HARDENING SOFT INFORMATION IN CREDIT RATING: THE ROLE OF NATIONAL CULTURE

By

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Dalhousie University is located in Mi'kma'ki, the
ancestral and unceded territory of the Mi'kmaq.
We are all Treaty people.

TABLE OF CONTENTS

LIST OF TABLES

ABSTRACT

Credit ratings play a central role in disseminating credit information to market participants and in shaping a firm's financing and capital structure. However, recent evidence suggests that global rating standards change over time and a firm that maintains the same fundamentals over time may receive different ratings, suggesting that soft information plays a role in credit ratings. This study provides one of the first pieces of evidence on the determinants of soft information in credit ratings. Using Hofstede's four cultural dimensions (uncertainty avoidance, collectivism, power distance, and masculinity) as proxies for culture, we show that soft information in credit ratings is positively (negatively) associated with uncertainty avoidance (power distance). This new evidence is discernible primarily in developed countries. Taken together, our evidence indicates that credit ratings in countries with increased levels of uncertainty avoidance (and power distance) are more (less) likely to incorporate soft information.

LIST OF ABBREVIATIONS USED

CR	Credit Rating
CRA	Credit Rating Agency
CRSI	Credit Rating Soft Information
GDP	Gross Domestic Product

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CHAPTER 1 INTRODUCTION

In Modigliani and Miller's (1958) perfect capital market, the relevance of credit ratings is deemed negligible. However, in the presence of imperfect information, Credit Rating Agencies (CRAs) play an essential role as information intermediaries and gatekeepers in the financial markets (Bonsall et al. 2017) by disseminating valuable and unbiased information about firm credit quality (Attig et al. 2020). CRAs are important information certifiers (Kisgen 2006) and disseminate credit information to market participants through their ratings of firms and their debt issues (e.g., Nguyen et al. 2023). These credit ratings are expected to reflect a forward-looking assessment of firms' creditworthiness, beyond other publicly available information (Kisgen 2006), which will play a relevant role in mitigating information asymmetry and in a firm's financing and capital structure (e.g. Kliger and Sarig, 2000, Blume et al., 1998; Faulkender and Petersen, 2006, Kisgen 2006, 2009). That is why credit rating continues to be an important contemporaneous area of interest for both academics and practitioners.

In academia, credit rating (CR) has produced a large body of knowledge that has evolved into two main lines of inquiry. A first line of inquiry is confined to understanding the economic implications of credit rating. For instance, Nguyen et al. (2023) document a decline in the likelihood of firm-specific stock price crashes after the announcement of credit rating downgrades. The second line of research focuses on the antecedents of a firm's CR. Related recent evidence indicates that asset redeployability (Habib and Ranasinghe 2022), economic regimes (Edirisinghe et al. 2022), financial cycle (Liu et al. 2023), corporate social responsibility (Bannier et al. 2021), and financial openness and domestic financial development (Andreasen and Valenzuela 2016) play an important role in CR.

Against this backdrop, CRAs have drawn criticism in the aftermath of perceived CR failures exposed by high-profile bankruptcies (e.g., Enron and WorldCom) and the 2007–2009 financial crisis. This has in turn given renewed impetus to study the timeliness and informational value of credit ratings. This has recently attracted new empirical attention, still seeking to gather momentum, to bear on the timeliness and informational value of credit ratings as well as the changes in the rating standards over time. Blume et al. (1998) and Baghai et al. (2013), for instance, provide evidence of increased rating conservatism in the US. More recently, Attig et al. (2020), using panel data on S&P's credit ratings for firms from 63 countries, show that while firms in the US and other developed countries receive lower ratings, emerging country firms earn better ratings, suggesting divergent patterns in the global rating standards over time. The authors also show that a firm that maintains the same fundamentals over time receives a different rating today than in prior years.[1] These findings suggest that soft information plays a pivotal role in CR. Surprisingly, little is known about the determinants of soft information in CR. The challenge of measuring soft information has possibly contributed to keeping this area relatively untapped in empirical research. Our study addresses this gap by providing one of the first pieces of evidence on the determinants of soft information in credit ratings across countries. We find at least as much merit in addressing this question since the regulatory scrutiny of CRAs has recently gained considerable momentum beyond U.S. borders[2] and documenting evidence on the

[1] The issuer-pays model of CRAs can arguably introduce a conflict of interest, providing CRAs with an incentive to inflate CR. However, reputational concerns can limit CRAs' incentive to issue unjustified ratings.

