Industry Characteristics and Debt Contracting*

Dan Amiram, Alon Kalay, and Gil Sadka†

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Abstract

This paper provides empirical evidence for the extant theory that suggests industry characteristics have a distinct affect on capital allocation and debt contracts in particular, in addition to firm-level characteristics. We address the empirical challenges faced by prior research by utilizing proprietary time-varying and forward-looking industry risk rating scores from IBISWorld Inc., to examine how industry characteristics shape debt contracts. The industry characteristics we examine include growth risk, sensitivity risk and structural risk, all measured at the six-digit NAICS level. Our results, obtained using industry fixed-effect regressions and controlling for firm-level measures of credit risk, suggest lenders demand compensation for growth risk and sensitivity risk. However, structural risk, which reflects certain aspects of competition, can be beneficial to lenders. Our results also highlight that different industry characteristics have varying effects on debt contracts.

JEL classification: G31, G32, G33, M21

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†Dan Amiram, Alon Kalay and Gil Sadka are from Columbia Business School, e-mail addresses *da2477@columbia.edu*, *ak3318@columbia.edu*, and *gs2235@columbia.edu*.

1 Introduction

Lenders claim they spend significant resources analyzing a borrower's industry, in addition to the borrower's firm-level (business) fundamentals (Bobrow et al., 2007). This behavior is consistent with extant theory which predicts firms' interactions with capital providers are affected by distinct industry-level forces that differ from the common firm-level forces (e.g., Maksimovic and Zechner, 1991; Shleifer and Vishny, 1992; Williams, 1995). Despite the theoretical and anecdotal evidence highlighting the importance of industry-level analyses to lenders, the empirical literature on debt contract design has focused almost exclusively on firm-level forces. Our study aims to fill this gap in the literature by utilizing proprietary data on three time varying and forward looking industry characteristics. The nature of the data allows us to overcome the empirical difficulties that presumably limit prior literature from analyzing the relation between industry characteristics and debt contracting. More specifically, understanding how industry forces shape the design of debt contracts.

Providing evidence on the role of industry characteristics in debt contracts is important for several reasons. First, debt is a crucial source of external financing for firms and it is important to understand the factors that shape debt contracts. To date, there is scant empirical evidence to support the theoretical predictions that industry-level forces affect the risk that lenders are compensated for, and the extent to which industry-level frictions are addressed in debt contracts. Second, debt contracts have implications for firms' future operations and value (Chava and Roberts, 2008; Nini, Sufi and Smith, 2012). Therefore, understanding the impact of industry forces on debt contracting enhances our knowledge of how industry forces affect real decisions and value. Third, our understanding of which industry-level characteristics matter to capital providers is limited. Overall, the importance of this research question stems from the need to better understand the equilibrium forces that affect debt contract design (Sufi and Roberts, 2009).

There are several industry characteristics that define the economics of an industry. Four different but related characteristics include: industry concentration, the structure of an industry which reflects aspects such as competition, barriers to entry, regulatory protection and openness to international trade (industry structure hereafter), industry growth, and the sensitivity of an industry to external shocks (industry sensitivity hereafter). While these characteristics may be related to each other, each one describes a different aspect of the industry.[1] For example, an industry can be competitive and have high stable expected future growth, due to an expected increase in the demand for the product. Moreover, industry growth may, or may not, be sensitive to aggregate shocks to demand. Therefore, the relation between these different characteristics is not clear ex-ante. Furthermore, each one of these characteristics has different implications for the risk lenders bear. Consequently, the relation between industry characteristics and debt contracts may vary across the specific industry characteristics. Therefore, when examining the relation between industry characteristics and debt contracting it is important to examine the effect of each industry characteristic on debt contracting, as opposed to focusing on one particular characteristic.

The main determinants of the compensation lenders demand are as follows: the probability of default, the loss given default, and the risk premium associated with the debt (Elton et al., 2001). Industry characteristics can shape debt contracts through each one of these components. First, industry characteristics affect firms' fundamentals (Maksimovic and Zechner, 1991; MacKay and Phillips, 2005), which in turn affects both the probability of default (Altman, 1968) and loss given default (Amiram, 2013). Thus, industry characteristics can affect debt contract terms through their effect on firm-level fundamentals. Second, when economic conditions in an industry are poor there is a higher likelihood of bankruptcy contagion among firms, less so in competitive industries (Jarrow and Yu, 2001; Das et al., 2007). Since the likelihood of default within an industry is correlated across firms (in the same industry), and the correlation increases during periods of poor economic performance, lenders will require a higher premium to lend money to firms in poorly performing industries. However, contagion concerns decline in more competitive industries (Jarrow and Yu, 2001). Therefore, lenders may require lower premiums in more competitive industries. This risk premium is over and above the risk implied by the firm-level probability of default. Thus,

[1] We make an important distinction between competition as captured by concentration, and competition as measured by industry structure. We discuss this distinction in further detail throughout the paper.

industry characteristics may affect debt contracts through their systematic effect on the probability of default. Third, Shleifer and Vishney (1992) hypothesize that the value of assets in liquidation depends on the health of the industry. That is, assets in liquidation are sold at a slower pace and for lower prices when an industry is in distress. This occurs because there are fewer buyers with less financial resources to purchase assets from defaulted firms. This in turn increases loss given default (see Acharya, Bharath and Srinivasan (2007) for empirical evidence). If loss given default is higher in times of industry distress, lenders may ask for higher risk premiums to hold loans in poorly performing industries. This premium is over and above the effect of firm-level loss given default on overall expected loss. Thus, industry characteristics may affect debt contracts through their systematic effect on loss given default.

The likely reason for the lack of empirical evidence on the relation between industry characteristics and debt contracting, is the challenges researchers face in measuring industry characteristics such as industry structure, industry growth, and industry sensitivity.[2] First, there are very few candidates a researcher can use to measure these industry characteristics. Second, detailed industry specific measures (e.g., for a firm's six-digit NAICS membership) are currently unavailable, and cannot be computed using CRSP and Compustat due to the lack of data at the six-digit NAICS level. Third, potential empirical measures based on Compustat and CRSP rely on U.S. public firms, despite the fact that significant industry activity occurs internationally and in private firms. Fourth, Compustat based measures are backward looking, making them less useful when attempting to answer the questions raised in this paper. Fifth, the lack of time varying data forces researchers to employ either industry-fixed effects or other time invariant measures to estimate the relation between industry affiliation and the dependent variable of choice. This limits the identification strategies used to cross-sectional variation across industries. These strategies are very sensitive to a correlated omitted variable concern, which limits the interpretation of the results.

[2]There is intra-industry evidence related to the effect of collateral risk and liquidation values on debt contract terms (Benmelech, Garmaise, and Moskowitz 2005, Benmelech 2009, Benmelech and Bergman, 2008, 2009, 2011). We discuss these papers in more detail in Section 2.

In this paper, we utilize a novel dataset from IBISWorld Inc. (henceforth IBIS) that allows us to overcome most of these challenges. IBIS is a leading industry risk data provider. Their data is used by leading institutions such as Bank of America, Deutsche Bank, and American Express. IBIS produces industry-level reports, which cover both public and private firms in an industry. Their data includes approximately 700 industries, where an industry is defined at the six-digit NAICS classification level. The Industry Risk Rating report produced by IBIS evaluates the inherent risks associated with a particular industry, and includes proprietary forward-looking risk ratings (scores) that aim to capture industry-level risk characteristics. The Industry Risk score is forward looking and the methodology used to create it is designed to identify and quantify risks inherent in specific industries both now and 12-18 months into the future. To calculate the overall risk score, IBIS assesses the risks pertaining to the industry across three dimensions. First, risks that arise from the industry's structural forces, such as the amount of competition, product differentiation, barriers to entry, regulatory protection and openness to international trade. This risk is called structural risk. We note that this measure does not explicitly measure the level of concentration in the industry, which is an alternative proxy for industry structure and competition (e.g., Hoberg and Phillips 2010; Hoberg and Phillips, 2012; Valta, 2012). Second, the risk related to the expected future performance of the industry, or growth risk. Third, the risks arising from economic forces external to the industry, such as changes in raw material prices or GDP per capita. This risk is called sensitivity risk. The three types of risk are scored separately, then weighted and combined to derive an overall risk score.[3] In our validation tests we show that: 1) Growth risk is negatively related to future economic value added (EVA) growth, 2) Structural risk is negatively related to future industry wide profit margin changes, and 3) Sensitivity risk is positively related to the correlation between industry-level EVA growth and GDP growth.

The IBIS dataset allows us to address the empirical challenges researchers face when attempting to analyze the relation between debt contracts and industry characteristics. First,

[3]IBIS uses the term risk to define the various industry characteristics. While they may not be risks in the classical economic sense, they describe the industry characteristics of interest. Structural risk measures issues related to industry structure. Growth risk captures expected future industry growth. Sensitivity risk measures industry sensitivity. We refer to these characteristics as 'risks' to be consistent with IBIS's definition.

IBIS data is available at the six-digit NAICS classification level, providing detailed industry specific measures. Second, the estimates capture different industry characteristics, which allow for differential predictions. Third, the estimates are forward looking, which increases the statistical power and construct validity of our tests. Fourth, using the IBIS measures avoids the endogeneity involved with aggregating backward looking firm-level characteristics to measure industry characteristics. Fifth, the estimates take into account international and private firms, avoiding data selection biases present in CRSP and Compustat. Finally, the measures vary over time, which allows us to employ industry fixed-effects in our analysis. Thus, the identification strategy used in this paper utilizes time series variation in industry characteristics to identify the relation between industry and debt contracting. This significantly reduces concerns related to correlated omitted variables. Moreover, we show that when we construct proxies for industry structure, industry growth, and industry sensitivity using data available in Compustat and CRSP, we fail to replicate the results found using the IBIS data. Additionally, the results using the IBIS measures are also obtained after controlling for the alternative Compustat and CRSP proxies.

Based on the theoretical arguments discussed, we expect loans issued in industries with higher overall risk, higher growth risk and higher sensitivity risk to have higher spreads, smaller loan amounts, shorter maturities, more covenants and to be more likely to use explicit collateral. However, the effect of structural risk on the debt contract terms is more nuanced and is ultimately an empirical question. On the one hand, competition is expected to reduce the risk of default contagion in the industry (Jarrow and Yu, 2001; Das et al. 2007). On the other hand, increased competition can increase the probability of default. Consistent with the later argument, Valta (2012) finds that industry concentration is negatively associated with loan spreads using an indicator variable which measures low levels of concentration using the Hoberg and Phillips (2010, 2011) HHI data sets.[4] However, the theoretical arguments above suggest the relation between loans spreads and industry structure may be different.

