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Explaining the variation in U.S. corporate bond credit spreads using Dun & Bradstreet data and analytics

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EXECUTIVE SUMMARY*

– To illustrate the power of Dun & Bradstreet's unique data and analytics, we specify a corporate bond model that explains *over* half of the variation in credit spreads. Given the breadth and depth of D&B's unique commercial credit data, we believe that investment managers will find many factors that can help them better explain, price and ultimately, invest in corporate bonds and other corporate risk assets. Specifically, given the findings in this study, we think that D&B's unique data assets will be instrumental in pricing any corporate risk asset, whether it be investment grade corporate bonds, high yield bonds, credit default swaps, stock volatility (stock options or variance swaps) or for modeling equity risk.

– After controlling for aggregate interest rate and credit spread risks, for bond maturity, for industry, and for time, we find that our selected Dun & Bradstreet predictors explain 15% to 35% of the total variation in credit spreads. We find that much of this explanatory power comes from 10 unique and statistically significant predictors which we categorize into one of the following three groups:

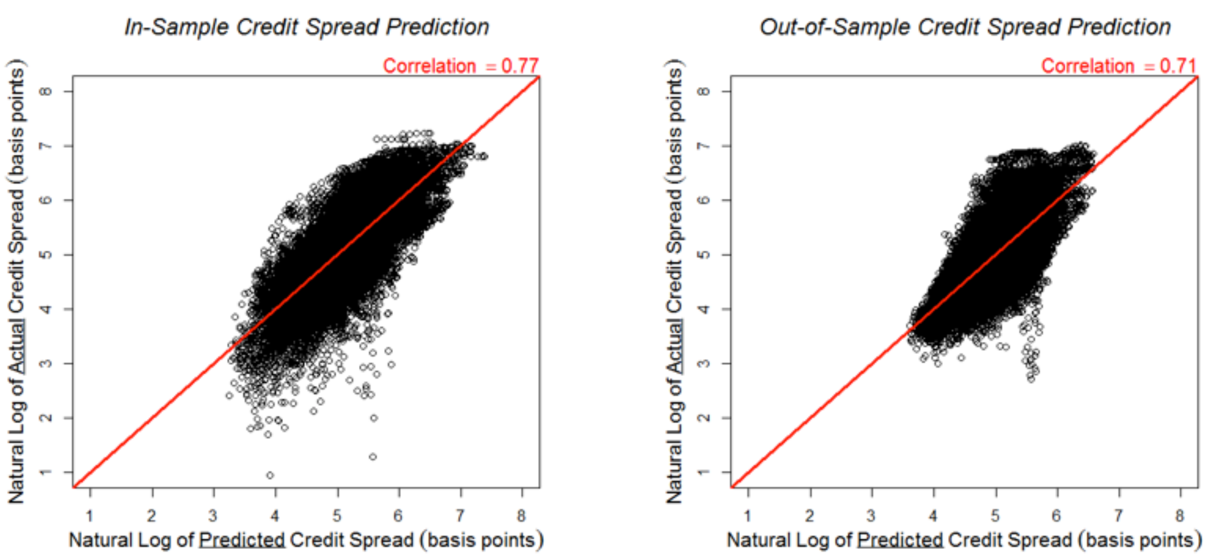
  - **Payment Burden:** When a company's *overdue* payables or cash payables to suppliers is large relative to a company's sales, we find that credit spreads tend to be higher.

  - **Leverage Over Suppliers:** Suppliers display many signals about their willingness to engage in business with a company, regardless of whether this business is to sell goods and services to this company, to lend to this company or to invest in this company. If a company has leverage over its suppliers, it can sometimes benefit by delaying a payment to a supplier of goods or services, or by securing a lower borrowing rate from a supplier of debt capital or by attaining a higher price from a supplier of equity capital. With greater leverage over suppliers, we find that credit spreads tend to be lower.

  - **Risk Exposure:** What is the likelihood that a company will experience financial stress, operating difficulty or failure in the coming year? Established D&B credit models define these probabilities. Using only D&B data, we develop and include a new risk factor in our corporate bond model. As expected, as risk exposure increases, credit spreads tend to increase too.

– In the graphs below, we show actual vs predicted credit spreads for our model for an in-sample period (Dec, 2010 to Mar, 2012) and an out-of-sample period (Apr, 2012 to Oct, 2014). Given these results and our robustness checks, we believe that we have a broad and deep list of unique factors that can help price and ultimately invest, in any corporate risk asset.

ACTUAL VS. PREDICTED CREDIT SPREADS: POOLED SCATTER PLOTS AND CORRELATIONS



Source: Dun & Bradstreet

* We thank everyone from Dun & Bradstreet's Advanced Analytics Services team for their helpful comments and suggestions.

INTRODUCTION

Over the last 20 years, several corporate bond and/or credit default swap spread statistical pricing models have been introduced in academic and practitioner literature.[1] All of these models have essentially relied on the following types of data:

1. Market Data (e.g., stock volatility, stock returns, market capitalization, etc.)

2. Accounting Data (e.g., sales, net income/total assets, etc.)

3. Credit Ratings Data from one or several of the Nationally Recognized Statistical Rating Organizations (e.g., Moody's, Standard & Poors, etc.) which rely heavily on publicly available financial statements.[2]

4. Structural Model Output (e.g., Merton's Model[3] or one of several underlying structural default probability models).

Although these statistical models have achieved considerable explanatory power, they continue to leave a significant portion of the variation of credit spreads unexplained. Sometimes, new research introduces a new factor or set of factors which can considerably improve the explanatory power of such models.[4] *We find that Dun & Bradstreet's unique data assets are such a source*. Since Dun & Bradstreet has, for many decades, collected and modelled payment and credit related data for commercial purposes, we aren't entirely surprised by this. This is especially true since, to our knowledge, nobody in the investment management or investment services area of securitized credit, has ever used Dun & Bradstreet data.

Dun & Bradstreet is considered to have the largest commercial database in the world. At its core is a proprietary trade program composed of thousands of participants. This trade program is the largest commercial payment database in the credit information industry. The information collected allows Dun & Bradstreet to define and better understand how companies pay each other and what factors are significant in determining credit risk. Importantly, this trade credit information is continuously updated and cannot be extracted from quarterly financial statements. However, it is this payment and risk modeling information that, up until now, has yet to be applied to help price and invest in the US corporate bond market or any corporate risk asset class for that matter.

Like many statistical models in financial literature, we link credit spreads to a number of explanatory variables via ordinary least squares. While limiting ourselves to Dun & Bradstreet data, we adhere to rigorous statistical methods of model development. While many other researchers have developed statistical credit models with the aim of maximizing explanatory power[5], we adhere to a rigorous process of factor selection that is designed to minimize multicolinearity while also maximizing explanatory power and interpretability of each factor. This way, we remain consistent in our ability to interpret the meaning and significance of the Dun & Bradstreet based data. However, if 'credit pricing' without the interpretability of the factors were paramount, we could, given the enormous breadth and depth of the Dun & Bradstreet data, have added many more highly significant factors to meet or beat the explanatory power of other credit pricing models.

Since Merton's paper in 1974, and with the advent of credit default swaps, practitioners and academics alike have acknowledged that there is a common set of risk factors across corporate risk assets. To this end, we believe that the findings in this study should be helpful for participants in any corporate risk asset, whether it be investment grade corporate bonds, high yield bonds, credit default swaps, stock volatility (stock options or variance swaps) or for modeling equity risk.

[1] For more information, please see "The Determinants of corporate credit spreads", Robert Jarrow, Li Li, Mark Mesler and Donald van Deventer, August 2008, *Risk Magazine*.

[2] Dun & Bradstreet is not a Nationally Registered Securities Ratings Organization (NRSRO). The firm does not rate securities, but instead, quantitatively rates a firm's credit worthiness in a number of different ways, regardless of whether the firm has issued any securities. Accordingly, Dun & Bradstreet is not regulated by the SEC in this respect.