[2] In the aftermath of the financial crisis, the E.U. implemented Regulation No 1060/2009, subsequently revised in 2011 and 2013, to restore market confidence and enhance investor protection (European Commission, 2014). In 2011, the International Organization of Securities Commissions (IOSCO) assessed the regulatory adherence of CRAs in Australia, the E.U., Japan, Mexico, and the U.S., focusing on four principles: rating process quality, independence, transparency, and confidential information handling.

factors that are associated with increased CR soft information can inform both investors and regulators.

We use 1-adjusted R-squared from a regression of CR on a set of controls (following Baghai et al. (2013) and Attig et al. (2020)) as a measure of soft information in CR (CRSI).[3] We generate CRSI at the country-year level and focus on the impact of national culture and other country-level variables as potential determinants of CRSI. We focus on the influence of national culture because of its impact on market transactions and other economic outcomes, beyond its influence through the country's institutional factors. Recent evidence, for instance, suggests that national culture influences corporate debt maturity choice (Zheng et al. 2011) and dividend policy (Shao et al. 2010), and moderates the relationship between International Financial Reporting Standards (IFRS) adoption and stock price synchronicity (Abdallah et al. 2022), the effects of legal protection, peer underpricing behavior pressure, and information asymmetry on IPO underpricing (Zhou et al. 2022).[4]

Using Hofstede's (2001) cultural dimensions of uncertainty avoidance, collectivism/individualism, power distance, and masculinity/femininity, we document a positive (negative) association between soft information in credit ratings and uncertainty avoidance (power distance). This new evidence remains valid after controlling for various country-level legal, political, financial, and economic factors. Importantly, this new evidence is discernible primarily in developed countries. Taken together, our evidence indicates that credit ratings in countries with increased levels of the dimensions of national

[3] While CRSI can be viewed as a reliable proxy for soft information in CR, since it captures the unexplained variance in CR, one should take caution in interpreting the findings of this study given the potential measurement errors, model misspecification, or the inherent complexity of credit rating determinants.

[4] El Ghoul et al.'s (2021) evidence suggests that the prevalence of zombie firms is not related to national culture.

culture, specifically uncertainty avoidance (and power distance), are more (less) likely to incorporate soft information.

The rest of this study is organized as follows. In Chapter 2, we review the literature. Chapter 3 describes our sample construction and variables. Chapter 4 discusses the methodology and empirical findings. Chapter 5 portrays the robustness tests. Chapter 6 concludes with the key findings of the study.

CHAPTER 2 LITERATURE REVIEW

The literature probing the determinants of credit rating is scanty and to our best knowledge, there has been no research focused on uncovering the role of soft information in credit ratings. Most of the previous studies in this arena used specific financial ratios like leverage, interest coverage, profitability, asset size, and earnings stability of firms to predict credit ratings.

Altman (1968) attempted to assess the significance of ratio analysis in the performance analysis of business entities amidst the growing doubt from academicians on the relevance of ratios in this regard. His study focused on predicting the bankruptcy of manufacturing firms using a set of financial and economic ratios combined in a discriminant analysis approach. This model came out very successful (~95% accuracy) in predicting bankruptcy within the sample. Since then, there have been a good number of studies conducted using a similar set of ratios to predict credit ratings. Pinches and Mingo (1973) opined that bond ratings are partly based on the financial and operating performance metrics of the firm. The firm's ability to pay off debt is a crucial determiner of ratings. Gupta (2023) found size, profitability, and leverage to be the most significant factors in predicting credit ratings for Indian firms. Brazilian firms on the other hand showed that the explanatory power of credit ratings belongs to leverage, internationalization, financial market performance, profitability, and growth (Murcia et al., 2014). Bhandari et al. (1983) a set of seven financial ratios to predict changes in bond quality rating and suggested that ROA is the single most important factor in explaining rating followed by the trend in ROA.

Hwang et al. (2010) deployed and proposed an ordered semiparametric probit model incorporating four market-driven variables, nineteen accounting variables, and industry effects to improve credit rating prediction capacity. Their model proved to be more powerful in predicting credit ratings compared to the regular ordered probit model.

Following a different path, Ederington et al. (1984) attempted to relate bond ratings to interest rate structure and financial accounting ratios. They concluded that market yields, bond ratings, and financial accounting ratios are highly correlated and at the same time their findings suggest that ratings reveal information beyond the accounting ratios. This finding gives us a hint for this study that there might be some more information content contained in credit ratings that can be captured possibly by soft information.