Consistent with our predictions, we find that increases in overall industry risk, growth risk and sensitivity risk result in higher spreads, shorter maturities and smaller loans. A

[4]Li, Lundholm, and Minnis (2013) also develop a measure of firm-level competition using textual analysis.

one standard deviation increase in overall risk results in an increase in loan spreads of approximately 12 basis points, which is economically significant. We also find evidence using cross-sectional Logit regressions that the likelihood of using explicit collateral increases with industry risk. However, this effect arises from variation in structural risk, which suggests lenders use collateral when it is more likely to be valuable as opposed to when industries are riskier. We find no association between the number of debt covenants and industry risk. Our main findings hold after controlling for firm-level probability of default, firm-level loss given default, and other firm-level risk measures. To the extent that our firm-level variables are adequate, our results suggest that part of the effect of industry risk on debt contracts is via risk premiums. We further find either no relation between loan spreads and structural risk, or a negative relation when controlling for the probability of default and the loss given default. This result highlights that the construct of industry structure differs from concentration, and that some elements of a competitive environment may actually benefit lenders.

To further establish the relation between industry risk and loan terms we study how industry-level productivity interacts with the role of industry risk in debt contracts. The aim of this analysis is to show that the association between industry risk and debt pricing varies in a predictable fashion cross-sectionally, providing further support for our main findings. Specifically, we split the sample based on two industry productivity measures: average wage per employee, and value added per employee. We employ these measures because they capture productivity. For example, higher value-add per employee suggests total factor productivity in the industry is higher and thus the value of the assets given default is higher as well. In less productive industries lenders are likely to be more sensitive to industry risk because smaller changes in productivity can lead to more industry-wide default episodes. Our results support these conjectures. We find that the relation between industry risk and spreads is larger in less productive industries.

One of the advantages of the IBIS risk measures is that it is available at the six-digit NAICS classification level. In order to further illustrate the advantage of the IBIS data, we generate alternative measures for these industry characteristics using Compustat three-digit

SIC codes.[5] To measure growth risk, we employ the growth in industry-level operating earnings. To measure structural risk, we employ industry-level profit margins as industrial organization theory suggests more competitive industries have lower margins. To measure sensitivity risk, we employ the correlation between industry-level earnings growth and aggregate GDP growth. Finally, we employ the Hoberg and Philips (2011) industry concentration measure. Our findings suggest that the relation between the IBIS industry risk measures and loan spreads is incremental to these alternative risk measures. Adding the alternative measures to our fixed-effects regressions does not materially change our results. Moreover, the Compustat based measures do not have a significant association with loan spreads.

This paper contributes to the literature in several ways. First, this paper is the first study to examine how expected industry performance (growth) and sensitivity to external factors affect the design of debt contracts. While prior literature focuses on firm-level characteristics, and industry concentration, this paper uses a robust industry fixed-effect research design to document an industry effect over and above firm-level fundamentals. Moreover, we find that growth risk and sensitivity risk matter more for debt contract design, relative to structural risk. Second, this paper introduces a novel dataset which provides industry-level forward looking risk assessments. This dataset may help answer additional questions that have empirically challenged related prior research. Third, the paper provides new evidence on how different types of industry characteristics deferentially affect various contract terms. Fourth, the results provide initial evidence that the effect of industry on debt prices does not necessarily result from the direct effect of industry risk on firm-level loss given default and probability of default, but rather via its affect on risk premiums. Finally, since industry characteristics are priced when we include industry fixed-effects in our regressions, our findings imply that temporal variations in industry characteristics are important for debt pricing, and that industry dummies do not fully control for the effects of industry characteristics on debt contracts.

[5] Using three-digit SIC codes ensures that there are a sufficient number of firms in each industry, while maintaining a relatively precise definition of an industry. This level of granularity is still significantly less than the six-digit NAICS codes employed by IBIS.

Our paper proceeds as follows. Section 2 discusses our motivation, hypothesis development, and empirical predictions in more detail. Section 3 presents our data and empirical results. Section 4 concludes.

2 Motivation and Hypothesis Development

2.1 Motivation

Extant theory shows that industry-level forces affect firms' interactions with capital providers through distinct channels, which differ from the familiar firm-level forces (e.g., Maksimovic and Zechner, 1991; Shleifer and Vishny, 1992; Williams, 1995). Moreover, anecdotal evidence suggests that lenders utilize significant resources to analyze a borrower's industry. During the credit decision process, a borrower will assess various industry characteristics and trends in the borrower's industry, in addition the borrower's firm-level (business) fundamentals (Bobrow et al., 2007). For example, lenders analyze the industry's strengths and weaknesses, growth opportunities, technological shifts, labor status, regulatory environment, and competitiveness (Bobrow et al., 2007). This analysis is above and beyond the analysis of the borrower's fundamentals and projections of the borrower's position in the industry. Furthermore, the industry analysis is an integral piece of the loan offering materials discussed in the credit meeting (Page et al., 2007). Despite the importance that lenders place on industry characteristics, and the theoretical importance of industry characteristics to debt contracts, there is limited empirical evidence on how industry characteristics shape debt contracts. The lack of empirical evidence presumably arises from the empirical challenges involved in examining this relation.

Theoretical debt pricing models suggest lenders care about the probability of default, loss given default, and the fact that debt is a risky asset which requires a risk premium (or other contractual characteristics to mitigate the risk). Elton et al. (2001) document that loss given default, probability of default, and risk premium are all significant determinants of credit spreads. Industry characteristics can affect each one of these elements and thus can affect the initial contract terms.

The first channel through which industry characteristics can affect debt contracts is through their affects on firm-level fundamentals. Prior literature finds that industry wide shifts significantly affect firm fundamentals (Maksimovic and Zechner, 1991). Maksimovic and Zechner (1991) demonstrate that a firm's cash-flow risk is also determined by the decisions of all the other firms in the industry.[6] MacKay and Phillips (2005) provide further empirical support for this hypothesis. Prior research also shows that firm fundamentals affect both the probability of default and loss given default (Altman, 1968; Amiram, 2013).[7] Therefore, industry characteristics can affect debt contract terms through their effect on firm-level fundamentals. Industry analyses conducted by lenders may therefore shed light on firms' probability of default and loss given default.

A second channel through which industry characteristics may affect the design of debt contracts is via their effect on probability of default related risk premiums. More specifically, the risk premium lenders require for the probability that a firm will default, over and above the effect firm-level probability of default has on expected loss. Jarrow and Yu (2001) hypothesize that the probability of default depends on the firm's industry structure. Specifically, Jarrow and Yu (2001) suggest that when economic conditions in the industry deteriorate, there is a higher likelihood of bankruptcy contagion among firms, more so in less competitive industries. Empirical validation of this idea is found in Das et al. (2007), which finds defaults tend to cluster in certain industries, especially less competitive ones. Furthermore, Page et al. (2007) report loan defaults cluster in recession periods, and private loans defaults tend to cluster in industries as well. If loans tend to default (perform badly) during times when defaults are more common in a certain industry, then lenders will require higher risk premiums to hold loans of firms in poorly performing industries. Thus, industry

[6]As the number of firms adopting a given production technology increases, the price of the good sold more closely reflects their production cost. Thus, firms become better hedged against changes in the cost of production and generate less risky cash flows as the number of firms in the industry increases. Since technologies associated with higher expected production costs are adopted by fewer firms, firms that use higher-cost technologies exhibit riskier cash flows than firms using lower-cost technologies.

[7]For example, the real estate industry has more deployable assets than the high-tech industry, which will make it more useful for lenders in case of default.

risk may affect debt contracts through its systematic effect on the probability of default. However, the relation is not obvious ex-ante.

A third channel through which industry characteristics can affect debt contract design is through their effect on loss given default related risk premiums. Shleifer and Vishny (1992) hypothesize that the value of assets in liquidation depends on the health of the industry. That is, assets are sold faster and at a higher price in healthier industries. When an industry is in financial distress, there are fewer buyers with less financial resources to purchase assets from defaulted firms. This increases the loss given default in industries that are distressed. Acharya, Bharath and Srinivasan (2007) provide empirical support for this theory. They show loss given default is higher in distressed industries, due to the lower values of the firm's *implicit* collateral, or the firm's asset values during distressed times. If loss given default is higher in times of industry distress, lenders may ask for higher risk premiums to hold loans in poorly performing industries. Thus, industry characteristics may affect debt contracts through their systematic effect on loss given default.

Collateral and liquidation values are also central to debt contracting theory (Aghion and Bolton, 1992; Hart and Moore, 1994) since the optimal debt contract depends on how costly it is for creditors to liquidate assets at the time of default. However, as Benmelech et al. (2005) note, empirical evidence on this issue is scarce. The growing evidence in this literature utilizes special settings to examine the link between liquidation values, collateral and debt characteristics. Benmelech et al. (2005) focus on the ability to redeploy property assets (redeployability) as determined by commercial zoning regulation, and find that properties that are more deployable receive larger loans, longer maturities and lower interest rates. Benmelech (2009) finds that asset salability in the 19th century railroad industry led to longer debt maturities. Benmelech and Bergman (2009) utilize a sample of loans in the airline industry to show that collateral and redeployability are negatively correlated with yield spread. Benmelech and Bergman (2011) use a novel dataset of secured debt tranches issued by U.S. airlines which includes a detailed description of the underlying assets that serve as collateral. Their results suggest the occurrence of bankruptcy has a sizeable impact on the cost of debt financing for other (remaining) industry participants. Benmelech and

Bergman (2011) further demonstrate how the collateral channel can create contagion effects which amplify the business cycle during industry downturns, and thus lead to increases in the cost of external debt financing for the entire industry. In contrast to these important contributions which focus on intra-industry variation, our study focuses on changes across different industries over time. This allows us to draw broader conclusions about the role of industry characteristics as a whole.

2.2 IBISWorld Data

The dataset we utilize is produced by IBIS. IBIS is a leading industry risk data provider whose data is used by leading institutions such as Bank of America, Deutsche Bank and American Express. IBIS produces industry-level reports which cover public, private, and international firms in an industry. The analysis is conducted for each six-digit NAICS industry, across approximately 700 industries. In addition to risk assessments, the industry reports include information about industry-level characteristics such as value-add and wages.