[3] For more information, please see "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates", RC Merton, May 1974, *Journal of Finance*.

[4] For example, please see "Corporate Bond Credit Spreads and Forecast Dispersion", Levent Guntay, Dirk Hackbarth, March 2010, *Journal of Banking & Finance*. In this research, the authors find highly significant explanatory power from the dispersion of equity analysts' earnings forecasts; this appears to proxy for future cash flow uncertainty in corporate bond markets.

[5] For more examples, please see "The Determinants of Corporate Credit Spreads", Robert Jarrow, Li Li, Mark Mesler and Donald van Deventer, August 2008, *Risk Magazine*.

DATA

CORPORATE BOND UNIVERSE

We investigate the US corporate bond universe (both investment grade and some high yield) on a monthly basis from December, 2010 to March, 2012 as our in-sample period. Specifically, we include all fixed-rate USD denominated senior unsecured issues without optionality that have active end-of-day pricing as reported to FINRA TRACE (Trade Reporting and Compliance Engine) over this period. After mapping to Dun & Bradstreet data, this included 288 to 370 issuers per month that had issued 1 to 30-year maturities. Accordingly, across the maturity spectrum, we investigate, and ultimately model 2,304 to 2,960 pricing observations per month over these 16 months.[6] We use this same corporate bond filter to test an out-of-sample period from April, 2012 to October, 2014 (31 months). This, out-of-sample period included 289 to 407 issuers per month with 2,240 to 3,248 pricing observations per month. We do not eliminate financial issuers as many academic studies have done[7] because most of our selected predictors, as discussed below, do not directly reflect capital structure.

CREDIT SPREADS

Our dependent variable **CS**, is the natural log of the corporate bonds' credit spread. The credit spread is simply the difference between the yield-to-maturity of the corporate bond and the Constant Maturity Treasury (CMT) yield of the same maturity (supplied directly from the Federal Reserve System). Accordingly, we construct credit spreads for 1, 2, 3, 5, 7, 10, 20 and 30-year maturities. Because we are taking the natural log, we need to preserve positive credit spreads.[8] Because our in-sample universe of spreads included two slightly negative 1-year spreads, we scaled credit spreads slightly upward by the absolute value of the minimum credit spread. Specifically, we transform our dependent variable as follows: **CS = ln(abs(min(credit spread)) + 1 + credit spread)**. This way, we're able to preserve all credit spreads. Furthermore, we do not omit any maturities or correct for any apparent mis-pricings or liquidity issues.

DUN & BRADSTREET DATA

Over the in-sample period, we ran initial tests on about 800 predictors from some of the core datasets that are used at Dun & Bradstreet to model credit risk. Any missing data are either left as such or, when appropriate, replaced with a value of zero. We screen these predictors by running correlations to check for linear relationships and other processes to check for discrete or non-linear relationships. Although we find a long list of highly significant univariate predictors that are unique to Dun & Bradstreet, we aim to produce a group of economically meaningful predictors that work consistently well on both a univariate and multivariate basis while minimizing multicolinearity. Ultimately, we select 10 proprietary predictors that are unique to Dun & Bradstreet and five other predictors which aren't necessarily proprietary to Dun & Bradstreet, but are commonly used in Dun & Bradstreet credit modeling and are extremely helpful in explaining the variation in credit spreads. Below, we discuss the economic value of these predictors, and share some univariate findings. In later sections we review modeling results. We create panel datasets using the selected predictors described below.

PROPRIETARY DUN & BRADSTREET PREDICTORS

We qualify our ten proprietary predictors into one of the following three groups:

– **Payment Burden**

– **Leverage Over Suppliers**

– **Risk Exposure**

For each of these three groups and their associated predictors, we explain the economic rationale for the expected impact on credit spreads. For each predictor, we provide the explicit D&B factor specification in brackets.

[6] We reserve this longer out-of-sample period for back-testing purposes. Although we don't explicitly back-test in this paper, we plan to do so in future.

[7] For example, please see "Structural Models of Corporate Bond Pricing: An Empirical Analysis", Young Ho Eom, Jean Helwege, Jing-Zhi Huang, 2004, *The Review of Financial Studies*. In this research, the authors eliminate financial firms because they *don't* have "simple and consistent capital structures" and because "financial firms, such as banks, routinely have leverage ratios above 90%, whereas only the least creditworthy nonfinancial firms use as much debt".

[8] While this is common practice, other researchers have used a logistic transformation, but both functional forms preclude negative credit spreads.

- **Payment Burden:** When *overdue* payables or cash payables to suppliers is large relative to a company's sales, credit quality should deteriorate. Factors which shed light on a firm's ability to pay off outstanding supplier payments should shed light on credit quality. *The greater the payment burden, the higher we'd expect credit spreads to be.*

1. **Total USD payments that are 31+ days past due divided by sales [d_30P / sales].** The greater the overdue payments relative to the most recently reported sales, the greater the financial burden it is for a company to pay off its suppliers. *We expect firms with higher **d_30P/sales** to also have higher credit spreads.*

2. **Total USD payments that are in cash-only accounts divided by sales [(d_oth - d_neg) / sales].** Suppliers sometimes require customers to do business with them in cash-only accounts. These accounts are typically not invoiced and service is not rendered without an up-front cash payment. When a supplier requests a cash-only account, a red flag should go up because it can signal that the supplier is less willing to provide trade credit to the company. The definitions and explanations for **d_oth** and **d_neg** are shown below in the text box. When cash payments are large relative to sales, the credit-worthiness of a firm becomes more questionable. *Accordingly, we expect firms with higher (**d_oth - d_neg**) / sales to also have higher credit spreads.*

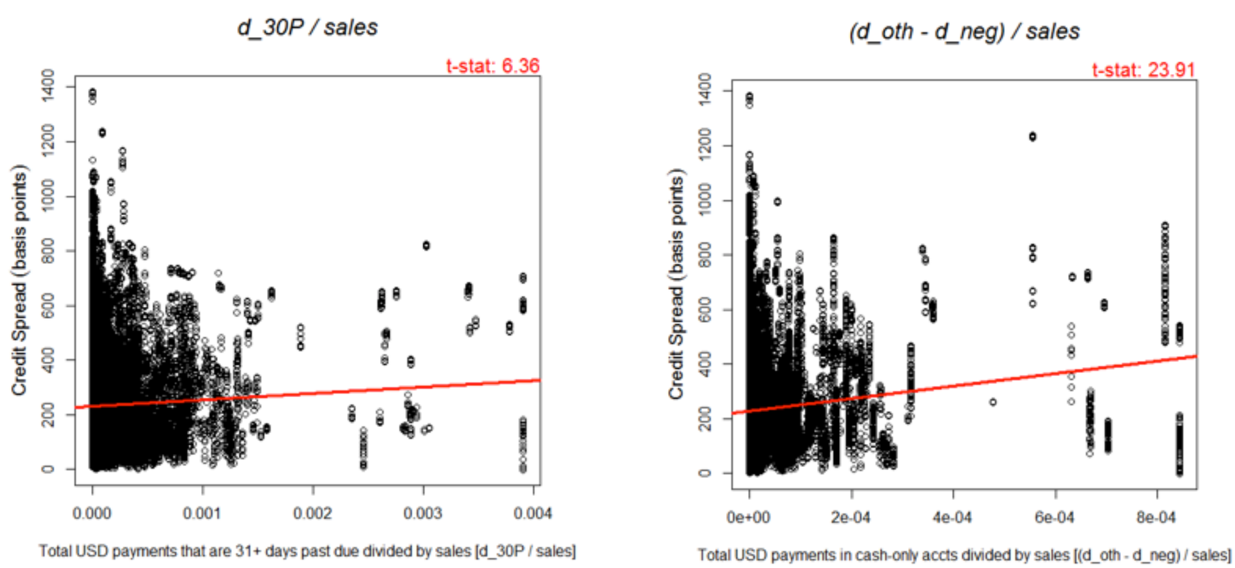
- **d_oth:** Dollar aging buckets keep track of the dollar amounts that are, for example, 30 days past due or 60 days past due, etc. Any dollar amounts that are in non-aging buckets and have commentary are placed under **d_oth** (i.e., dollars other). Commentary for **d_oth** can be either positive or negative.