Hilscher and Wilson (2011) investigated the information contained in credit ratings. They concluded that credit ratings are not the best in predicting corporate defaults. However, ratings capture systematic default risk and raw default probability well.

Some papers conducted event studies to find relevant information content in credit ratings which is not explained by the financial variables. Dilly (2014) reviewed a range of literature on rating quality and found that regulation plays a role in determining the ratings. This conclusion is supported by Krishnan and Basu (2023) who examined the factors determining the credit ratings of bonds issued by Indian firms once the Indian market regulator passed a new Transparency and Disclosure Norms in 2010. Their findings suggest that apart from the firm-level financial ratios, non-financial information is also contained in credit ratings which is evidenced by the fact that CRAs became more conservative in their rating standards after the regulatory disclosure requirements were changed. Therefore, the existence of other non-financial information, or in other words, soft information in credit ratings can be a new avenue to explore.

The information content of credit ratings can be viewed from another perspective: whether credit ratings only reflect publicly available information, or they contain something more than that. Kraft and Czarnitzki (2004) conducted a study on manufacturing firms in Western Germany. They investigated whether credit ratings offer any additional valuable information that is not offered by already available public information of the firm whose creditworthiness is in question. They conclude that credit ratings significantly improve the regression fit in the loan default model in addition to the publicly available information. It implies that it is worth exploring what are the other factors than the firm's financial information that contribute to the information contained in credit ratings. For example, Ho and Rao (1993) suggested the inclusion of macro variables because the weights assigned to different financial ratios vary greatly with economic cycles. However, Bissoondoyal-Bheenick and Treepongkaruna (2011) conducted a study with macroeconomic and market risk variables included in the model but found nothing contributory to credit ratings for banks in the United Kingdom and Australia. Ashbaugh-Skaife et al. (2006), and Bhojraj and Sengupta (2003) found that a strong corporate governance culture helps firms to get higher credit ratings. Therefore, it leaves room for exploring the idea of incorporating other soft information variables and expanding the study to a broader range of countries.

Another phenomenon that sparks the interest to uncover the information content in credit ratings is the declining trend in corporate debt over the years. Blume et al. (1998) demonstrated that during the 1980s and 1990s, U.S. corporate debts received lower ratings, and this can partially be attributed to the change in rating standards. It implies that the information contained in ratings in the past is not the same as it is today, and the standards might reflect information that is not explicitly available in the financial picture of the firm.

Gray et al. (2006) confirmed similar results for Australian firms. Although firm-level ratios have pronounced effects on credit ratings, a firm's standard requirement to keep the same rating level is ever on the rise.

Baghai et al. (2013) also documented the same phenomenon for an extended period till 2009 and concluded that credit ratings have become more conservative with an average 3-notch drop in 24 years. Although they have explored what implications this conservatism has had on the firm's cash holdings, capital structure, and capital market reactions, they did not explore why the conservatism happened. Therefore, it is an empirical question to ask why a firm with the same sort of financial position is rated lower today than it would be a couple of decades ago. The hint for non-financial soft information content in credit ratings seems conspicuous yet not explored in the literature.

Different scenarios cause variations in credit rating standards and many studies have attempted to capture that. One such scenario is the period of heightened policy uncertainty. Dilly (2014) found that incentives within the rating process and rating analysts' misconduct play a role in determining the quality of ratings. Attig et al. (2020) demonstrated that increased policy uncertainty in the U.S. weakens rating standards. They included macroeconomic variables in the models as well, but the findings prevailed that policy uncertainty makes credit ratings less informative about the credit quality of firms. This paper comes close to our work since it investigates the determinants of credit ratings and includes a range of macro variables along with firm-level financial ratios. However, our study extends this paper further by conducting the study using a global dataset and by investigating other soft information contents in credit ratings beyond what the model used by Attig et al. (2020) captured. Another study dealt with investment horizon, institutional variables, and credit ratings (Driss et al., 2021). This study used a global dataset and concluded that institutional investment horizon is positively correlated with credit ratings even when the authors incorporated controls for macroeconomic variables and institutional environment factors.

