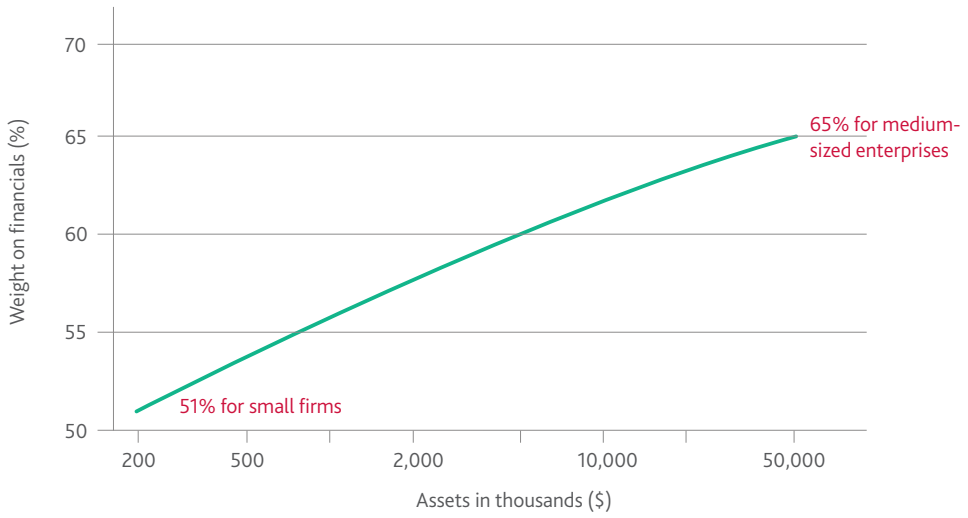
Comparing a Dynamic Weight to a Fixed Weight

What are the implications of using a dynamic weight on financials? Using a dynamic weight makes the model more complicated; is the added complexity worth the bother? When does the added complexity make a difference?

In building a model, one of the challenging questions is how complicated to make it. As models become more complex, they tend to be more difficult to use and support. Further, the factors driving the model's risk assessment typically become less transparent. Nevertheless, the complexity likely improves the fit of the model. If so, when and by how much? If a much better model always produces a probability of default (PD) that is within 20% of the PD produced by the simpler model (e.g., a PD that increases from 2.0% to 2.4%), it will be difficult to convince a practitioner that the much better model is, in fact, much better. Alternatively, if the much better model typically produces a PD very similar to the simple model's but produces contrasting results under specific circumstances that appeal to intuition, then the practitioner could be convinced that the much better model is, in fact, much better

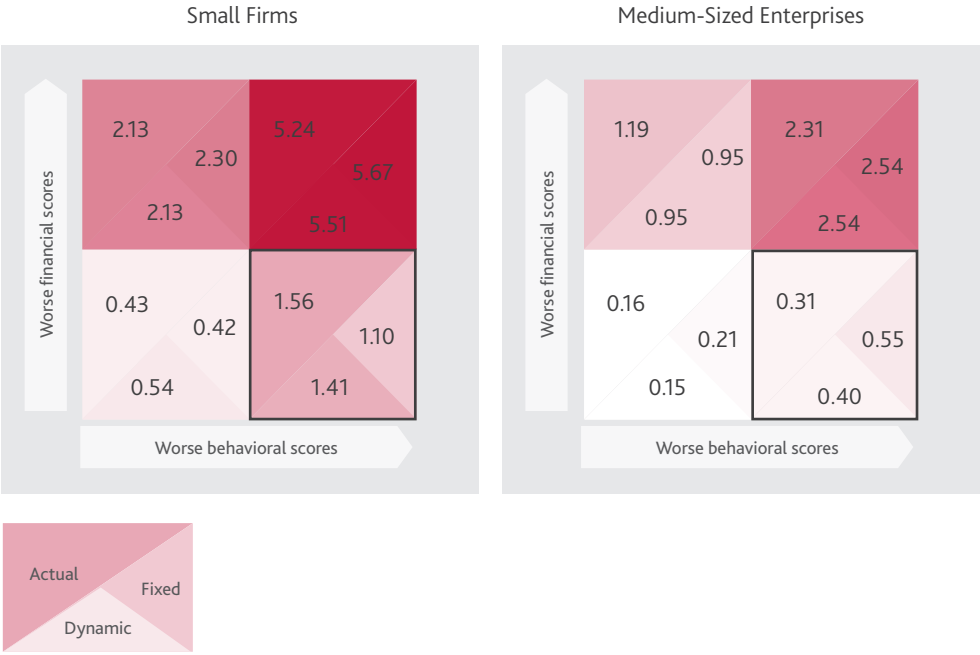
2 We compute this saving as the difference between the expected default rate (5.58%) and the yield in excess of the funding costs (4%) and then multiply by ¼ to reflect that approximately one-quarter of the portfolio would be in this quadrant. This calculation does make a number of assumptions including that both the risk and the return are homogeneous within the quadrant and that LGD is 100%. The true cost benefit calculation of rejecting these potential borrowers is more involved, but the results are indicative of a substantial savings from using a combined model.