The IBIS Industry Risk Rating report evaluates the inherent risks associated with a particular industry.[8] Industry Risk is defined as "the difficulty, or otherwise, of the business operating environment." The reports include proprietary forward-looking IBIS risk ratings (scores), which aim to capture industry-level (risk) characteristics. The Industry Risk score is forward looking and the methodology used is designed to identify and quantify risks inherent in specific industries both now and 12-18 months into the future. IBIS states that "Industry-based information would, for example, enable the examination of a loan book (portfolio) with regards to risk, which would enable a more sophisticated assessment of risk spread and pricing to risk. Alternatively, individual exposures can be better evaluated using an assessment of structure and key drivers of change in the industry of the exposure."

IBIS relies on both public and proprietary sources to produce their reports. IBIS categorizes their data sources into four groups. First, publically available catch all sources such as the U.S. census Bureau and U.S. International Trade Commission reports. Second,

[8] A sample risk report can be viewed at http://www.ibisworld.com/about/products.aspx

industry specific publically available resources such as trade association reports, reports issued by specific industry federations (e.g., The National Retail Federation), and reports from major industry players. Third, direct industry contacts obtained from industry specific conferences and clients. Fourth, an in-house database of statistics and analysis on 700 US industries in addition to over 2,000 Business Environment reports on U.S. and world macroeconomic variables, and demographic and consumer trends. The forecasts made by IBIS, which are an integral part of the risk scores, rely on the above sources and are further supported by in-house data and economic modeling, the analyst's knowledge of the industry's operating conditions (e.g., competition, barriers to entry, life cycle), and expected future movements of key external drivers (IBISWorld, 2012).

To calculate the overall risk score, IBIS assesses the risks pertaining to the industry across three dimensions. First, risks that arise from the industry's structural forces, such as the amount of competition and product differentiation, potential barriers to entry, and the industry's openness to international trade. This risk is called structural risk. This measure does not explicitly capture industry concentration, which is a separate element of competition. Second, the risk related to the expected future performance of the industry, or growth risk. As IBIS states, "a high revenue growth rate in an industry is associated with a lower overall difficulty of operation in the industry. That is, success comes relatively easily in a quickly growing market while a contracting market tests management's skill to a much greater level, as each dollar earned requires a greater level of effort for the average company." The growth risk measure is a weighted function of both historical growth rates (25%), and forecasted growth rates (75%) estimated using IBIS's in-house models. Third, risks arising from economic forces external to the industry such as changes in GDP per capita, input costs, number of housing starts, or commodity prices. This risk is called sensitivity risk. The sensitivity risk score includes two broad groups of sensitivities: macroeconomic sensitivities (e.g., GDP per capita) and not-independently quantifiable sensitivities (e.g., changes in consumer tastes). The risk score is a function of both the potential change in the sensitivities identified for the industry, and the significance of the sensitivities to the industry. The three types of risk are scored separately, then weighted and combined to derive an overall risk score. IBIS uses the term risk to define the various industry characteristics. While these may not be risks in the classical economic sense, they describe the industry characteristics we are interested in examining. We therefore refer to these characteristic as 'risks' throughout the paper to be consistent with IBIS's definition. IBIS has internally tested the efficacy of their risk model. Overall industry risk scores were used to gauge the difficulty of the operating environment for each of the S&P 500 companies between 2006 and 2009 and project their ability to generate an operating profit. The results of the tests run by IBIS show that the operating environment, as captured by IBIS's risk scores, plays a statistically significant role in a company's ability to turn a profit (IBISWorld, 2012). In sum, these risk scores can be utilized to provide empirical evidence on how industry characteristics affect debt contracting at loan initiation.[9]

The IBIS dataset allows us to address the empirical challenges researchers face when attempting to analyze the relation between debt contracts and industry characteristics. First, IBIS data is available at the six-digit NAICS classification level, providing detailed industry specific measures. Second, the estimates capture different industry characteristics, which allows for differential predictions. Third, the risk estimates are forward looking, which increases the statistical power and construct validity of our tests. Fourth, using the IBIS risk measures avoids the endogeneity involved with aggregating backward looking firm-level characteristics to measure industry risk. Fifth, the risk estimates take into account international and private firms, avoiding data selection biases present in CRSP and Compustat. Finally, the risk measures vary over time, which allows us to employ industry fixed-effects in our analysis. Thus, the identification strategy used in this paper utilizes time series variation in industry risk to identify the relation between industry risk and debt contracting. This significantly reduces concerns related to correlated omitted variables.

[9] We further validate the risk scores in Section 3.2

2.3 Empirical Predictions

Private debt contracts design is a complicated task. A lender and a borrower can negotiate terms related to the price of the loan over Libor (spread), the maturity of the loan, the size of the loan, and the covenants that restrict the borrower's behavior and help protect the lender's interests. These loan characteristics are considered substitutes rather than complements (Bradley and Roberts, 2004). Specifically, a lender and a borrower can negotiate a lower interest rate if the lender is willing to accept more covenants. Empirically however, since contract characteristics are simultaneously determined, it is not a straightforward exercise to identify the magnitude of the effect of industry risk on each one of the characteristics separately. Therefore, we study the effects of industry risk on all five main characteristics of a debt contract: spread, loan size, maturity, and the use of collateral and covenants. The rationale behind this approach is to identify the change across most of the decision variables available to the lender at the time of the contract.

Our main predictions relate to the effect of industry risk on loan pricing, since the professional literature claims that the pricing of the loan is the most important characteristic of the loan contract (Page et al., 2007). The granular structure of the IBIS industry data allows us to examine different predictions based on the industry characteristic being examined. As discussed above, industry risk affects fundamentals and can increase both the probability of default and loss given default. This in turn is likely to increase the interest rate lenders demand on the loan. Moreover, since defaults are clustered in industries during bad times, and liquidation values are lower when the industry is distressed, lenders are likely to require a higher risk premium for riskier industries. This leads us to our first prediction, industry risk is positively related to the spread lenders require for providing a loan. This line of reasoning holds for risks related to expected future performance, or growth risk, and for risks relating to economic forces external to the industry, or sensitivity risk.

The prediction with respect to structural risk, which relates to industry structure, is more nuanced. On the one hand, structural risk which is mainly driven by high levels of competition increases the probability of default and thus should increase the spread lenders demand on the loan. This argument is consistent with the negative relation between spreads and industry concentration documented by Valta (2012). On the other hand, competition increases the number of potential buyers for the firm's assets in the case of default, thus reducing loss given default. Moreover, prior literature shows that defaults are less clustered in competitive industries (Das et al., 2007). This implies structural risk may actually reduce the risk premium lenders require for originating loans. These two latter effects suggest higher structural risk should be negatively correlated with spread. Thus, our second prediction is that the overall effect of structural risk on spreads is lower than the effect of growth and sensitivity risks on spreads. More specifically, the correlation between structural risk and spread is predicted to be lower than the correlations between growth risks and spread, and sensitivity risk and spread. Moreover, the relation between structural risk and spreads may be negative.

Since we view spread and other loan characteristics such as term, size, collateral and covenants as substitutes rather than complements we predict that overall risk, growth risk and sensitivity risk are negatively correlated with term and size, and positively correlated with the use of collateral and covenants. The relation between structural risk and the other loan characteristics should be weaker than for growth risk and sensitivity risk, and may have the opposite sign.[10]

Our final prediction explores cross-sectional differences in the effect of industry risk on debt contracts. The aim of this analysis is test whether the association between industry risk and debt pricing varies in a predictable fashion cross-sectionally, a result that would provide further support for our primary hypotheses. Specifically, we examine how industry productivity affects the relation between industry risk and debt contracting. We expect industry risk to matter more in less productive industries. Hence, we predict loan terms to be more sensitive to industry risks when industry productivity is lower. To test this hypothesis, we sort our observations based on the productivity of employees, measured as the value add per employee, and average wage per employee. We predict spreads to be more

[10] The relation between industry risk and the use of explicit collateral is slightly more nuanced. We discuss this relation in more detail in Section 3.4

sensitive to industry risk when value add and wage per employee are lower.

3 Data and Empirical Evidence

3.1 Sample Construction

To create our sample we begin by downloading debt contract terms from Dealscan. We download data for the following: loan spread (AllInDrawn), maturity, loan size, number of covenants, and the use of collateral for all firm-level facilities issued after 2003, which we can link to Michael Roberts's linking file.[11] We begin our sample in 2003 because the IBIS risk data is available beginning in 2003. Data are available for 9,114 loans issued to 3,099 distinct firms during the sample period. We then proceed to collect six-digit NAICS codes from Compustat and link the contract terms to the IBIS risk ratings using the six-digit NAICS codes available on Compustat. We are able to link 6,036 loans (2,051 firms) to the IBIS risk data. Finally, we require CRSP and Compustat data for a set of control variables commonly used in the literature. These additional data requirements further reduce our sample to 4,951 loans (1,698 firms). In alternative specifications, we include firm-level estimates of the probability of default and loss given default, which results in a reduced sample of 3,654 loans (1,332 firms).

Table 1 presents summary statistics for the IBIS risk scores, the debt contract terms and the control variables used in our empirical analysis. IBIS risk scores are assigned a value on a scale of 1 to 9, where higher scores indicate riskier industries.[12] The mean (median) overall risk score in our sample is 4.64 (4.57), with an interquartile range of 0.99. Sensitivity risk has the lowest mean (median) score of 4.41 (4.23), and an interquartile range of 1.65. Structural risk has the highest mean (median) score of 5.29 (5.26), and an interquartile range

[11] We require an observation to have data available for all fields except the number of covenants. If data is missing for the number of covenants, we assume that the number of covenants in the contract is zero. In untabulated tests we find similar results when we require data for the number of covenants to be available as well.

[12] For example, higher growth risk implies that the industry is more likely to experience declines in growth and profitability going forward. Higher sensitivity risk implies that the industry is more likely to be shocked by changes in factors external to the industry.

of 1.46. Growth risk has a mean (median) score of 4.46 (4.77), and an interquartile range of 1.09. In Figure 1, we plot the cross-sectional average risk scores over time. For each year in our sample, we compute the average score for each risk metric across all six-digit NAICS industries (hereafter industries) in our sample. We then plot the average risk score over time. Figure 1 highlights that there is variation in the risk scores over time. The figure also reveals that a majority of the variation in overall industry risk comes from variation in growth risk and sensitivity risk. As the competitive forces in an industry tend to be relatively more time invariant, structural risk is much more stable over time. To further examine the variation in risk scores, we also plot the cross-sectional dispersion in each risk metric over time. Each year we compute the standard deviation of each risk metric across all industries covered by IBIS. We then plot the standard deviation over time. The result is displayed in Figure 2. Once again, the figure highlights that structural risk is the most stable industry risk characteristic, while sensitivity risk varies considerably across industries. It is also interesting to note that the dispersion in growth risk across industries has grown significantly over time.