Ever since Hofstede (1980) unfolded the world of national cultural traits (i.e., individualism, uncertainty avoidance, masculinity, power distance), it has gained a lot of attention from both academicians and firms. There has been a good number of studies on the importance of culture in Corporate Finance. Chang et al. (2012) used cross-country samples to prove that national culture and corporate governance factors play a determining role in the debt maturity choice for both the lenders and the borrowers. They found that debt maturity negatively loads on uncertainty avoidance, masculinity, and long-term orientation indices. This finding implies that during uncertain economic conditions, risk-averse lenders and borrowers prefer short-term debt. These findings add to the literature that national culture is a key determiner in financing decisions. Zheng et al. (2011) also confirm similar results that national culture plays a key role in explaining cross-country variations in the term structure of debt. Using samples from seven Asian countries from 2002 to 2018, Hu and Qi (2022) show that higher leverage is more common with firms in countries that encourage individualism, masculinity, and uncertainty avoidance. However, firms in countries with higher power distance are on the lower side of using debt. Lu et al. (2020) investigated how the three national culture dimensions (individualism, short-term orientation, and uncertainty avoidance) affected debt risk in 65 Belt and Road Initiative countries between 2008 and 2017. They show that higher national debt risk is prevalent in countries with strong individualism and short-term orientation. On the contrary, lower national debt risk persists in strong uncertainty avoidance countries. They also conclude that international cooperation moderates national culture and debt risk relationship by mitigating the negative effect individualism and short-term orientation have on national debt risk. Khan et al. (2022) conducted a study on 55 emerging and developing economies between 1984 to 2018 and found that individualism and masculinity accelerate financial sector development while uncertainty avoidance acts as an impediment to it. Mihet (2013) examined how national culture affects firm risk-taking decisions. He used a sample covering 50,000 firms in 400 industries in 51 countries. Firms in low uncertainty avoidance and high individualism countries are more likely to take risks. Although there has been a lot of research on how culture affects a firm's financing decisions, financial markets, and behaviors, there has been no research on the role of national culture in soft information in credit ratings. The closest study to ours is by Dang (2018) who, using survival analysis, included 50 countries in the sample to find out the potential impact national culture may have on rating migration. His findings suggest that countries appreciating long-term orientation are less likely to have firms whose ratings are downgraded rather they might receive upgrades. Downgrades happen to be more common in countries that have strong uncertainty-avoidance culture and higher power distance. The key difference between our study and Dang (2018) is that we focus on filling the empirical gap of probing the possible soft information content in credit rating using primarily national culture and not focusing on the transition aspect. However, the observed rating migration is a motivation for our study. We hypothesize that soft information contents especially national culture capture the variations in credit ratings unexplained by the financial information of firms.

CHAPTER 3 DATA

Following Attig et al. (2020), we rely on the S&P Capital IQ database to select foreign-currency, long-term, issuer-level ratings between 2000 and 2016. We exclude unsolicited ratings and retain ratings of C or above, limiting the selection to firms with a non-missing GVKEY identifier. To perform the analysis, we convert the categorical rating data into numerical rating scores where the highest rating AAA is set equal to 1 and the lowest rating (included in our study) C is set equal to 21. Table A.1 of the Appendix contains the full list of the numerical rating conversions. Accounting data is sourced from the Compustat Global database, with exclusions for financials (SIC 6000–6999), utilities (SIC 4900–4999), and governmental or quasi-governmental entities (SIC 9000 and above). Table A.2 of the Appendix contains the definition and source of each of these firm-level variables. Next, we merge the numerical ratings dataset with the accounting dataset. To ensure that ratings reflect the financial information of the firm, we employ a lag of at least 3 months. We match the financial ratios of a particular fiscal year with the rating score published at least 3 months after the fiscal year ends. The merged dataset with non-missing values contains 26,082 firm-year observations from 63 unique countries and 3,486 unique firms from 2000 to 2016 period. However, since we further sort the dataset by country-year to run the OLS regression to generate the proxy for soft information (i.e., CRSI) for each set of country-year observations, we analyze the data and make sure that for each country-year combination, we have at least 12 observations which is the number of independent variables in the model too. The final dataset contains a sample of 24,162 firm-year observations from 21 countries (Australia, Brazil, Canada, Chile, China, France, Germany, Hong Kong SAR, Indonesia, Italy, Japan, South Korea, Mexico, Netherlands, Russian Federation, Spain, Sweden, Switzerland, Thailand, United Kingdom, and United States) and 3,249 unique firms. All continuous variables are winsorized at the 1^{st} and 99^{th} percentile levels.