- **d_neg:** This is the dollar amount that has negative commentary (also, a non-aging bucket). Negative commentary includes payments that have been placed for collection or repossession, have had bad debt, have had a suit filed, have had credit refused, have been deemed unsatisfactory, or have had insufficient funds.

- Accordingly, when we calculate **d_oth – d_neg**, we are left with a non-aging dollar amount without negative commentary. These are cash accounts that don't age (no amount owing) and don't have negative commentary because they are paid in-full.

In **Figure 1** below, we show in-sample, raw scatter plots and univariate pooled linear regressions for credit spreads against **d_30P/sales** and **(d_oth – d_neg) / sales**. These preliminary results corroborate our expectations that credit spreads should increase as payment burden increases.

FIGURE 1. IN-SAMPLE SCATTER PLOTS AND UNIVARIATE LINEAR REGRESSIONS ON POOLED CREDIT SPREADS VS. D_30P/SALES AND (D_OTH – D_NEG) / SALES; T-STATS ARE SHOWN ABOVE EACH PLOT.



Source: Dun & Bradstreet

- **Leverage Over Suppliers:** Suppliers display many signals about their willingness to engage in business with a company, regardless of whether this business is to sell goods and services to this company, to lend to this company or to invest in this company. If a company has leverage over its suppliers, it can benefit by occasionally delaying a payment to a supplier of goods or services, or by securing a lower borrowing rate from a supplier of debt capital or by attaining more favorable terms from a supplier of equity capital. Suppliers are willing to accept these less favorable payments, rates or terms because they have determined that the opportunities outweigh the additional costs. The perceived opportunities could be due to the size or scale of the company, the growth prospects of the company, or simply the familiarity that the supplier has with the company. And, of course, the more suppliers that a company has for a particular product or service, the more leverage it has over its suppliers.[9] *Accordingly, the greater the leverage over suppliers, the lower we'd expect credit spreads to be.*

3. **Maximum PAYDEX Score over past 12 months [maximum pydx_1 for past 12 months]. In this study, we refer to this as maxPay.** The PAYDEX score is a unique dollar-weighted numerical indicator of how a firm paid its bills based on trade experiences reported to Dun & Bradstreet through its trade program. D&B data is continuously updated, so items like PAYDEX are known long before quarterly financial statements are reported. Regardless, it's items like PAYDEX that cannot be extracted from financial statements. Because US accounting standards have adopted accrual based accounting practices[10], companies record revenue when earned but not when received. As such, delaying payments does not affect net income, but does affect cash flow. The table below outlines the specific 1-100 PAYDEX score and what it means. A score of 80 denotes that payments reported to D&B have generally been made within terms. Scores over 80 indicate that payments reported to D&B have been made earlier than terms. Generally, for 99.9% of the 20 to 30 million US firms that are included in much of Dun & Bradstreet's credit modeling, a lower PAYDEX score means that a firm should be considered less credit-worthy because it pays its bills later. However, when we investigate publicly traded corporate issuers, we find that they are economically rewarded for consistently paying later. Specifically, these firms that tend to consistently pay later tend to experience lower credit spreads. The economic rationale for this is that companies that have leverage over their suppliers can, when needed, delay payments to a supplier which gives them the flexibility and control to generate more cash flow, when needed. Accordingly, we believe that this leverage allows them to smooth-out their reported quarterly cash flows. Another benefit is that it reduces a firm's need for short-term financing in order to pay accounts and that this reduction in short-term borrowing costs improves financial performance. **maxPay** reflects not only the level, but also the volatility of the PAYDEX score over the prior year; accordingly, a more volatile working capital strategy can result in a more volatile PAYDEX score and a higher **maxPay**. Conversely, a less volatile working capital strategy and lower average PAYDEX score will result in a lower **maxPay**. Therefore, **maxPay** effectively screens for companies that have the ability to consistently pay later, in aggregate, on a dollar-weighted basis. Again, these companies benefit because they can smooth-out reported cash-flows when needed while also reducing the need for short-term financing. *Accordingly, for our corporate bond universe, we expect firms with a lower **maxPay** to have lower credit spreads.*

PAYDEX SCORE:	INDICATES THE FOLLOWING PAYMENT PRACTICES:
100	Anticipates
90	Discounts
80	Prompt
70	15 days beyond terms
60	22 days beyond terms
50	30 days beyond terms
40	60 days beyond terms
30	90 days beyond terms
20	120 days beyond terms
0 – 19	Over 120 days beyond terms
UN	Unavailable

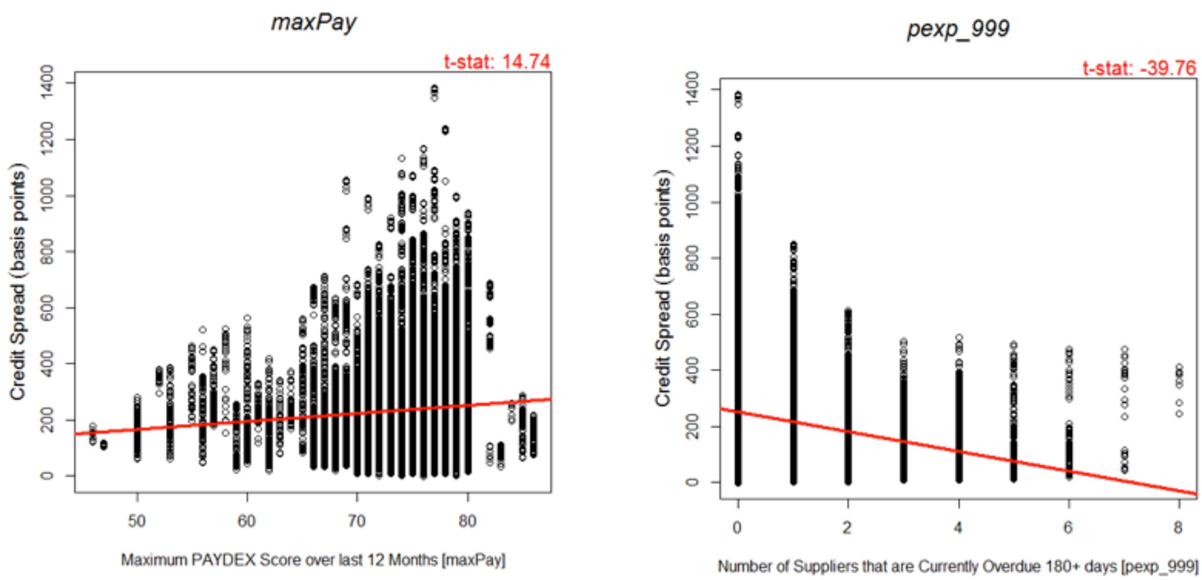
[9] This relates directly to Michael Porter's 5 Forces. Please see "How Competitive Forces Shape Strategy", by Michael Porter, 1979, *Harvard Business Review.*

[10] Generally Accepted Accounting Principles, also called GAAP or US GAAP, are the generally accepted accounting principles adopted by the U.S. Securities and Exchange Commission (SEC). While the SEC has stated that it intends to move from US GAAP to the International Financial Reporting Standards (IFRS), the latter differ considerably from GAAP and progress has been slow and uncertain.

4. **Number of trading relationships between the subject and its suppliers that are greater than 180 days past due [pexp_999].** **pexp_999** is a count of the number of suppliers that are currently overdue 180+ days. Accordingly, it is another metric that can measure the leverage that a company has over its suppliers. Firms with more leverage over their suppliers (perhaps because they have more suppliers from which to select) will have the ability to pay a greater number of suppliers much later. *Therefore, with a higher **pexp_999**, we'd expect firms to have lower credit spreads.*

In **Figure 2** below, we show in-sample, raw scatter plots and univariate pooled linear regressions for credit spreads against **maxPay** and **pexp_999.** Both show that as leverage over suppliers increase, credit spreads decrease, per our expectations.