Table 2 reports the results from an AR(1) model for each industry risk metric, estimated for all available industry-year pairs in the IBIS data set, and all industry-year pairs in our final sample (the Debt Sample). The results in Table 2 reveal a similar pattern. Structural risk is very stable over time with coefficients above 0.9 and R-squared values ranging between 0.85 and 0.89. Growth risk and sensitivity risk vary more over time, with coefficients ranging between 0.47 and 0.73, and R-squared values ranging from 0.21 to 0.58. Overall risk has a coefficient of approximately 0.70 and a R-squared value of approximately 0.45. Since industry characteristics and the related risks do not change dramatically from period to period, it is not surprising that the coefficients and R-squares from the AR(1) models are all fairly high. However, as Figures 1 and 2 suggest, there is sufficient variation over time to identify the relation between debt contract terms and industry risk using industry fixed-effects.

Table 2, Panel C, reports the correlations for the risk measures and the probability of default. As discussed, the correlations between the different industry characteristics (risks) are not obvious ex-ante. Overall risk is positively correlated with the various risk metrics by construction. Furthermore, structural risk and sensitivity risk are positively related. In contrast, growth risk is negatively related to structural risk and sensitivity risk. However, we note that all the risk measures are positively related to the probability of default. Thus, while the different IBIS risk metrics capture different industry characteristics, they all capture an element of risk to lenders.

3.2 Validating the Risk Measures

As mentioned above IBIS validates its overall risk measure internally. As an additional validation test, we test how the various risk measures relate to other theoretical constructs they are meant to capture within our sample. First, we test whether growth risk is associated with future growth in industry EVA. Second, we test whether structural risk is associated with future changes in profit margins, which are expected to be lower in more competitive industries. Specifically, we measure industry margins as industry-wide EVA divided by industry-wide revenues. Finally, we test whether sensitivity risk is related to the correlation between industry-wide EVA growth and GDP growth. While the actual risk measures are estimated ex-ante, we test whether these measures capture ex-post outcomes. The results are reported in Table 3.

The results in Table 3 show that the risk measures are indeed associated with the ex-post outcomes in a predictable fashion. Growth risk is negatively related to future three-year growth in EVA. In a similar vein, industries which are considered more competitive have lower future profit margins. Finally, industries which are considered to be more sensitive to aggregate shocks (have higher sensitivity risk) have a higher correlation between future industry EVA growth and future changes in GDP. These tests support the notion that the risk measures indeed capture the industry characteristics described in section Section 2.2.

3.3 Industry Risks and Debt Contracting

As we discuss in section 2, our empirical analysis focuses on the relation between industry risk and loan spread, in addition to the other contact terms that serve as substitutes for loan spreads. We begin the analysis by documenting the relation between loan spread and the various industry characteristics. Our model includes a variety of firm-level and facility-level controls. We control for maturity, loan size and the number of covenants. We also include an indicator variable that receives the value of one if the loan has specific collateral. As for our firm-level controls, we include return on assets (ROA), operating profit margins, tangibility, and leverage. In alternative specifications, we also control for the probability of default (PD) defined as in Hillegeist et al. (2004), and expected loss given default (LGD) defined as in Amiram (2013). Finally, we include the aggregate stock market risk premium (extracted from Kenneth French's web site) to control for time varying systematic changes in risk premiums over our sample period. The variables are defined in detail in Table 1.

In addition to these controls, we include industry fixed-effects (dummies). These dummies capture the average cross-sectional effect of industry membership on spread. Therefore, the coefficients on our risk measures capture the effects of changes in risk on loan spreads rather than the average cross-sectional effect. Our ability to include industry fixed-effects when analyzing this relation significantly improves our ability to identify the effect of an industry characteristic on spreads. It is much more likely that changes in industry risk affect debt contract terms, as opposed to a reverse causality explanation. Furthermore, the industry dummies remove the effect of time invariant industry characteristics on loan spreads. Therefore, it is also much less likely that our results are attributed to riskier industries that happen to have riskier firms with higher loan spreads (a correlated omitted variable concern). Finally, if the risk measures explain differences in loan spreads, then our findings suggest that industry dummies do not fully capture the effects of industry characteristics on debt contracts. It is also important to note that the granular nature of the IBIS data allows us to include industry fixed-effects based on the six-digit NAICS code of the borrower. Thus, our typical regression includes close to 350 industry dummies.

As we note above, we predict higher risk levels are associated with higher loan spreads to compensate lenders for undertaking increased risk. The results in Table 4 are consistent with this prediction. Loans in industries with higher overall risk have higher loan spreads. The coefficient of 17.71 (t-statistic of 2.86) suggests that a one standard deviation increase in overall risk results in an approximately 13 basis points increase in loan spread. Our findings hold after controlling for firm-level measures of probability of default and loss given default, which are both positively and significantly associated with loan spread. To the extent that our firm-level variables are adequate, this result suggests that industry risk has a systematic effect on the expected loss given default and/or probability of default.

The relation between overall industry risk and loan spread is driven mostly by growth risk and sensitivity risk. Structural risk is statistically insignificantly positive when we exclude PD and LGD from the regression. In contrast, structural risk is negative and weakly significant at the 10% level when PD and LGD are included. These findings are consistent with our second prediction, that structural risk has a lower correlation with loan spreads relative to growth and sensitivity risk. While structural risk poses a risk for a single firm's operation, it is beneficial for a debt holder to lend money to a firm in a more competitive industry where the value of the firm's assets are higher in the case of default and bankruptcy contagion is less likely to occur.

Table 5 documents the empirical relation between industry risk and loan size. Consistent with Table 4, in Table 5 we control for the other debt characteristics: spread, maturity, the number of covenants, and the use of collateral. Consistent with our hypothesis, riskier loans are generally smaller. The coefficient on overall risk is negative and statistically significant.

When we break out the overall risk to its different components, we find that the relation between industry risk and loan size is driven largely by sensitivity risk (sensitivity to aggregate shocks). The exposure to sensitivity risk can be thought of as follows. During bad times, when the value of the entire loan portfolio is declining, industries with high sensitivity risk will likely decline as well. Hence, lenders prefer to make smaller loans to industries with high sensitivity risk. The coefficient on structural risk is once again insignificant, which is consistent with our prediction that structural risk differs from sensitivity risk and growth risk. However, we do note that the magnitude of the coefficients on structural risk appear to be similar to those for sensitivity risk.

Table 6 documents the empirical relation between industry risk and debt maturity. Consistent with Tables 4 and 5 we control for the other debt characteristics: spread, loan size, the number of covenants and the use of collateral. Consistent with our findings in Table 4, we find that overall industry risk is negative related with loan maturities. Excluding PD and LGD, the coefficient is -2.715 (t-statistic of -2.89). The coefficient does not change significantly when PD and LGD are included.

When analyzing the different risk components, we find that the results are driven mainly by growth risk. These findings suggest that lenders provide loans with shorter maturities for firms in industries with higher growth risk. To interpret these findings consider the following example. Two firms in two different industries have similar expected growth rates. However, one industry has a 10% probability of negative growth (independently per period), while the other industry has a 20% chance of negative growth (independently per period). For a similar number of periods, the latter industry is more likely to experience a period of negative growth. Therefore, ceteris paribus, the duration of the loan should decline with growth risk.

Sensitivity risk is negatively related to loan term. However, it is only statistically significant (t-statistic of -2.09) when PD and LGD are excluded. Structural risk is positive but is statistically insignificant. This result is consistent with the findings in prior tables that structural risk includes positive aspects that can benefit lenders. Thus, in the case of loan term, the negative relation between loan term and overall industry risk is driven largely by growth risk.

There are several other findings worth noting. First, PD and LGD are positively related to loan spread and negatively related to loan term, but do not have a strong association with loan size. Also, collateral is positively related to loan spread and loan term and negatively related to loan size. These findings suggest that longer term loans and riskier loans (with higher spreads) tend to use collateral. Finally, the relation between industry risk and debt contracting is consistent across the three characteristics examined so far: spreads, loan size, and maturity. On average, loans issued to firms in riskier industries have higher spreads, smaller loan amounts and shorter maturities. For completeness, we also examine the relation between industry risks and the number of covenants in the loan contract. We find no evidence of a relation between industry risk and the number of covenants in debt contracts. For brevity, these findings are not tabulated. We discuss the relation between the use of collateral and industry risk in more detail below.

In Tables 4-6, we employ the individual risk measures as well as overall risk, which is a weighted-average of the three risk scores. In Table 7, we include all three risk measures simultaneously in the regression model. Using all three risk scores simultaneously allows the individual characteristics to receive different weights, which also likely differ from the weights employed by IBIS to generate the overall risk score. The results in Table 7 are consistent with our findings in Tables 4-6. Growth risk is positively associated with spread, suggesting that higher growth risk results in higher spreads. Growth risk is also negatively correlated with the term of the loan. Sensitivity risk is positively related to loan spread, but negatively related loan term and loan size. Finally, the results using structural risk are significantly weaker than the results using growth risk and sensitivity risk. In sum, our findings in Table 7 suggest that the various industry characteristics are indeed different, and have varying implications for debt contracts.

3.4 Industry Risk and the Use of Explicit Collateral

In addition to loan spread, maturity, and size, we also test the relation between industry risks and the use of explicit collateral. We expect lenders to use explicit collateral when the collateral is more likely to maintain its value. Specifically, we expect the use of collateral to increase in the number of competitors. This is because more competitive industries suffer less from bankruptcy contagion. Additionally, a larger number of competitors increases the potential demand for collateralized assets and reduces the loss given default. Therefore, we predict a positive association between the use of collateral and structural risk in the industry.

The use of collateral differs from the other contract terms examined because it tends to be relatively time invariant with respect to the firm's industry. Therefore, we cannot employ industry fixed-effect regressions to examine the relation between industry risk and the use of explicit collateral. Hence, for this test we employ a pooled OLS specification. The results are reported in Table 8.

We find that industries with higher overall risk tend to use more explicit collateral.