National culture, as defined by Hofstede (2001, 1980) encompasses shared values, beliefs, norms, customs, behaviors, and other cultural elements transmitted across generations. This collective mental programming distinguishes members of one human group from another, shaping not only their patterned ways of thinking, feeling, and acting but also their responses to different environments. Importantly, culture shapes how individuals perceive the external world and influences their decisions and behaviors (Zheng et al. 2011), which can influence market transactions (e.g. Williamson 1979, Williamson 2000) and other economic outcomes. Following extant literature (e.g., Zheng et al. 2011, El Ghoul et al. 2021, Abdallah et al. 2022, Zhou et al. 2022, among many others), we measure national culture using the widely accepted Hofstede's (2001) four cultural dimensions: (i) uncertainty avoidance, which is based on people's preference for certainty and the extent of their discomfort with unstructured or ambiguous situations; (ii) individualism, which assesses and measures how much a society emphasizes individual versus group roles;[5] (iii) power distance, which measures the degree to which individuals of lower power expect and accept unequal power distribution; and (iv) masculinity, which gauges the general inclination towards assertiveness (masculine) or nurturing behavior (feminine), without prescribing specific gender distinctions but focusing on stereotypical associations. The cultural dimension dataset is collected from Geert Hofstede's website.[6] The score for each dimension ranges from 0 to 100, with 50 as a mid-point. A score under 50 means a country

[5] Individualism characterizes societies with loose interpersonal ties, primarily focusing on individual goals.
[6] Geert Hofstede's website makes the latest cultural dimension data (2015) available and generously allows researchers to use them without asking for permission. Link: https://geerthofstede.com/research-and-vsm/dimension-data-matrix/

is relatively low on that dimension and above 50 means high. The country dimensions are relative; for example, if a country has a score of 60 on individualism, it is more individualistic than a country that has a score of 55 on individualism.

CHAPTER 4 METHODOLOGY AND FINDINGS

4.1. Soft Information Proxy (CRSI)

To construct our soft information proxy (i.e., CRSI), we perform a regression on the determinants of CR for each set of country-year observations, following the approach outlined in Attig et al. (2020) and Baghai et al. (2013). We run the following OLS regression model for each set of country-year observations:

$$CR_{i,t} = \alpha_0 + \alpha_1 FIRMCTRL_{i,t} + \varepsilon_{i,t},$$

where $CR_{i,t}$, the dependent variable, is S&P's rating of firm i in year t. We convert S&P's rating into numerical scores on the following scale: AAA = 1; AA+ = 2; AA = 3; AA- = 4; …; and C = 21. The model controls for the following firm characteristics: Total debt ratio, Debt to cash flow ratio, Interest coverage ratio, Convertible debt ratio, Firm size, Operating margin, Operating margin volatility, Cash ratio, Rent ratio, Tangibility, Capital expenditures ratio, and bound firm dummy (a dummy variable indicating whether a firm has a rating at or above its country sovereign rating).[7] Table A.2 of the Appendix contains the definition and source of each of these firm-level variables.

As stated at the outset, we consider '1 minus Adjusted R-squared' as our proxy for CRSI. We make this choice because Adjusted R-squared accounts for potential overfitting, improving only when an explanatory variable enhances the model fit. In certain country-year combinations, we observe the R-squared reaching 1, while the Adjusted R-squared is zero, signaling to overfit with variables lacking explanatory power. To address this, we exclude observations where the R-squared is 1, and the Adjusted R-squared is zero.

[7] We match these variables with CR by ensuring that their information content is accessible to Credit Rating Agencies before rating announcements (Attig et al. 2020)

4.2. Culture and CRSI

We start our empirical analysis of the linkage between culture and CRSI by running the following model:

$$CRSI_{i,t} = \alpha_0 + \alpha_1 Culture_{i,t} + \alpha_2 ICONV_{i,t} + \varepsilon_{i,t},$$

where i denotes individual countries, and t denotes years. Culture is one of Hofstede's dimensions of national culture. ICONV is a set of institutional control variables. We include GDP growth (GDP Growth) to account for the effects of business cycle and economic changes and use data from the International Country Risk Guide (ICRG) obtained from the Political Risk Services Group (e.g., Dimic et al. 2015, Aziz 2018) to control for the quality of a country's institutional factors. We namely consider (i) political risk (Political Risk), which is a combination of government stability, socioeconomic conditions, investment profile, internal conflict, external conflict, corruption, military in politics, religious tensions, law and order, ethnic tensions, democratic accountability, and bureaucracy quality, (ii) socioeconomic conditions (Socioeconomic Conditions), an index that reflects consumer confidence, poverty, unemployment and other socioeconomic conditions, (iii) risk for foreign debt, and (iv) risk for inflation.