FIGURE 2. IN-SAMPLE SCATTER PLOTS AND UNIVARIATE LINEAR REGRESSIONS ON POOLED CREDIT SPREADS VS. MAXPAY AND PEXP_999; T-STATS ARE SHOWN ABOVE EACH PLOT.



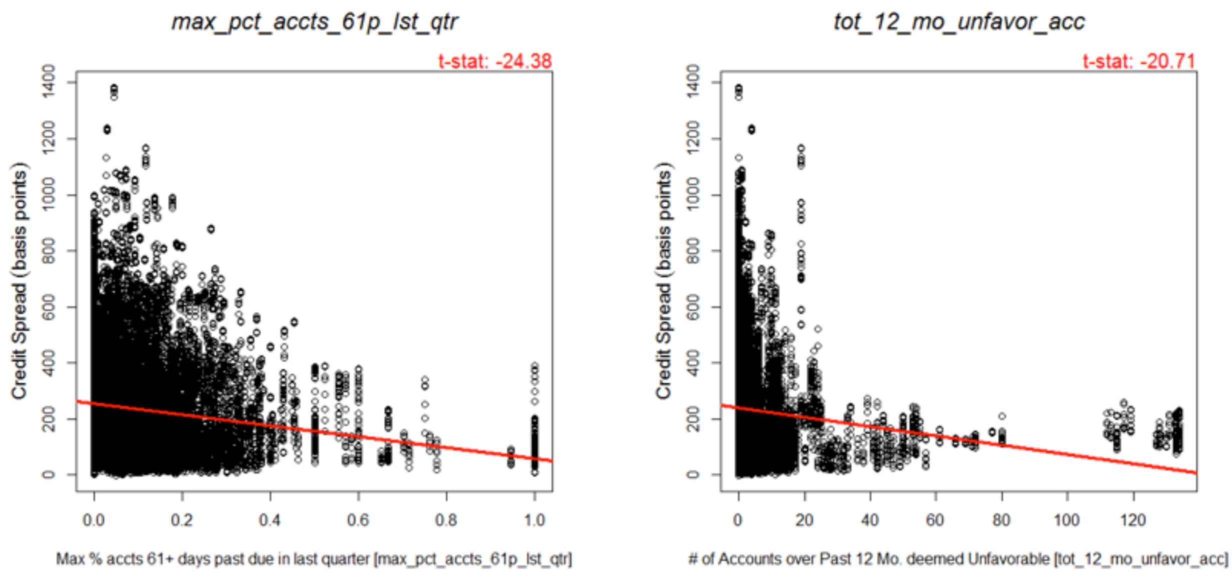
Source: Dun & Bradstreet

5. **Maximum percent of accounts with 61+ days past due in the last quarter [max_pct_accts_61p_lst_qtr].** Because **max_pct_accts_61p_lst_qtr** is measured as a percentage of accounts, it is a scaled predictor. However, within the corporate bond universe, it also works as a proxy for the trading strength that a company has over its suppliers. Within this universe, firms with leverage over their suppliers will tend to let a greater percentage of accounts become delinquent. *Accordingly, with higher **max_pct_accts_61p_lst_qtr**, we'd expect lower credit spreads.*

6. **Number of accounts that are unfavorable (this can mean the account has been placed for collection, written off, unsatisfactory payment, etc.) [tot_12_mo_unfavor_acc].** As with the two previous predictors, **tot_12_mo_unfavor_acc** also works as a way to measure the leverage that a company has over its suppliers. Within the corporate bond universe, issuers that have more accounts and relatively more unfavorable accounts are also exhibiting leverage over their suppliers. *Therefore, we'd expect higher **tot_12_mo_unfavor_acc** to correspond with lower credit spreads.*

In **Figure 3,** we show in-sample, raw scatter plots and univariate pooled linear regressions for credit spreads against **max_pct_accts_61p_lst_qtr** and **tot_12_mo_unfavor_acc.** Again, both show that as leverage over suppliers increases, credit spreads decrease, per our expectations.

FIGURE 3. IN-SAMPLE SCATTER PLOTS AND UNIVARIATE LINEAR REGRESSIONS ON POOLED CREDIT SPREADS VS. MAX_PCT_ACCTS_61P_LST_QTR AND TOT_12_MO_UNFAVOR_ACC; T-STATS ARE SHOWN ABOVE EACH PLOT



Source: Dun & Bradstreet

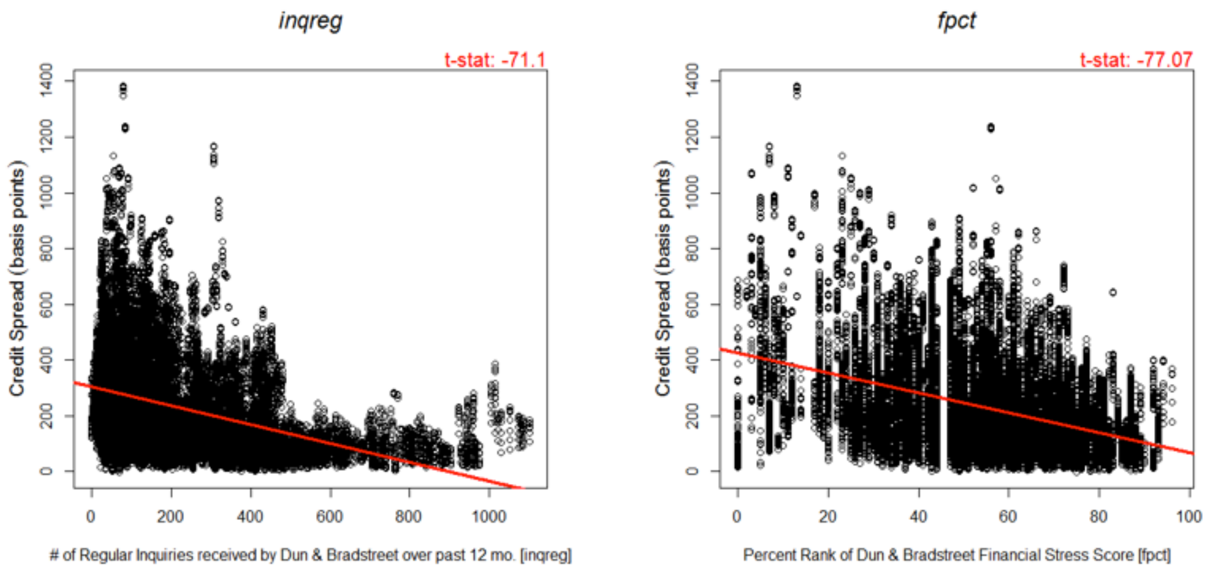
7. **Natural log of number of regular inquiries received by Dun & Bradstreet over the previous 12 months [ln(1+inqreg)].** Inquiries are made to Dun & Bradstreet because firms are often checking the credit-worthiness of other firms to engage in trade, to lend or to invest. We take the natural log of **inqreg** not only to linearize the data, but to also mitigate correlation to other predictors. Typically, more inquiries are made on firms that attract more trade, lending and investing. *Consequently, we'd expect firms that have high* ***ln(1+inqreg)****, to have lower credit spreads.*

- **Risk Exposure:** What is the likelihood that a company will experience financial stress, operating difficulty or fail in the coming year? Dun & Bradstreet credit models define these exposures and estimate these probabilities. *The greater the risk exposure, the higher we'd expect credit spreads to be.*