However, when we decompose the IBIS overall risk score, we find that this relation is driven mostly by structural risk. The relation between structural risk and the use of collateral is not significantly affected by the inclusion of the firm-level estimates of probability of default and loss given default. When we exclude PD and LGD from the regression, the coefficient is 0.226 (t-statistic of 3.65). When we include PD and LGD in the regression, the coefficient is 0.213 (t-statistic of 3.10). Again, we interpret this result as an increase in the likelihood of using collateral when it is more likely to be valuable, as opposed to during periods of higher industry risk. We also find that growth risk is marginally negatively related to the use of collateral. This findings is consistent with the notion that assets in industries with higher growth risk have lower values conditional on default. Finally, we document a weak positive association between sensitivity risk and the use of collateral. One possible interpretation of this findings is that assets in industries which are more strongly associated with the macroeconomy are more easily deployable in other industries. Therefore, the value of the assets given default is higher because there is more potential demand for the asset (from other industries) in case of default.

While these results are consistent with our predictions and highlight the differences across the industry characteristics, we caution that these results are more prone to correlated omitted concerns because we are unable to utilize industry fixed-effects in this analysis. However, taken together with our results related to spreads, loan size and maturity, they support out main predictions and findings.

3.5 Productivity and Industry Risk

The IBIS industry risk measures examine the potential risk in industry productivity and performance. We expect such risk to matter more in less productive industries. In such industries, declines in productivity are more likely to result in default. To test our hypothesis, we sort firms based on the productivity of employees in the industry. Specifically, we employ two alternative measures of employee productivity: value added per employee and average wage per employee. To sort observations (industries) we use the average productivity during our entire sample period. Thus, an industry is classified as either a low or high productivity industry and the classification does not vary across periods. An industry is defined as a high productivity industry when the productivity measure is above the sample median. We then estimate the regression in Table 4 for the two groups separately. We expect debt contracting to be less sensitive to risk in more productive industries, where employees earn higher wages. The results from this analysis are reported in Table 9.

Consistent with our hypothesis, we find that the positive association between industry risk and loan spread is driven largely by industries with lower productivity per employee. For example, for industries with high value added per employee, the coefficient is 11.50 and statistically insignificant (t-statistic of 1.35). Alternatively, for industries with lower employee productivity, the relation between loan spread and overall risk is positive (coefficient of 24.87) and statistically significant (t-statistic of 3.15). We find similar results using wages to proxy for productivity. Using nonparametric simulations, we also find that the difference in the coefficients across the wage groups is statistically positive with a *p-value* of 0.016, and the difference in the coefficients across the value added groups is statistically positive with a *p-value* of 0.073.

3.6 Alternative Industry Measures

As discussed, one of the advantages of the IBIS risk measures is that they are available at the six-digit NAICS classification level. Due to data limitations, we are unable to create alternative measures for these industry characteristics, at the same level of specificity, using available Compustat data. Therefore, in order to illustrate the advantage of the IBIS data we generate alternative measures utilizing three-digit SIC codes. Using the three-digit SIC classification ensures a sufficient number of firms in each industry, while maintaining a relatively specific definition of an industry. To measure industry growth risk, we employ the growth in industry-level operating earnings (using the most recent period prior to the loan date). To estimate structural risk, we employ industry-level profit margins (using operating income after depreciation scaled by revenues). We follow industrial organization theory which suggests that more competitive industries have lower margins. To measure industry sensitivity risk, we employ the correlation between industry-level earnings growth and aggregate GDP growth. We follow a similar approach to the one used in our validation tests, and employ two years of forward earnings growth and three years of prior growth to estimate five year rolling correlations. Because our main prediction relates to the effect of industry risk on loan pricing, and for brevity, we only report results using spreads. The findings are reported in Table 10.

Our findings imply that the relation between the IBIS industry characteristics and spreads are incremental to the industry level characteristics that can be measured using available Compustat data. The results are largely unchanged when the alternative measures are included in the regressions. The only exception is the result for structural risk, which becomes marginally insignificant. Moreover, the alterative measures are statistically insignificant in the regression models. These findings illustrate the advantage of employing the IBIS data in our analyses.

3.7 Robustness Tests

We preform a variety of robustness tests (untabulated) for our results. First, we exclude all financial firms from our sample (SIC codes between 6000 and 6999). This reduces our final sample size by approximately 110 observations. We find similar results using this smaller sample. Therefore, our results are not attributable to financial firms. Second, we cluster our standard errors by industry as opposed to by firm. Our results remain unchanged using this approach. Third, we use GDP, industrial production, and aggregate market-to-book ratios as separate alternative proxies for market risk premiums (as opposed to the aggregate stock market risk premium). We find similar results using these alternative proxies. Fourth, we include loan class fixed effects (Drucker and Puri, 2009). Our results remain largely unchanged in this specification as well. Finally, we include the Hoberg and Phillips (2011) HHI industry concentration measure in our loan spread regressions.[13] Following Valta (2012),

[13] We do not include the Hoberg and Phillips (2011) measure in our main regressions because its inclusion significantly reduces our sample size.

we include an indicator variable equal to one for observations in the lowest quartile of the HHI distribution in a given year. Low concentration captures one element of competition that is not specifically captured by the IBIS industry structure measure. Consistent with Valta (2012), we find that the concentration measure is positively related to loan spreads. Furthermore, the IBIS measure of industry structure becomes more negative when the concentration measures is added to the regression (reinforcing our main findings in Section 3.3). This result also suggests that competition as measured by concentration differs from the IBIS measure of industry structure.

4 Conclusions

In this paper, we utilize a novel dataset provided by IBISWorld Inc. to examine how industry characteristics shape debt contracts. Using detailed industry risk ratings (scores) based on the firm's six-digit NAICS classification, we empirically measure the relation between industry characteristics and the following debt contract terms: loan spread, loan size, maturity, the number of covenants, and the use of explicit collateral. Employing industry fixed-effect regressions, we show that loans issued in poorly performing industries, and industries with higher levels of exposure to macroeconomic shocks, have higher spreads shorter maturities and smaller loan amounts. We further show that the relation between industry risk and spreads is more pronounced in less productive industries. Finally, we show that the use of explicit collateral is more likely to occur in more competitive industries, where the value of the collateral is likely to be higher upon default.

While prior literature focuses on firm-level characteristics, and industry concentration, this paper uses a robust industry fixed-effect research design to document an industry effect over and above firm-level fundamentals. Moreover, we find that growth risk and sensitivity risk matter more for debt contract design, relative to structural risk.

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Table 1: Summary Statistics

The table contains summary statistics for the variables employed in our analysis. Overall risk is the weighted average score of the IBIS six-digit industry risks metrics: growth risk, sensitivity risk and structural risk. We obtain data for the number of covenants, loan size, maturity, use of explicit collateral and spread from Dealscan. Spread equals the spread between the interest rate on the loan and the relevant Libor rate, per dollar of loan, measured in basis points. Collateral is defined as an indicator variable that receives the value of one if the debt is collateralized and zero otherwise. Maturity is the term of the loan in months. Loan size equals the natural log of the amount of the loan in dollars. The number of covenants equals the number of financial and net worth covenants reported on Dealscan. If no data is available we assume the number of covenants in the contracts is zero. The variables are measured per facility. We define loss given default (LGD) following Amiram (2013): $LGD = 0.292 + 0.063 \cdot LTA + 0.018 \cdot STTOLDEBT + 0.003 \cdot INTANGIBLE\_RATIO - 0.005 \cdot NET\_WORTH - 0.907 \cdot ROA$. The variables used to estimate LGD are defined as follows: ROA is defined as income before extraordinary items divided by total assets, net worth is defined as total assets minus total liabilities scaled by common shares outstanding, intangible ratio is defined as intangibles scaled by property plant and equipment, $STTOLDEBT$ is defined as the ratio of short-term to long-term debt, and finally, LTA is defined as the log of total assets. Computed LGD values above 1 and below 0 are assigned missing values. Probability of default (PD) is the estimated probability of bankruptcy based on the Black–Scholes–Merton model. The estimation follows Hillegeist et al. (2004). Firm size equals the log of the firm's market value of equity. Return on assets (ROA) is defined as operating income after depreciation divided by beginning of period total assets. Profit margins are defined as operating income after depreciation divided by beginning of period total assets. Tangible equals the firm's total assets, minus its intangible assets, divided by total assets. Leverage is defined as total debt (short-term debt plus long-term debt) divided by total assets. All the continuous contract terms and control variables, other than LGD, are winzorized at the 1% level.

	Overall Risk	Growth	Sensitivity	Structure	# of Covenants	Loan Size	Maturity	Spread
Mean	4.64	4.46	4.41	5.29	2.85	18.80	51.12	209.43
Median	4.57	4.77	4.23	5.26	3.00	18.98	60.00	175.00
std	0.75	1.26	1.34	1.04	1.45	1.59	22.18	145.54
25%	4.09	4.07	3.51	4.51	2.00	17.82	36.00	100.00
75%	5.08	5.16	5.16	5.97	4.00	19.87	60.00	275.00
	LGD	PD	Collateral	Firm Size	ROA	Profit Margin	Tangible	Leverage
Mean	0.67	0.02	0.74	7.06	0.09	0.09	0.81	0.34
Median	0.67	0.00	1.00	6.92	0.09	0.08	0.88	0.31
std	0.13	0.10	0.44	1.78	0.11	0.21	0.20	0.25
25%	0.59	0.00	0.00	5.87	0.04	0.04	0.69	0.15
75%	0.75	0.00	1.00	8.24	0.14	0.16	0.98	0.47

Table 2: Risk Measure Correlations

Panels A and B of this table report the slope coefficients and related R^2s from AR(1) models of the IBIS risk scores. Overall risk is the weighted average score of the IBIS six-digit NAICS industry risks metrics: growth risk, sensitivity risk and structural risk. Panel A reports results for our sample. Panel B reports results for all industries covered by IBIS. Panel C reports correlations for the risk measures and the probability of default (defined in Table 1). The above (below) diagonal reports the Spearman (Pearson) correlations. All correlations significant at the 5% level are highlighted in bold.