We also include a proxy for a country's legal origin (Legal Origin) and the ratio of private credit to gross domestic product (Private Credit / GDP). Legal Origin reflects the effects of the legal system and country's governance standards since it captures a country's norms and social preferences (Jelic et al., 2023; Döring et al., 2023) and reflects the extent of shareholder protection (La Porta et al. 1999, 2000; Aggarwal et al. 2011). Private Credit / GDP measures financial sector growth and captures the power of creditors (Djankov et al.

2007) and the effect of the size of a country's banking system (Driessen and Laeven 2007). We employ a binary dummy variable to capture the occurrence of a systemic banking crisis, with a value of 1 denoting the presence of a crisis and 0 otherwise (sourced from the World Bank Global Financial Development Database).

4.3. DESCRIPTIVE STATISTICS

Panel A of Table 1 provides descriptive statistics. We then examine the distribution of CRSI over the years (Panel B) and across countries (Panel C). Notably, CRSI exhibits discernible heterogeneity both temporally and geographically.

Table 1 Descriptive Statistics for Key Variables: Panel A of this table presents the descriptive statistics of our key regression variables. Our test variable is CRSI (1), our proxy for soft information in credit rating. Our measures of national culture are uncertainty avoidance (2), individualism (3), power distance (4), and masculinity (5). Our controls are GDP Growth (6), Common Law (7), Political Risk (8), Socioeconomic Risk (9), Banking Crisis (10), and Private Credit / GDP (11). We then report the distribution of CRSI over the years (Panel B) and across countries (Panel C). All continuous variables are winsorized at the 1^{st} and 99^{th} percentile levels.

Panel A: Descriptive Statistics

	N	Mean	P25	P50	P75	SD
(1) CRSI	255	0.44	0.31	0.45	0.54	0.21
(2) Uncertainty Avoidance	255	61.39	46	58	85	21.63
(3) Individualism	255	59.5	38	68	80	25.41
(4) Power Distance	255	52.93	35	40	68	19.28
(5) Masculinity	255	52.66	42	57	66	21.77
(6) GDP Growth	255	2.47	1.38	2.48	3.88	2.52
(7) Common Law	255	0.35	0	0	1	0.48
(8) Political Risk	255	79.07	73.13	81.63	86.46	9.55
(9) Socioeconomic Risk	255	8.37	7.5	8.54	9.38	1.46
(10) Banking Crisis	255	0.09	0	0	0	0.29
(11) Private Credit / GDP	243	112.16	80.74	113.84	154.98	51.31

Panel B: Annual Distribution of CRSI

YEAR	2000	2001	2002	2003	2004	2005	2006	2007	2008
CRSI	0.49	0.45	0.36	0.46	0.45	0.48	0.43	0.35	0.43
YEAR	2009	2010	2011	2012	2013	2014	2015	2016	-
CRSI	0.45	0.48	0.48	0.49	0.38	0.45	0.48	0.41	-

Panel C: CRSI Distribution of across countries

Country	AUS	BRA	CAN	CHE	CHL	CHN	DEU	ESP	FRA	GBR	HKG
CRSI	0.43	0.53	0.47	0.38	0.72	0.26	0.56	0.88	0.52	0.45	0.28
Country	IDN	ITA	JPN	KOR	MEX	NLD	RUS	SWE	THA	USA	-
CRSI	0.44	0.24	0.52	0.42	0.41	0.42	0.46	0.26	0.37	0.46	-

The CRSI reports the 1-adjusted r-squared value for each 255-country-year combination and it appears to be normally distributed. The median uncertainty avoidance, masculinity, and individualism seem to be relatively high across the countries while power distance is low. The distribution of CRSI across countries and years indicates that most of the countries exhibit a nice room for unexplained variance in credit ratings which is worth exploring.