8. **Percent Rank of D&B's Financial Stress Score [fpct].** The Financial Stress Score predicts a business's likelihood of experiencing financial stress over the next 12 month period. Dun & Bradstreet defines a financially stressed business as one that seeks legal relief from its creditors, ceases business operations without paying all its creditors in full, voluntarily withdraws from business operation and leaves unpaid obligations, goes into receivership or reorganization, or makes an arrangement for the benefit of creditors over the next 12 month period. The scores and underlying models are based upon the observed characteristics of millions of businesses in Dun & Bradstreet's database and the relationship these characteristics have to the probability of a business experiencing financial stress over a period of 12 months. *The percent rank of this score is such that a 1 represents businesses that have the highest probability of financial stress, and a 100 represents businesses with the lowest probability of financial stress.* This percentile shows you where a business falls among the 20 to 30 million businesses that are modeled. This variable is referred to as **fpct**. *We expect firms with a low* ***fpct*** *to have high credit spreads.*

In **Figure 4** we show in-sample, raw scatter plots and pooled univariate linear regressions for credit spreads against **inqreg** and **fpct**. We define inqreg as a measurement of leverage over suppliers and **fpct** as a measurement of corporate risk, but we show them together in **Figure 4** because they are the two strongest in-sample univariate predictors of credit spreads as can be seen from their relatively large t-stats. These preliminary results confirm our economic rationale that as leverage over suppliers increases, credit spreads should decline and as corporate risk decreases, credit spreads should decline.

FIGURE 4. IN-SAMPLE SCATTER PLOTS AND UNIVARIATE LINEAR REGRESSIONS ON POOLED CREDIT SPREADS VS. INQREG AND FPCT; T-STATS ARE SHOWN ABOVE EACH PLOT.



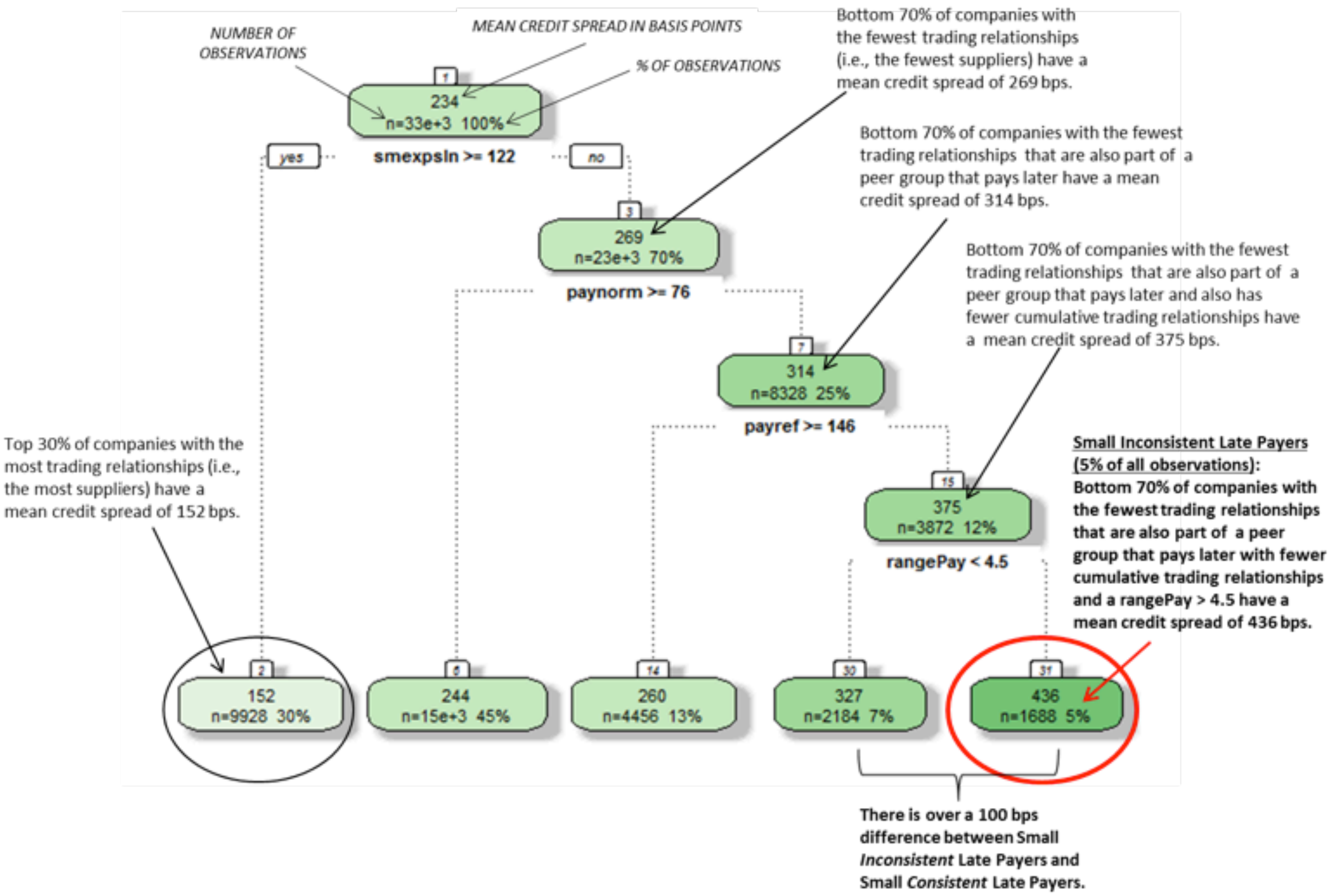
Source: Dun & Bradstreet

9. **D&B's Business Deterioration Indicator [bd_ind].** This is a dummy variable where a 1 indicates imminent business failure or operating difficulty. This is based on Dun & Bradstreet's proprietary combination of modeling output, facts, business conditions and events (e.g., judgements, lawsuits, etc.) *With a **bd_ind** of 1, we expect higher credit spreads.*

10. **Small Inconsistent Late Payers. This is a dummy variable where 1 occurs when smexpsln < 122 & paynorm < 76 & payref < 146 & rangePay > 4.5 [Small_Inconsistent_Late_Payers].** This dummy variable is a result of our investigation of our in-sample period for interaction and segmentation effects using Dun & Bradstreet's payment scoring and payment related elements. We develop an in-sample Classification and Regression Tree (CART) model as shown as in **Figure 5**. The definitions for each of the 4 selected elements is shown below in the shaded text box. Essentially, **smexsln** serves as a measure of scale and leverage over suppliers (larger companies have more suppliers), **paynorm** is the median PAYDEX score for 91 peer groups, **payref** is a proxy for size, age and leverage over suppliers while **rangePay** captures the variability in a company's PAYDEX score. (rangePay = Maximum - Minimum PAYDEX over past 12 months) Accordingly, we surmise that the **Small_Inconsistent_Late_Payers** are paying later, <u>not</u> because they have leverage over their suppliers, but because they are actually having difficulty paying their suppliers. In the regression tree, notice that rangePay separates "Small Inconsistent Late Payers" from "Small Consistent Late Payers" with over a 100 bps difference between each group's mean credit spread. We further surmise that, **Small_Inconsistent_Late_Payers** are companies that don't have a consistent working capital strategy. Instead, the variability of their late paying behavior implies that they are having difficulty paying at regular intervals because their income stream might be irregular. *Accordingly, we'd expect firms that are identified as **Small_Inconsistent_Late_Payers** to have higher credit spreads.*

- **smexpsln:** The number of trade experiences between the subject and its suppliers that have a summarized experience that includes any slowness or negative commentary. Negative payment commentary includes payments that have been placed for collection or repossession, have had bad debt, have had a suit filed, have had credit refused, have been deemed unsatisfactory, or have had insufficient funds.
- **paynorm:** The *median* PAYDEX score for each peer group across SIC industries and size buckets. Specifically, there are 7 size buckets (measured on sales and/or number of employees) and 13 SIC industries. Accordingly, each of these 91 peer groups (= 7 x 13) has its own paynorm value.
- **payref:** The number of suppliers that now have or ever had a trading relationship with the subject.