Panel A: Debt Sample				
	Overall Risk	Growth	Sensitivity	Structure
Coefficient	0.69	0.59	0.73	0.96
R^2	0.45	0.25	0.58	0.89

Panel B: Full IBIS Sample				
	Overall Risk	Growth	Sensitivity	Structure
Coefficient	0.69	0.47	0.70	0.92
R^2	0.48	0.21	0.49	0.85

Panel C: Correlation Table					
	Overall Risk	Growth	Sensitivity	Structure	PD
Overall Risk		**0.22**	**0.30**	**0.87**	**0.06**
Growth	**0.15**		**-0.22**	**-0.09**	**0.06**
Sensitivity	**0.40**	**-0.30**		**0.07**	**0.09**
Structure	**0.89**	**-0.18**	**0.19**		**0.03**
PD	**0.08**	0.01	**0.05**	**0.06**	

Table 3: The Relation between the IBIS Risk Measures and Future Economic Outcomes

This table reports the results for the OLS regressions of future growth in industry Economic Value Add (EVA), future changes in industry margins, and the correlation of future industry EVA growth and GDP, on the IBIS risk measures. Future EVA growth is computed as the average percentage growth in EVA over the next three years for each industry observation (i) and year (t). Industry margins = Industry EVA / Industry revenues. Changes in future industry margins are computed as the average change in industry margins over the next three years, for each industry observation (i) and year (t). The correlation between future industry EVA growth and future GDP growth equals the correlation between next year's EVA growth and the change in next year's GDP, for each industry (i) and year (t), computed over the time period $t-4$ and $t+1$ (with a minimum of three years; $t-2$, $t+1$). Industry wide EVA and Revenues are provided by IBIS. t-statistics based on robust standard errors clustered by industry are reported below the coefficients.

	Dependent Variable		
	$\Delta EVA_{i,t\rightarrow t+3}$	$Corr_{i,t-4\rightarrow t+1}\,(\Delta EVA_{i,t\rightarrow t+1}, \Delta GDP_{i,t\rightarrow t+1})$	ΔIndustry Margins$_{i,t\rightarrow t+3}$
Growth Risk	-0.021***		
	[-7.74]		
Sensitivity Risk		0.066***	
		[7.36]	
Structural Risk			-0.0006*
			[-1.70]
Obs.	3,966	3,966	3,966
R^2	6.3%	2.2%	0.1%

Table 4: Loan Spreads and Industry Risk

This table reports results for the OLS regressions of loan spreads on industry risk, and various control variables. VW_RET is the value weighted market excess returns extracted from Kenneth French's webpage. All the remaining variables are defined in Table 1. All the regression models include industry fixed-effects based on the firm's six-digit NAICS industry classification. t-statistics based on robust standard errors clustered by firm are reported below the coefficients.

	Dependent Variable: Loan Spread							
Overall Risk	17.71***	15.37**						
	[2.86]	[2.54]						
Growth			6.590**	6.723**				
			[2.15]	[2.08]				
Sensitivity					9.037**	8.523**		
					[2.40]	[2.23]		
Structure							8.505	-19.89*
							[0.56]	[-1.66]
Maturity	0.103	0.0899	0.0944	0.0909	0.0939	0.0800	0.0785	0.0751
	[0.78]	[0.64]	[0.71]	[0.64]	[0.71]	[0.57]	[0.59]	[0.53]
Loan Size	-19.15***	-19.49***	-19.59***	-19.79***	-19.20***	-19.50***	-19.63***	-19.94***
	[-7.16]	[-5.95]	[-7.35]	[-6.06]	[-7.15]	[-5.94]	[-7.32]	[-6.06]
# of Covenants	0.474	0.786	0.370	0.711	0.422	0.785	0.315	0.730
	[0.22]	[0.31]	[0.17]	[0.28]	[0.20]	[0.31]	[0.15]	[0.29]
Collateral	98.95***	86.46***	98.81***	86.29***	99.12***	86.54***	99.16***	86.17***
	[17.50]	[14.27]	[17.43]	[14.27]	[17.51]	[14.25]	[17.50]	[14.21]
Firm Size	-5.853**	-15.58***	-5.777**	-15.67***	-5.765**	-15.48***	-5.726**	-15.46***
	[-2.22]	[-3.74]	[-2.20]	[-3.75]	[-2.18]	[-3.72]	[-2.18]	[-3.69]
ROA	-234.8***	-127.1***	-234.4***	-126.7***	-237.0***	-129.1***	-238.1***	-130.2***
	[-8.04]	[-3.12]	[-7.98]	[-3.11]	[-8.09]	[-3.17]	[-8.09]	[-3.21]
Prof Margin	-17.81	-40.98*	-14.90	-37.92	-17.67	-40.86*	-14.69	-36.95
	[-1.11]	[-1.75]	[-0.92]	[-1.63]	[-1.10]	[-1.75]	[-0.91]	[-1.59]
Tangible	-2.079	-12.42	-1.129	-11.17	-2.344	-13.05	-1.961	-11.76
	[-0.13]	[-0.66]	[-0.07]	[-0.60]	[-0.14]	[-0.69]	[-0.12]	[-0.62]
Leverage	103.7***	71.34***	104.1***	70.46***	103.8***	71.53***	104.5***	70.55***
	[8.31]	[4.13]	[8.28]	[4.06]	[8.32]	[4.14]	[8.34]	[4.09]
PD		184.1***		188.7***		185.3***		191.6***
		[3.75]		[3.82]		[3.78]		[3.88]
LGD		142.4***		143.5***		141.9***		142.2***
		[2.93]		[2.92]		[2.94]		[2.91]
VW_RET	19.31	0.188	21.13	1.717	21.05	0.892	26.14*	1.598
	[1.40]	[0.01]	[1.54]	[0.12]	[1.52]	[0.06]	[1.86]	[0.11]
Obs.	4,951	3,654	4,951	3,654	4,951	3,654	4,951	3,654
R^2	0.468	0.506	0.466	0.506	0.467	0.506	0.465	0.505

Table 5: Loan Size and Industry Risk

This table reports results for the OLS regressions of loan size on industry risk, and various control variables. VW_RET is the value weighted market excess returns extracted from Kenneth French's webpage. All the remaining variables are defined in Table 1. All the regression models include industry fixed-effects based on the firm's six-digit NAICS industry classification. t-statistics based on robust standard errors clustered by firm are reported below the coefficients.

	Dependent Variable: Loan Size							
Overall Risk	-0.121***	-0.096**						
	[-2.99]	[-2.31]						
Growth			-0.006	-0.005				
			[-0.30]	[-0.22]				
Sensitivity					-0.084***	-0.062**		
					[-3.25]	[-2.37]		
Structure							-0.051	-0.107
							[-0.70]	[-1.45]
Maturity	0.010***	0.008***	0.011***	0.008***	0.010***	0.008***	0.011***	0.008***
	[8.50]	[6.43]	[8.48]	[6.51]	[8.53]	[6.45]	[8.50]	[6.52]
# of Covenants	0.076***	0.082***	0.077***	0.083***	0.076***	0.082***	0.077***	0.083***
	[4.48]	[3.89]	[4.53]	[3.93]	[4.48]	[3.87]	[4.53]	[3.95]
Spread	-0.001***	-0.002***	-0.002***	-0.002***	-0.001***	-0.002***	-0.002***	-0.002***
	[-7.92]	[-6.61]	[-8.15]	[-6.75]	[-7.91]	[-6.61]	[-8.16]	[-6.80]
Collateral	-0.245***	-0.188***	-0.244***	-0.187***	-0.246***	-0.189***	-0.244***	-0.189***
	[-3.85]	[-2.68]	[-3.81]	[-2.66]	[-3.87]	[-2.68]	[-3.82]	[-2.68]
Firm Size	0.572***	0.586***	0.572***	0.586***	0.571***	0.585***	0.572***	0.586***
	[21.07]	[17.43]	[20.93]	[17.38]	[21.07]	[17.39]	[21.03]	[17.42]
ROA	0.500*	0.528	0.512*	0.545	0.511*	0.539	0.516*	0.548
	[1.83]	[1.51]	[1.87]	[1.55]	[1.87]	[1.53]	[1.89]	[1.56]
Prof Margin	-0.058	0.021	-0.080	-0.003	-0.051	0.024	-0.080	-0.003
	[-0.39]	[0.10]	[-0.55]	[-0.02]	[-0.35]	[0.12]	[-0.55]	[-0.02]
Tangible	-0.194	-0.234	-0.198	-0.236	-0.190	-0.229	-0.196	-0.231
	[-1.24]	[-1.24]	[-1.26]	[-1.25]	[-1.22]	[-1.22]	[-1.25]	[-1.23]
Leverage	0.253**	0.225	0.253**	0.232	0.254**	0.223	0.252**	0.232
	[2.27]	[1.25]	[2.25]	[1.29]	[2.27]	[1.24]	[2.24]	[1.29]
PD		-0.204		-0.247		-0.204		-0.249
		[-0.55]		[-0.67]		[-0.55]		[-0.68]
LGD		-0.057		-0.059		-0.052		-0.062
		[-0.17]		[-0.18]		[-0.16]		[-0.19]
VW_RET	-0.183	-0.086	-0.217*	-0.112	-0.185	-0.087	-0.229**	-0.130
	[-1.60]	[-0.69]	[-1.92]	[-0.90]	[-1.62]	[-0.69]	[-2.02]	[-1.05]
Obs.	4,951	3,654	4,951	3,654	4,951	3,654	4,951	3,654
R^2	0.658	0.668	0.657	0.667	0.658	0.668	0.657	0.668

Table 6: Loan Maturity and Industry Risk

This table reports results for the OLS regressions of loan maturity on industry risk, and various control variables. VW_RET is the value weighted market excess returns extracted from Kenneth French's webpage. All the remaining variables are defined in Table 1. All the regression models include industry fixed-effects based on the firm's six-digit NAICS industry classification. t-statistics based on robust standard errors clustered by firm are reported below the coefficients.