4.4. FINDINGS

We now turn our focus to our main research question: the potential impact of culture on CRSI. The related results are reported in Table 2. OLS regression results are in column 1. In column 2, we add year-fixed effects to control for any time-varying factors, and in column 3 we cluster errors at the country level to account for potential serial correlations. Interestingly, across all specifications of Table 2, Uncertainty Avoidance loads positively and significantly, whereas Power Distance bears a negative and significant effect on CRSI.

Since uncertainty avoidance refers to a cultural dimension that reflects the extent to which members of a society feel uncomfortable with ambiguity, uncertainty, and unpredictability, its positive association with CRSI may appear surprising at first glance. This is because CRAs in high-uncertainty avoidance countries may be more inclined to prioritize hard information over soft information in their ratings to provide a sense of certainty and predictability. However, such a positive association indicates that CRAs place some weight on qualitative and subjective information in their ratings, to plausibly avoid uncertainty that may result from non-quantifiable factors.

Power Distance measures the extent to which individuals in a society anticipate and embrace unequal power distribution. In cultures characterized by higher Power Distance, where hierarchical structures are more widely accepted, the observed negative relationship suggests that credit rating agencies (CRAs) in these countries may tend to prioritize quantitative and objective metrics in their ratings. The inclination to eschew soft information in such cultures could be ascribed to a preference for more structured and hierarchical decision-making processes.

The significance of the estimated coefficients for both uncertainty avoidance and power distance underscores the impact of cultural dimensions on determining the role of soft information in credit ratings.

Turning to the other control variables, only legal origin (Common Law) bears a significant effect on CRSI. Its positive coefficient suggests that common law countries are associated with more soft information in credit ratings. La Porta et al. (1999) argue that common-law countries, compared to civil-law countries, have stronger investor protection and, therefore, have higher corporate governance quality.

Table 2 National Culture and Credit Rating Soft Information: This table reports the results of multivariate regression analysis examining the link between a firm's CRSI and Hofstede's dimensions of national culture. We namely examine the effect of uncertainty avoidance, individualism, power distance, and masculinity. We control for the country's GDP Growth, legal origin (Common Law), Political Risk, Socioeconomic Risk, Banking Crisis, and the ratio of Private Credit / GDP. In column 2, we include year-fixed effects, and in column 3 we cluster errors at the country level. All continuous variables are winsorized at the 1^{st} and 99^{th} percentile levels. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)
Uncertainty Avoidance	0.005***	0.005***	0.005***
	(4.366)	(4.248)	(4.352)
Individualism	-0.000	0.000	0.000
	(-0.220)	(0.121)	(0.099)
Power Distance	-0.005**	-0.005**	-0.005**
	(-2.534)	(-2.373)	(-2.450)
Masculinity	0.000	0.000	0.000
	(0.027)	(0.318)	(0.299)
GDP Growth	0.001	0.007	0.007
	(0.235)	(0.825)	(0.983)
Common Law	0.096**	0.088*	0.088**
	(2.107)	(1.879)	(2.252)
Political Risk	-0.004	-0.003	-0.003
	(-0.976)	(-0.740)	(-1.144)
Socioeconomic Risk	-0.013	-0.015	-0.015
	(-0.734)	(-0.804)	(-0.670)

	(1)	(2)	(3)
Banking Crisis	-0.010	-0.016	-0.016
	(-0.229)	(-0.270)	(-0.384)
Private Credit / GDP	-0.000	-0.000	-0.000
	(-0.187)	(-0.188)	(-0.258)
Constant	0.742**	0.693**	0.693**
	(2.576)	(2.013)	(2.430)
Year Fixed Effects	NO	YES	YES
Clustered Errors	NO	NO	YES
Observations	243	243	243
R-squared	0.127	0.173	0.173

CHAPTER 5 ROBUSTNESS TESTS

In Table 3, we test the stability of our findings to the inclusion of additional variables to curtail the effect of the potential bias of omitted variables. We sequentially and then concurrently control for the following additional variables: Long-Term Orientation, a salient aspect of national cultural values, reflecting the emphasis on future planning, consideration, and the value placed on traditions (Nevins et al., 2007), and government effectiveness. Results of using these additional controls, reported in columns 1-3 of Table 3, indicate that our fresh evidence of positive (negative) association between CRSI and uncertainty avoidance (power distance) continues to hold. In the last column of Table 3 (i.e. column 4), we add the extent of disclosure index (Extent of Disclosure). Collected by the World Bank, the Extent of Disclosure measures the quality of business disclosure (e.g., the extent to which a corporate body provides legally sufficient approval for transactions and the timeliness of their disclosure). While caution is merited in expanding on the related findings since we lose more than 25% of our sample, the estimated coefficients of uncertainty avoidance and power distance remain unchanged.