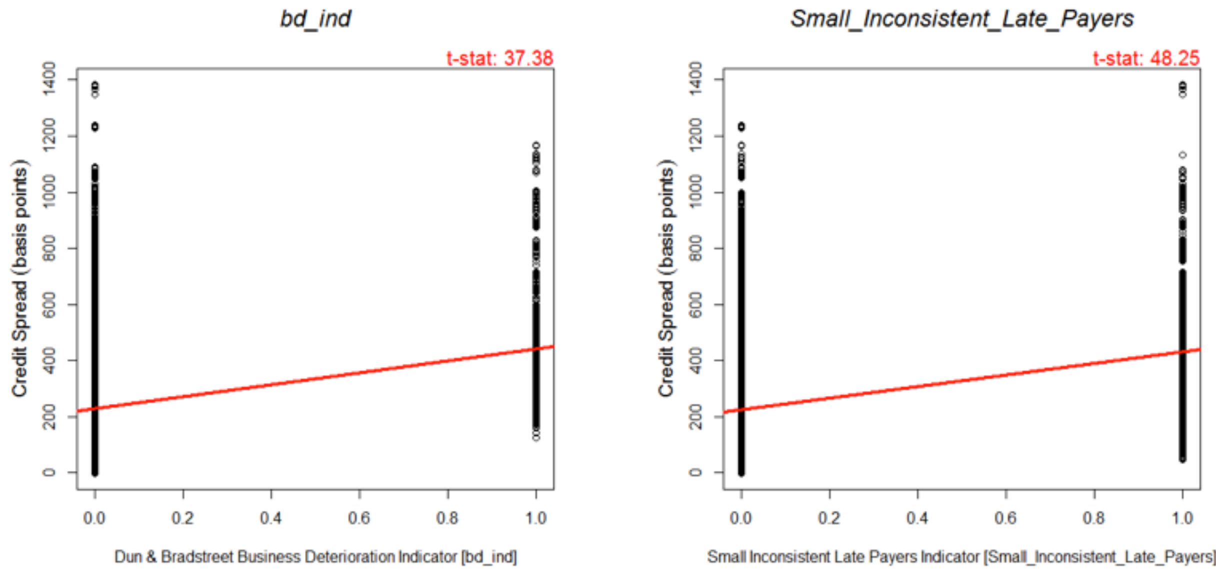
FIGURE 5. IN-SAMPLE CLASSIFICATION AND REGRESSION TREE THAT IDENTIFIES "SMALL INCONSISTENT LATE PAYERS" WITH A MEAN CREDIT SPREAD OF +436 BPS (OVER 200 BPS ABOVE THE MEAN).



Source: Dun & Bradstreet

In **Figure 6** below, we show the in-sample, raw scatter plots and pooled univariate linear regressions for credit spreads against **bd_ind** and **Small_Inconsistent_Late_Payers**. Both dummy risk factors show that as risk increases, so do credit spreads, per our expectation.

FIGURE 6. IN-SAMPLE SCATTER PLOTS AND UNIVARIATE LINEAR REGRESSIONS ON POOLED CREDIT SPREADS VS. BD_IND AND SMALL_INCONSISTENT_LATE_PAYERS; T-STATS ARE SHOWN ABOVE EACH PLOT.



Source: Dun & Bradstreet

OTHER DUN & BRADSTREET PREDICTORS

We include the following five additional predictors, some of which, have been used in other Dun & Bradstreet credit modeling:

11. **Natural log of networth [ln(abs(min(networth)) + 1 + networth)].** This is the retained profits and invested capital, representing the equity of the business. Because we need to preserve a positive value for the log transformation, we scale networth upwards so that there are no negative values. *We expect firms with high **networth** to have lower credit spreads.*

12. **Age of firm since establishment (in years) [age].** Older companies have weathered more business cycles and have a longer track record. *Accordingly, we'd expect older firms to have lower credit spreads.*

13. **Number of secured loans [sec_loan].** A firm that taps the commercial loan market too many times could become a credit concern. *Accordingly, we'd expect a higher **sec_loan** count to be associated with higher credit spreads.*

14. **Natural log of dollar amount of firm's outstanding liens. This includes all liens, but are mostly composed of tax liens and judgement liens [dlien].** The dollar value of all liens that a company has is another way of capturing the scale of a business. *Accordingly, we'd expect higher **dlien** to be associated with lower credit spreads.*

15. **The average number of purchases made online over the past month. [avg_ordrs_o].** The number of online orders is another way of capturing the scale of a business. Newer businesses that don't own property (i.e, don't necessarily have a high dlien), but have a large online business can be captured with this predictor. *Accordingly, we'd expect higher **avg_ordrs_o** to also be associated with lower credit spreads.*

CONTROL PREDICTORS

We need to account for aggregate risks in interest rates and credit spreads. We also need to account for the variation in credit spreads due to bond maturity, issuer industry, and time. We do this with the following control predictors:

- **Aggregate Risk Factors:** General market-wide conditions for interest rates and credit spreads might explain the variation in credit spreads. To test and control for this, we include the following four aggregate risk factors[11]:

16. **Treasury Yield of 10-Year (constant maturity) [TY10].** The effect that the long-term risk-free rate of interest has on credit spreads is largely dependent on the maturity and leverage at the firm-level.

17. **Slope of Treasury Yield Curve (10-Year CMT - 2-Year CMT) [Slope].** The slope of the Treasury yield curve is a strong predictor of future economic health and, accordingly, default risk.

18. **Corporate Bond Risk Premium (Moody's Seasoned Aaa Corporate Bond Yield© - TY10) [Corp].** This captures the corporate bond risk premium which can be due to tax and liquidity issues relative the Treasury market.

19. **Corporate Bond Default Risk Premium (Moody's Seasoned Aaa Corporate Bond Yield© - Moody's Seasoned Baa Corporate Bond Yield©) [Def].** This captures the default risk premium as defined by Moody's ratings.

- **Maturity Dummies:** To capture the effect of the term structure of credit spreads, we include the following seven bond maturity dummies: two, three, five, seven, 10, 20 and 30 years.[12]

- **Industry Dummies:** To capture industry effects we define 15 SIC4 industry groupings which, during our in-sample period, explained the most amount of credit spread differentiation without over-fitting. In the model, we include seven of these industry dummy groupings as shown below.

- **Monthly Dummies:** To capture time varying effects on credit spreads, we include monthly dummies.

GROUP #	SIC4 CODES	INDUSTRY DESCRIPTION
1	2021 to 2099	Food Manufacturing
2	3525 to 6286	Industrial Manufacturing, Transportation, Communications, Electric and Gas Utilities, Whole Sale Trade, Retail Trade, Depositary Institutions
3	2829 to 3399	Chemical, Petroleum, Rubber, Leather, Concrete and Metal Manufacturing
5	2111 to 2813	Tobacco, Textile, Apparel, Lumber, Furniture, Paper and Printing Manufacturing
8	3400 to 3525	Fabricated Metal and Commercial Machines
11	> 8736	Engineering Services and Government Services (Correction Institutions, Housing Development, Economic Programs)
12	7514 to 8029	Automotive Repair, Parking & Services, Motion Pictures, Leisure, Amusement Parks

[11] Supplied directly from the Federal Reserve System H.15.
[12] We exclude a one-year maturity dummy in order to avoid a singular matrix.