Figure 4 The weight on a financial score increases with firm size



Source: Moody's Analytics

Figure 5 Dynamic weight more accurately predicts defaults in all four quadrants for small firms and medium-sized enterprises



Source: Moody's Analytics

We address this question with two 2x2 grids and include three numbers inside each cell of each grid, as shown in Figure 5. Small firms are represented in the first grid, and medium-sized enterprises are in the second. The behavioral factors are again on the horizontal axis, and the financial scores are on the vertical axis. The upper left triangle of each cell contains the actual default rate. The right-hand triangle in each cell is the predicted default rate based on the fixed-weight model, which is the simple model. And the bottom triangle in each cell is the predicted default rate based on the dynamic weight model, the complex model. Once again, each triangle is color-coded to match the intensity of the cell's numbers.

Note that the color of the bottom triangle largely coincides with the color of the upper left triangle in all eight cells. This indicates that the complex model's predictions are in line with the realized default rates. For the right-hand triangles, the color differential is largest in the lower right quadrant for both small firms and medium-sized enterprises. This quadrant is where the financials are good but the behaviorals are bad. For small firms in this quadrant, the simple model understates the risk (1.10% predicted versus 1.56% realized), and for medium-sized enterprises, the model overstates the risk (0.55% versus 0.31%). This finding is intuitive: By using the same weight on small firms as for medium-sized enterprises, one overstates the importance of financial statements for small firms and therefore overstates the risk in this quadrant; likewise, one understates the importance of financial statements for medium-sized firms.

Such differences are not huge, representing about a notch in ratings (e.g., Baa3 versus Ba1). They are large enough, however, to justify the added complexity of the model. In a sense, this approach is simpler than the conventional approach. The conventional approach uses different models for medium-sized enterprises and small businesses and requires a somewhat arbitrary cutoff for which borrower fits into which segment. With this approach, a modeler can use one scorecard for both small businesses and medium-sized firms, with a weight on the financials that gradually increases with firm size.

Conclusion

In this article, we have demonstrated the implications of combining financial and behavioral information in the credit assessments of both small businesses and medium-sized enterprises. Both types of information are important for both types of borrowers, with behavioral information being somewhat more important for small firms than for larger ones. For medium-sized enterprises, one should place a two-thirds weight on financial statement information and a one-third weight on behavioral factors. For small firms, one should weight financial and behavioral information equally. This finding may surprise some, as small businesses' financial statement information may not even be collected as part of the credit assessment process.

Going forward, successful lenders will likely start using automated approaches to collect both financial statement information and behavioral information for small firms for two reasons. First, one will increasingly be able to automatically collect such data. Second, collecting and using both types of information allows the lender to make better decisions. In this article, we have shown how to complete one step required for this transformation of the credit risk management process: how to combine both types of information into a better assessment of credit risk.

Appendix

For this article, we estimated the combined model on the North American CRD sample that includes more than 1.1 million quarterly observations from more than 100,000 firms with more than 5,000 defaults. The data begins in 1990 and runs through 2014. In this sample, we are able to get both firm-level financial statement information as well as information on credit line usage, payment status on current balances, and history of late payments. Finally, we are able to link this borrower information to data on whether the firm defaulted within the next year.

The financial score is based on the RiskCalc Expected Default Frequency (EDF) credit measure. The behavioral score is based on a model that uses credit line usage, payment status on current balance, and borrower history to predict default. For the figures in this article, we first focused on a sample of small firms with less than $1 million in total assets. There were 250,000 observations from 30,000 unique firms with 2,000 default events.

For the figures in this article that contrast small firms to medium-sized enterprises, we used the small firm sample as described above and a medium-sized enterprise sample. The medium-sized sample includes firms with between $10 million and $50 million in total assets. This sample included 200,000 observations, 19,000 unique firms, and 700 defaults.

In order to combine the outputs of the RiskCalc EDF model with the behavioral model, we transformed both the RiskCalc EDF credit measure and the behavioral model PD. The specific transformation that we used was the inverse of a standard cumulative normal distribution. Such a transformation makes the distribution of financial scores and behavioral scores more bell-shaped and less skewed relative to the untransformed RiskCalc EDF credit measure or untransformed behavioral model PD.

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