	Dependent Variable: Loan Term							
Overall Risk	-2.715***	-2.610***						
	[-2.89]	[-2.82]						
Growth			-1.535***	-2.023***				
			[-3.29]	[-4.44]				
Sensitivity					-1.228**	-0.864		
					[-2.09]	[-1.48]		
Structure							1.206	1.783
							[0.64]	[1.03]
Loan Size	4.142***	3.266***	4.201***	3.299***	4.159***	3.294***	4.223***	3.335***
	[7.55]	[5.53]	[7.61]	[5.63]	[7.55]	[5.54]	[7.60]	[5.61]
# of Covenants	0.273	0.283	0.284	0.290	0.284	0.292	0.303	0.299
	[0.83]	[0.74]	[0.86]	[0.77]	[0.86]	[0.76]	[0.92]	[0.78]
Spread	0.003	0.003	0.003	0.003	0.003	0.003	0.002	0.003
	[0.78]	[0.64]	[0.71]	[0.65]	[0.71]	[0.57]	[0.59]	[0.54]
Collateral	11.48***	10.57***	11.55***	10.60***	11.50***	10.60***	11.58***	10.66***
	[9.00]	[7.59]	[9.01]	[7.60]	[9.01]	[7.60]	[9.03]	[7.62]
Firm Size	-0.504	0.824	-0.509	0.858	-0.521	0.805	-0.543	0.801
	[-0.79]	[1.11]	[-0.79]	[1.15]	[-0.82]	[1.08]	[-0.84]	[1.07]
ROA	19.11***	2.374	18.73***	1.793	19.43***	2.783	19.44***	2.880
	[3.57]	[0.35]	[3.48]	[0.26]	[3.63]	[0.41]	[3.61]	[0.42]
Prof Margin	2.556	2.822	2.127	2.399	2.482	2.539	2.060	2.141
	[0.96]	[0.87]	[0.79]	[0.74]	[0.93]	[0.78]	[0.76]	[0.65]
Tangible	-12.56***	-8.174**	-12.75***	-8.518**	-12.55***	-8.138**	-12.69***	-8.268**
	[-4.22]	[-2.25]	[-4.27]	[-2.36]	[-4.20]	[-2.23]	[-4.23]	[-2.26]
Leverage	3.041	6.023**	3.037	6.174**	3.047	6.093**	3.049	6.207**
	[1.62]	[2.28]	[1.62]	[2.33]	[1.62]	[2.30]	[1.62]	[2.34]
PD		-9.541*		-9.859*		-10.16*		-10.79**
		[-1.80]		[-1.84]		[-1.93]		[-2.04]
LGD		-17.17***		-17.37***		-17.17***		-17.20***
		[-2.67]		[-2.72]		[-2.67]		[-2.68]
VW_RET	-5.672**	-7.526***	-5.649**	-7.376***	-6.010**	-7.922***	-6.344***	-8.033***
	[-2.36]	[-3.06]	[-2.38]	[-3.03]	[-2.52]	[-3.22]	[-2.66]	[-3.24]
Obs.	4,951	3,654	4,951	3,654	4,951	3,654	4,951	3,654
R^2	0.295	0.296	0.294	0.298	0.293	0.294	0.292	0.294

Table 7: Debt Contract Terms and Multiple Industry Risks Measures

This table reports results for the OLS regressions of loan spread, loan size, and maturity on the various industry risk scores. All the regressions employ the three industry risk scores simultaneously, and include various control variables. VW_RET is the value weighted market excess returns extracted from Kenneth French's webpage. All the remaining variables are defined in Table 1. All the regression models include industry fixed-effects based on the firm's six-digit NAICS industry classification. t-statistics based on robust standard errors clustered by firm are reported below the coefficients.

	Spread	Spread	Loan Size	Loan Size	Term	Term
Growth	5.397*	5.393*	0.007	0.003	-1.357***	-1.927***
	[1.73]	[1.67]	[0.31]	[0.12]	[-2.85]	[-4.15]
Sensitivity	7.952**	7.651**	-0.085***	-0.062**	-0.987*	-0.547
	[2.11]	[1.97]	[-3.21]	[-2.34]	[-1.66]	[-0.92]
Structure	8.511	-19.35	-0.042	-0.106	1.096	1.571
	[0.58]	[-1.60]	[-0.56]	[-1.44]	[0.60]	[0.94]
Spread			-0.001***	-0.002***	0.003	0.003
			[-7.91]	[-6.65]	[0.78]	[0.71]
Loan Size	-19.17***	-19.57***			4.156***	3.288***
	[-7.16]	[-5.98]			[7.56]	[5.59]
Maturity	0.103	0.100	0.010***	0.008***		
	[0.77]	[0.71]	[8.52]	[6.48]		
# of Covenants	0.477	0.863	0.076***	0.082***	0.274	0.278
	[0.22]	[0.34]	[4.47]	[3.89]	[0.83]	[0.73]
Collateral	98.93***	85.89***	-0.246***	-0.190***	11.51***	10.60***
	[17.48]	[14.24]	[-3.87]	[-2.69]	[9.00]	[7.61]
Firm Size	-5.881**	-15.56***	0.571***	0.585***	-0.506	0.854
	[-2.23]	[-3.73]	[21.03]	[17.33]	[-0.79]	[1.15]
ROA	-234.5***	-125.8***	0.516*	0.541	18.73***	1.766
	[-8.01]	[-3.09]	[1.89]	[1.54]	[3.48]	[0.26]
Prof Margin	-17.57	-40.92*	-0.051	0.025	2.446	2.622
	[-1.09]	[-1.75]	[-0.34]	[0.12]	[0.91]	[0.81]
Tangible	-2.043	-11.44	-0.189	-0.225	-12.68***	-8.494**
	[-0.12]	[-0.61]	[-1.21]	[-1.20]	[-4.27]	[-2.36]
Leverage	103.8***	71.24***	0.253**	0.223	3.078	6.091**
	[8.30]	[4.11]	[2.26]	[1.24]	[1.64]	[2.31]
PD		182.8***		-0.205		-9.491*
		[3.70]		[-0.55]		[-1.77]
LGD		141.3***		-0.056		-17.24***
		[2.92]		[-0.17]		[-2.70]
VW_RET	19.74	-4.061	-0.195*	-0.104	-5.167**	-6.930***
	[1.42]	[-0.28]	[-1.73]	[-0.83]	[-2.12]	[-2.75]
Obs.	4,951	3,654	4,951	3,654	4,951	3,654
R^2	0.468	0.508	0.658	0.668	0.295	0.298

Table 8: The use of Collateral and Industry Risk

This table reports results for the Logit regressions of the use of collateral on industry risk, and various control variables. Collateral is defined as an indicator variable that receives the value of one if the debt is collateralized and zero otherwise. VW_RET is the value weighted market excess returns extracted from Kenneth French's webpage. All the remaining variables are defined in Table 1. t-statistics based on robust standard errors clustered by firm are reported below the coefficients.

	Dependent Variable: Collateral							
Overall Risk	0.172**	0.164*						
	[2.17]	[1.85]						
Growth			-0.0821*	-0.113**				
			[-1.71]	[-2.04]				
Sensitivity					0.0772	0.0879*		
					[1.61]	[1.66]		
Structure							0.226***	0.213***
							[3.65]	[3.10]
Maturity	0.028***	0.031***	0.027***	0.030***	0.028***	0.030***	0.028***	0.030***
	[8.53]	[8.38]	[8.37]	[8.32]	[8.50]	[8.40]	[8.67]	[8.48]
Loan Size	-0.193***	-0.115	-0.173**	-0.091	-0.186**	-0.109	-0.192***	-0.109
	[-2.58]	[-1.37]	[-2.44]	[-1.18]	[-2.51]	[-1.32]	[-2.72]	[-1.40]
# of Covenants	0.041	0.116*	0.036	0.112*	0.039	0.116*	0.045	0.114*
	[0.76]	[1.84]	[0.68]	[1.78]	[0.73]	[1.84]	[0.85]	[1.80]
Spread	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***	0.017***
	[12.88]	[11.08]	[13.03]	[11.26]	[12.90]	[11.09]	[13.05]	[11.25]
Firm Size	-0.337***	-0.585***	-0.351***	-0.614***	-0.343***	-0.591***	-0.335***	-0.603***
	[-4.87]	[-6.24]	[-5.28]	[-6.75]	[-4.98]	[-6.34]	[-5.09]	[-6.53]
ROA	-1.612**	-0.749	-1.750**	-0.859	-1.644**	-0.784	-1.682**	-0.679
	[-2.09]	[-0.71]	[-2.31]	[-0.83]	[-2.14]	[-0.75]	[-2.20]	[-0.65]
Prof Margin	-0.584	-0.562	-0.505	-0.480	-0.571	-0.574	-0.624	-0.621
	[-1.23]	[-0.91]	[-1.09]	[-0.81]	[-1.21]	[-0.93]	[-1.24]	[-0.99]
Tangible	-0.614*	-0.467	-0.620**	-0.490	-0.594*	-0.453	-0.834**	-0.679*
	[-1.95]	[-1.31]	[-1.97]	[-1.37]	[-1.89]	[-1.27]	[-2.56]	[-1.83]
Leverage	1.875***	1.910***	1.889***	1.924***	1.882***	1.928***	1.901***	1.892***
	[5.38]	[4.56]	[5.33]	[4.48]	[5.36]	[4.56]	[5.39]	[4.44]
PD		2.451*		2.335*		2.411*		2.377*
		[1.86]		[1.74]		[1.80]		[1.85]
LGD		3.575***		3.734***		3.550***		3.923***
		[3.18]		[3.31]		[3.18]		[3.39]
VW_RET	-0.132	-0.200	-0.0771	-0.148	-0.125	-0.195	-0.0278	-0.123
	[-0.35]	[-0.53]	[-0.21]	[-0.40]	[-0.33]	[-0.51]	[-0.08]	[-0.32]
Obs.	4,951	3,654	4,951	3,654	4,951	3,654	4,951	3,654

Table 9: Loan Spread, Productivity and Industry Risk

This table reports results for the OLS regressions of loan spreads on industry risk, and various control variables. Observations are sorted based on the average wage per employee and value-add per employee in the industry. These metrics are computed using industry total value-add, wages, and number of employees available in the IBIS data set. High productivity industries have value-add or wages per employee above the sample median. VW_RET is the value weighted market excess returns extracted from Kenneth French's webpage. All the remaining variables are defined in Table 1. All the regression models include industry fixed-effects based on the firm's six-digit NAICS industry classification. t-statistics based on robust standard errors clustered by firm are reported below the coefficients.