STATISTICAL MODEL AND EMPIRICAL RESULTS

Using the previously described predictors, we run pooled OLS regressions on our in-sample panel data. To avoid biases due to outliers, all of the selected predictors that are continuous (i.e., not discrete or bounded) are winsorized at the 5% level (i.e., at 2.5% and 97.5%).[13] In **Figure 7**, we show the in-sample correlation matrix of **CS** and the 15 D&B predictors. From this, we see that the correlation between CS and all 15 of the predictors is statistically significant at the 0.1% level and seven of the predictors have absolute correlations above 0.20. The signs, again, are all as expected. While there does exist significant correlation between some of the 15 predictors, we formally test for evidence of multicolinearity by calculating the variance inflation factor (VIF) for each predictor. We find that the highest in-sample VIF is 2.24, indicating that multicolinearity should not be a concern. Accordingly, we run pooled OLS regressions, both in and out-of-sample and report the results in **Figure 8**. t-Statistics are based on robust standard errors. When we re-estimate the standard errors clustered at the firm level, our t-statistics drop, but all 15 predictors continue to remain statistically significant, both in and out-of-sample. The predicted vs actual **CS** graphs on the first page were produced using this model.

From these results, we notice that, for all 15 of the D&B predictors, the multivariate coefficient signs are all consistent with their univariate signs, confirming that multicolinearity is not an issue. Furthermore, there is reasonable stability in the coefficients between the in-sample and out-of-sample results. Also, the robust t-statistics remain consistently strong for all 15 predictors over both sample periods despite the inclusion of the control predictors. Other D&B predictors like **networth, age** and **sec_loans** act like additional control variables because, while none are proprietary to D&B, they all, to some extent, serve as proxies for other commonly tested and modeled determinants of credit spreads. For example, **networth**, arguably our best predictor, is not commonly used in academic literature, but closely related factors like size (market capitalization), financial leverage and B/M are all commonly used. We think, however, that **networth** efficiently integrates elements from each and is, ultimately, a more powerful predictor. Also, while we don't explicitly include financial leverage as a factor, **sec_loans** serves as something of a proxy, but with other additional information that perhaps the credit markets are not, as of yet, utilizing.

The only predictor that actually changed sign between the in and out-of-sample periods is **Slope** of the Treasury yield curve (10-Year - 2-Year). Given that it wasn't statistically significant in either period, we're not terribly surprised by this.

In **Figure 9**, we show each factor group's marginal contribution to explanatory power[14] for the in-sample and out-of-sample periods. Moving from the in-sample period to the out-of-sample period, we see that the explanatory power of the maturity dummies doubled while everything else essentially halved. **Figure 10** sheds light on why we see this. During the in-sample period, we see a flatter, yet steepening term structure of credit (Dec, 2010 to Mar, 2012), but during the out-of-sample period (Apr, 2012 to Oct, 2014), we see a much steeper and more stable curve. Most importantly, the *mean* steepness of the term structure of credit spreads was about twice as large during the out-of-sample period relative to that of the in-sample period. Accordingly, if the explanatory power of all the other factors remained constant, the relative *power*, when compared to the maturity dummies, had to drop by close to a half. Accordingly, although the **Slope** of the Treasury yield curve may have changed between the two periods, it was the change in the term structure of *credit spreads* that really explained the variation in credit spreads.

The 15 D&B factors explained about 35% of the total variation in credit spreads in-sample and about 15% of the total variation in credit spreads out-of-sample.[15] The 10 proprietary D&B factors explained about 19% of the total variation in credit spreads in-sample and about 9% of the total variation in credit spreads out-of-sample.

Lastly, many of the outliers in the predicted vs. actual graphs on the front page were due to corporate actions (specifically, mergers and acquisitions) which we did not omit or specify in the model. In those instances, the credit spreads for a target firm (and sometimes the acquiring firm) will be very different than anticipated, all else being equal. Other outliers were due to liquidity issues at the short end. Again, we did not omit these observations nor did we include any liquidity specification. If we had, overall explanatory power would have been noticeably higher.

[13] In untabulated estimations, similar results are found on our predictors when we don't winsorize or, if we winsorize at the 1% or 10% level.

[14] This is estimated by dropping each predictor and calculating the percentage change in the residual sum of squares. We sum this marginal contribution to explanatory power for each factor group.

[15] We simply multiply the adjusted R-squared by the marginal contribution to explanatory power for each group to estimate the percentage of the total variation in credit spreads that each group explains.

FIGURE 7. CORRELATION MATRIX: USING MONTHLY PANEL DATA FOR THE IN-SAMPLE PERIOD (DEC, 2010 TO MAR, 2012), THIS TABLE SHOWS THE PEARSON CORRELATION MATRIX FOR BOND-LEVEL OBSERVATIONS ON CREDIT SPREADS (CS) AND 15 DUN & BRADSTREET PREDICTORS. CONTINUOUS PREDICTORS ARE WINSORIZED AT THE 5% LEVEL.

	CS	d_30P/sales	(d_oth - d_neg) / sales	maxPay	pexp_999	max_pct_accts_ 61p_lst_qtr	tot_12_mo_ unfavor_acc	inqreg	fpct	bd_ind	Small_Inconsistent_ Late_Payers	networth	age	sec_loan	dliens	avg_ordrs_o
CS	1.00															
d_30P / sales	0.03*	1.00														
(d_oth - d_neg) / sales	0.11*	0.12*	1.00													
maxPay	0.05*	- 0.26*	0.04*	1.00												
pexp_999	- 0.26*	0.19*	0.00	- 0.07*	1.00											
max_pct_accts_61p_ lst_qtr	- 0.16*	0.13*	- 0.04*	- 0.14*	0.19*	1.00										
tot_12_mo_unfavor_ acc	- 0.21*	0.28*	0.08*	- 0.12*	0.33*	0.09*	1.00									
inqreg	- 0.41*	0.30*	0.04*	- 0.12*	0.40*	0.19*	0.46*	1.00								
fpct	- 0.36*	- 0.18*	- 0.05*	0.18*	0.01	- 0.07*	- 0.11*	0.03*	1.00							
bd_ind	0.17*	- 0.01	- 0.06*	- 0.02	0.06*	-0.03*	0.06*	0.00	- 0.19*	1.00						
Small_Inconsistent_ Late_Payers	0.19*	0.02	- 0.07*	0.02	- 0.12*	0.01	- 0.12*	- 0.12*	- 0.15*	0.01	1.00					
networth	- 0.50*	- 0.13*	- 0.11*	- 0.06*	0.19*	0.14*	0.15*	0.30*	0.19*	- 0.08*	- 0.16*	1.00				
age	- 0.27*	0.05*	- 0.02	0.00	0.24*	0.10*	0.17*	0.40*	0.18*	0.02*	- 0.07	0.06*	1.00			
sec_loan	0.08*	0.08*	0.04*	0.01	0.01	0.12*	0.12*	0.08*	- 0.03*	0.02	- 0.03*	- 0.06*	0.09*	1.00		
dliens	- 0.22*	0.12*	0.03*	- 0.01	0.21*	0.11*	0.26*	0.42*	- 0.12*	- 0.01	- 0.11*	0.21*	0.22*	0.01	1.00	
avg_ordrs_o	- 0.22*	0.06*	- 0.04*	- 0.04	0.11*	0.05*	0.09*	0.24*	0.06*	- 0.03*	- 0.06*	0.20*	0.06*	- 0.01	0.21*	1.00

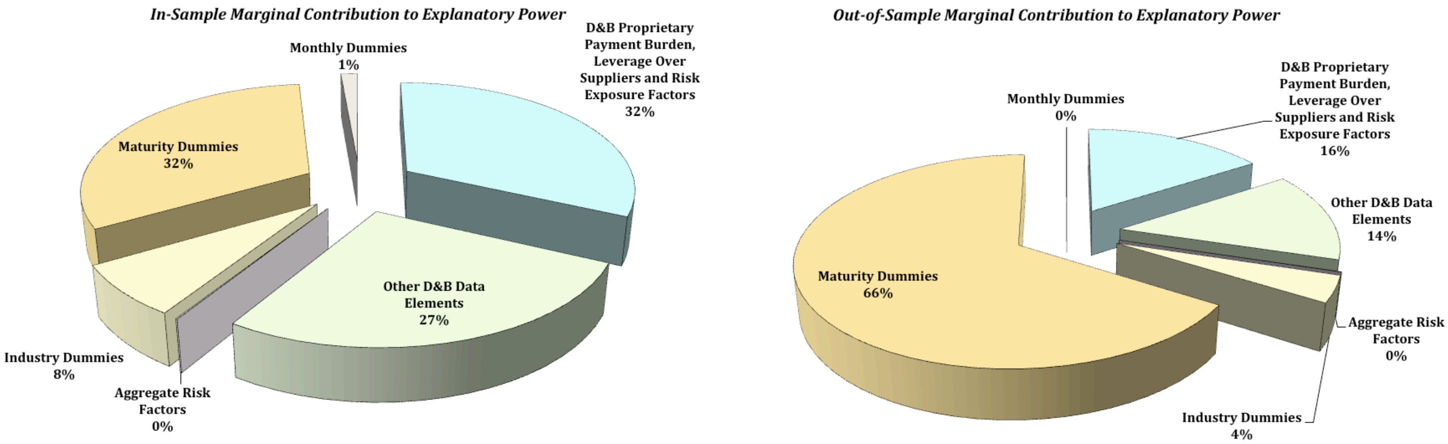
Source: Dun & Bradstreet *Significance at the 0.1% level.

FIGURE 8. CORPORATE BOND MODEL: USING MONTHLY PANEL DATA FOR AN IN-SAMPLE PERIOD (DEC, 2010 TO MAR, 2012) AND AN OUT-OF-SAMPLE PERIOD (APR, 2012 TO OCT, 2014), WE REGRESS CREDIT SPREADS (CS) AGAINST THE PREDICTORS LISTED BELOW. T-STATISTICS ARE BASED ON ROBUST STANDARD ERRORS. CONTINUOUS PREDICTORS ARE WINSORIZED AT THE 5% LEVEL.

			In-Sample		Out-of-Sample	
Factor Groups	Internal D&B Factor Specification	Brief Factor Description	Coef.	t-stat	Coef.	t-stat
--	--	Constant Term	13.3	29.8	9.0	7.9
Payment Burden	d_30P / sales	Total USD payments that are 31+ days past due divided by sales.	131.0	9.3	72.2	7.5
	(d_oth - d_neg) / sales	Total USD payments that are in cash-only accounts divided by sales. Cash-only is defined as d_oth - d_neg.	644.2	12.2	1154.0	13.5
Leverage Over Suppliers	maxPay	Maximum PAYDEX Score over past 12 months.	0.0087	16.1	0.0103	25.3
	pexp_999	The number of trading relationships between the subject and its suppliers that are greater than 180 days past due.	- 0.050	- 16.4	- 0.042	- 23.1
	max_pct_accts_61p_lst_qtr	Maximum percent of accounts with 61+ days past due in the last quarter.	- 0.763	- 22.1	- 0.274	- 19.3
	tot_12_mo_unfavor_acc	Number of accounts that are Unfavorable (this can mean the account has been placed for collection, written off, etc.)	- 0.015	- 21.2	- 0.011	- 25.0
	ln(1+inqreg)	Number of regular inquiries received by D&B over the previous 12 months.	- 0.135	- 31.7	- 0.040	- 19.7
Risk Exposure	fpct	Percent rank of D&B's Financial Stress Score; 1 is highest probability of financial stress and 100 is lowest probability of financial stress.	- 0.011	- 68.3	- 0.006	- 66.0
	bd_ind	D&B's proprietary business deterioration indicator; this is dummy variable where a 1 indicates imminent business failure or operating difficulty.	0.4781	28.8	0.3870	30.6
	Small_Inconsistent_Late_ Payers	Dummy Variable where 1 is occurs when smexpsln < 122 & paynorm < 76 & payref < 146 & rangePay > 4.5.	0.1965	17.0	0.0716	8.4
Other D&B Data Elements	avg_ordrs_o	The average number of purchases made online over the past month.	- 0.051	- 14.8	- 0.041	- 20.5
	ln(abs(min(networth)) + 1 + networth)	Natural log of networth (adjustment is made to preserve positive value for log transformation).	- 0.404	- 65.4	- 0.268	- 98.4
	age	In years, the age of the firm since establishment.	- 0.002	- 32.1	- 0.000	- 6.9
	sec_loan	Number of secured loans.	0.2314	31.8	0.0958	18.3
	ln(1 + dliens)	Natural log of dollar amount of firm's outstanding liens.	- 0.005	- 9.2	- 0.004	- 12.8
Aggregate Risk Factors	TY10	Treasury Yield of 10-Year (constant maturity)	0.1082	0.7	0.3547	1.6
	Slope	Slope of Treasury Yield Curve (10-Year - 2-Year)	0.0579	0.3	- 0.307	- 1.7
	Corp	Corporate Bond Risk Premium (Moody's Seasoned Aaa Corporate Bond Yield© - Treasury Yield of 10-Year)	0.4703	2.9	0.6268	1.3
	Def	Corporate Bond Default Risk Premium (Moody's Seasoned Aaa Corp Bond Yield© - Moody's	0.5497	4.4	0.6602	3.7
7 Maturity Dummies	--	--	--	--	--	--
7 SIC4 Industry Dummies	--	--	--	--	--	--
Monthly Dummies	--	--	--	--	--	--
Number of Observations			35,911		73,863	
Degrees of Freedom			35,867		73,805	
Adjusted R-Squared			0.587		0.507	

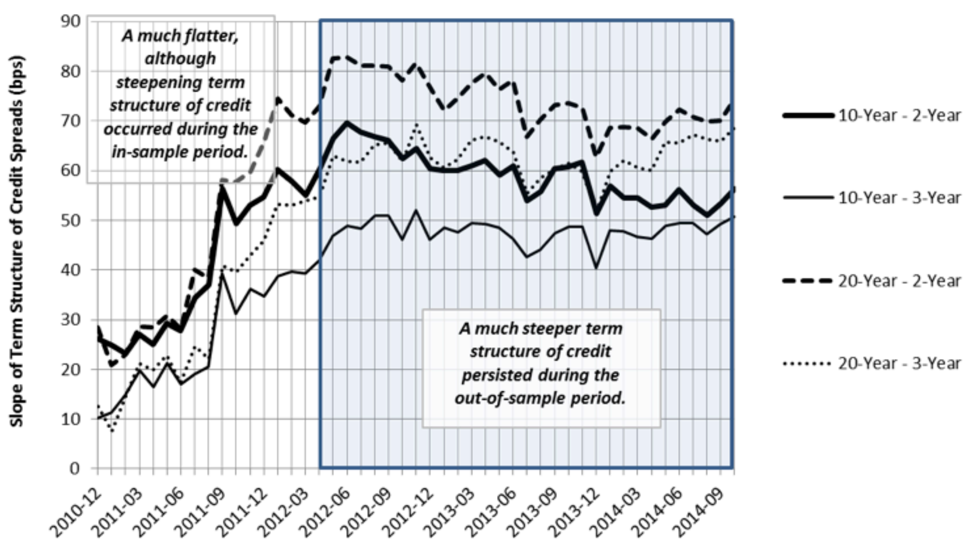
Source: Dun & Bradstreet *Significance at the 0.1% level.

FIGURE 9. WHERE DOES THE EXPLANATORY POWER COME FROM? WE SHOW THE AGGREGATED EXPLANATORY POWER OF EACH FACTOR GROUP FOR THE IN-SAMPLE PERIOD (DEC, 2010 TO MAR, 2012) AND THE OUT-OF-SAMPLE PERIOD (APR, 2012 TO OCT, 2014).



Source: Dun & Bradstreet *Significance at the 0.1% level.

FIGURE 10. TERM STRUCTURE OF CREDIT SPREADS OVER TIME: THE MEAN STEEPNESS OF THE TERM STRUCTURE OF CREDIT SPREADS WAS ABOUT TWICE AS LARGE DURING THE OUT-OF-SAMPLE PERIOD RELATIVE TO THAT OF THE IN-SAMPLE PERIOD.



Source: Dun & Bradstreet

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