Dependent Variable: Spread				
	High Value Added Per Employee	Low Value Added Per Employee	High Wage Per Employee	Low Wage Per Employee
Overall Risk	11.50	24.87***	9.075	30.23***
	[1.30]	[2.94]	[1.06]	[3.65]
Maturity	0.250	-0.197	0.352*	-0.233
	[1.35]	[-0.97]	[1.82]	[-1.22]
Loan Size	-25.94***	-12.91***	-27.20***	-12.46***
	[-7.31]	[-2.63]	[-6.89]	[-2.74]
# of Covenants	-0.566	3.251	2.038	-0.395
	[-0.15]	[0.98]	[0.54]	[-0.12]
Collateral	84.24***	89.48***	86.88***	85.20***
	[9.81]	[10.49]	[10.45]	[9.70]
Firm Size	-9.371*	-21.13***	-13.63***	-17.35***
	[-1.79]	[-3.60]	[-2.60]	[-3.05]
ROA	-167.8***	-112.8**	-92.71*	-156.6***
	[-3.17]	[-2.01]	[-1.58]	[-2.75]
Prof Margin	-31.24	-49.03**	-41.96	-49.93***
	[-0.94]	[-2.29]	[-1.19]	[-2.42]
Tangible	14.46	-18.13	-14.80	-5.448
	[0.55]	[-0.73]	[-0.54]	[-0.21]
Leverage	62.27***	90.74***	33.58	109.6***
	[2.63]	[4.01]	[1.44]	[4.87]
PD	-9.173	5.259	-6.448	11.50
	[-0.42]	[0.24]	[-0.30]	[0.54]
LGD	270.2***	154.3***	255.3***	137.4***
	[2.69]	[2.80]	[2.97]	[2.43]
VW_RET	109.9	165.4***	201.0***	76.50
	[1.36]	[2.95]	[2.56]	[1.40]
Obs.	1,763	1,855	1,754	1,864
R^2	0.495	0.544	0.479	0.558

Table 10: Alternative Compustat-Based Industry Risk Measures

This table reports results for the OLS regressions of loan spread on industry risk, including the alternative industry-risk measures computed using data available in Compustat. The alternative growth risk measure (Alt. Growth) equals the growth in industry-level operating earnings during the year prior to the loan origination date. The alternative structural risk measure (Alt. Structure) equals industry-level profit margins at the time of loan initiation. The alternative sensitivity risk measure (Alt. Sensitivity) equals the correlation between industry-level earnings growth and aggregate GDP growth. Five year rolling correlations are calculated using two years of forward earnings growth and three years of prior growth. All the additional control variables employed in Tables 4 - 7 are included in the regressions. All the regression models include industry fixed-effects based on the firm's six-digit NAICS industry classification. t-statistics based on robust standard errors clustered by firm are reported below the coefficients.

	Dependent Variable: Loan Spread							
Overall Risk	15.37**	15.21**						
	[2.54]	[2.52]						
Growth			6.723**	6.704**				
			[2.08]	[2.18]				
Sensitivity					8.523**	8.192**		
					[2.23]	[2.13]		
Structure							-19.89*	-16.24
							[-1.66]	[-1.44]
Alt. Sensitivity		-0.524		-0.578		-0.078		0.535
		[-0.08]		[-0.08]		[-0.01]		[0.08]
Alt. Growth		-3.117		-3.131		-2.564		-1.476
		[-0.45]		[-0.45]		[-0.39]		[-0.24]
Alt. Structure		-185.1		-175.4		-202.3		-198.4
		[-1.47]		[-1.40]		[-1.59]		[-1.58]
Maturity	0.090	0.096	0.091	0.096	0.080	0.088	0.075	0.082
	[0.64]	[0.68]	[0.64]	[0.68]	[0.57]	[0.62]	[0.53]	[0.58]
Loan Size	-19.49***	-19.33***	-19.79***	-19.62***	-19.50***	-19.35***	-19.94***	-19.75***
	[-5.95]	[-5.81]	[-6.06]	[-5.91]	[-5.94]	[-5.80]	[-6.06]	[-5.92]
# of Covenants	0.786	0.480	0.711	0.466	0.785	0.458	0.730	0.475
	[0.31]	[0.19]	[0.28]	[0.18]	[0.31]	[0.18]	[0.29]	[0.19]
Collateral	86.46***	87.10***	86.29***	86.93***	86.54***	87.24***	86.17***	86.95***
	[14.27]	[14.15]	[14.27]	[14.17]	[14.25]	[14.14]	[14.21]	[14.12]
PD	184.1***	175.0***	188.7***	180.2***	185.3***	175.8***	191.6***	182.9***
	[3.75]	[3.53]	[3.82]	[3.60]	[3.78]	[3.55]	[3.88]	[3.66]
LGD	142.4***	144.9***	143.5***	146.2***	141.9***	144.7***	142.2***	145.2***
	[2.93]	[2.95]	[2.92]	[2.94]	[2.94]	[2.95]	[2.91]	[2.93]
Additional Controls	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	3,654	3,522	3,654	3,522	3,654	3,522	3,654	3,522
R^2	0.506	0.505	0.506	0.504	0.506	0.504	0.505	0.503

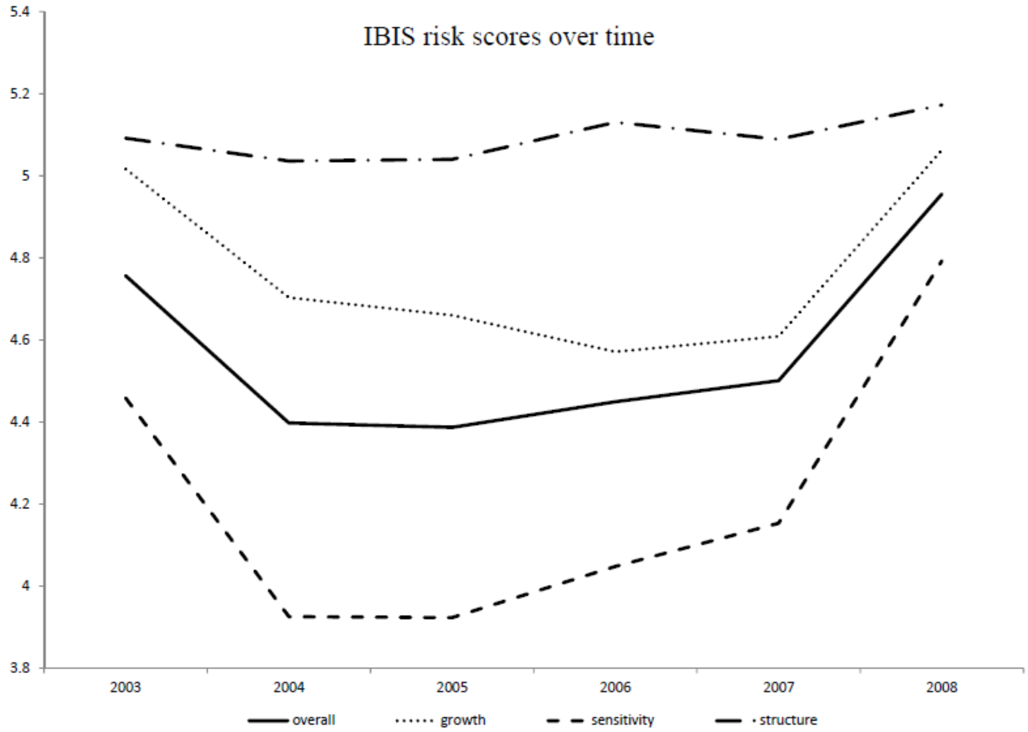

Figure 1: This figure plots the time trend of the cross-sectional average IBIS risk scores. Overall risk is the weighted average score of the three different industry risk categories: growth risk, sensitivity risk, and structural risk. Each year, we calculate the cross-sectional average of each industry risk score and then plot the averages over time.

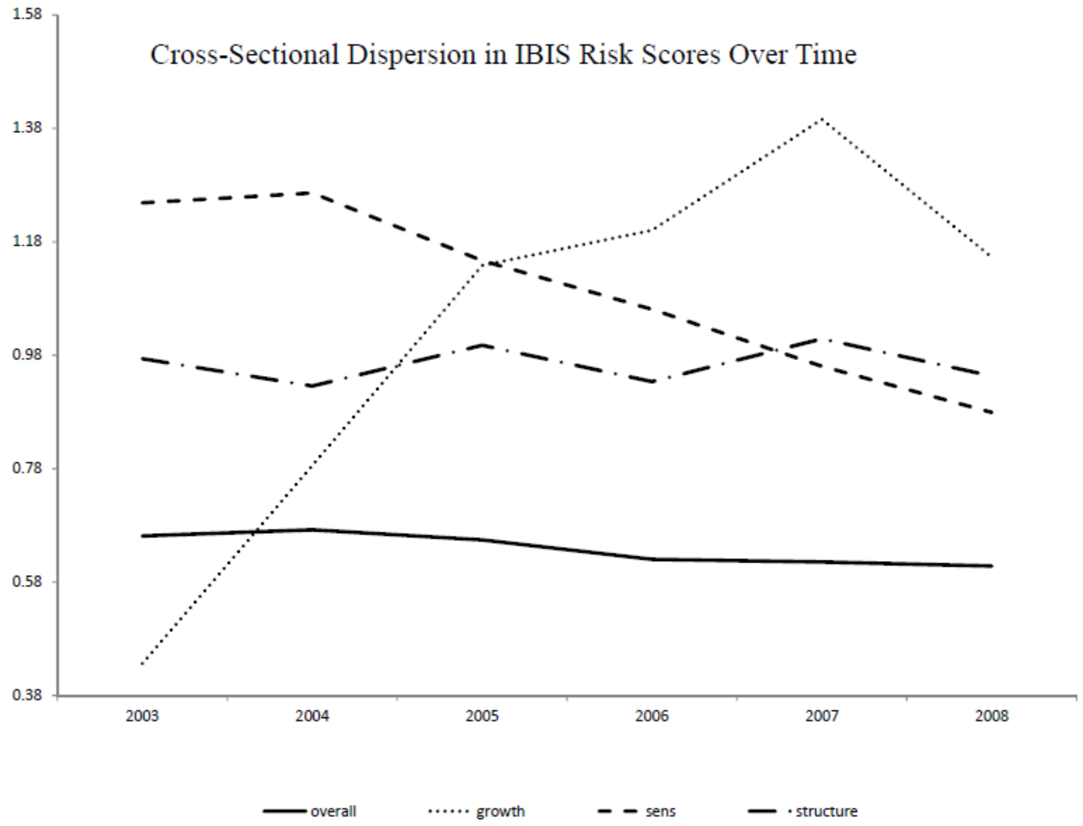

Figure 2: This figure plots the cross-sectional dispersion in the IBIS risk measures across industries, over time. Overall risk is the weighted average score for the three different industry risk categories: growth risk, sensitivity risk, and structural risk. Each year, we calculate the cross-sectional standard deviation of each industry risk category and plot the results by year.