Table 3 National Culture and Credit Rating Soft Information (potential omitted variables): This table reports the results of multivariate regression analysis examining the link between a firm's CRSI and Hofstede's dimensions of national culture. We reproduce the results of the last column of Table 2 after controlling separately for Long-Term Orientation' (column 1) and 'Government Effectiveness' (column 2). In column 3, we concurrently include these potentially omitted variables in the same regression. In column 4, we control for the Extent of Disclosure. We include year-fixed effects and cluster errors at the country level in all regressions. All continuous variables are winsorized at the 1st and 99th percentile levels. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)
Uncertainty Avoidance	0.005***	0.005***	0.005***	0.006***
	(4.093)	(4.738)	(4.584)	(5.428)

	(1)	(2)	(3)	(4)
Individualism	0.000	-0.000	-0.000	-0.002
	(0.028)	(-0.033)	(-0.190)	(-1.602)
Power Distance	-0.005**	-0.005**	-0.005**	-0.007***
	(-2.525)	(-2.553)	(-2.641)	(-4.457)
Masculinity	0.000	0.001	0.001	0.001
	(0.266)	(0.771)	(0.707)	(0.765)
GDP Growth	0.007	0.010	0.011	0.003
	(0.998)	(1.395)	(1.438)	(0.364)
Common Law	0.084**	0.086**	0.077*	0.087*
	(2.309)	(2.276)	(2.012)	(2.019)
Political Risk	-0.003	-0.009**	-0.009**	-0.005
	(-1.226)	(-2.160)	(-2.301)	(-1.095)
Socioeconomic Risk	-0.014	-0.021	-0.020	-0.043*
	(-0.636)	(-1.123)	(-1.058)	(-1.977)
Banking Crisis	-0.015	-0.006	-0.003	0.007
	(-0.362)	(-0.134)	(-0.080)	(0.144)
Private Credit / GDP	-0.000	-0.001	-0.000	0.000
	(-0.107)	(-1.444)	(-1.067)	(1.126)
Long-Term Orientation	-0.000		-0.000	-0.001
	(-0.235)		(-0.504)	(-0.956)
Government Effectiveness		0.110*	0.114**	0.043
		(2.025)	(2.142)	(0.726)
Extent of Disclosure				-0.006
				(-0.786)
Constant	0.718**	1.072***	1.135***	1.217***
	(2.627)	(2.912)	(2.999)	(3.320)
Year Fixed Effects	YES	YES	YES	YES
Clustered Errors	YES	YES	YES	YES
Observations	243	243	243	179
R-squared	0.173	0.191	0.192	0.225

So far, our findings suggest that credit ratings in countries with increased levels of the dimensions of national culture, specifically uncertainty avoidance (and power distance), are more (less) likely to incorporate soft information. In a final test, we investigate whether our findings vary across regions. To this end, we classify our sample countries as developed and emerging economies. The country classification has been done according to the World Economic Situation and Prospects Report 2023 by the United Nations Department of Economic and Social Affairs (UN DESA). We report the results in columns 1 and 2 of Table 4. The estimated coefficients of uncertainty avoidance and power distance maintain their signs and significance only in the sample of developed countries. The (absence of) influence of cultural dimensions on soft information in developed (emerging) countries may appear surprising at first glance, as one might expect credit ratings to reflect more hard and quantifiable information in these economies. However, this evidence corroborates Attig et al.'s (2020) findings that standards tightening for the U.S. and other developed countries is likely unwarranted, whereas standards loosening in emerging economies appears to be justified.

Table 4 National Culture and Credit Rating Soft Information: Developed vs Emerging Countries. This table reports the results of multivariate regression analysis examining the link between a firm's CRSI and Hofstede's dimensions of national culture. We reproduce the results of the last column of Table 3 separately for developed countries (column 1) and emerging countries (column 2). We include year-fixed effects and cluster errors at the country level in all regressions. All continuous variables are winsorized at the 1st and 99th percentile levels. Significance level: *** p < 0.01, ** p < 0.05, * p < 0.1.

	(1)	(2)
Uncertainty Avoidance	0.007***	-0.002
	(3.378)	(-0.978)
Individualism	-0.004	-0.003
	(-1.351)	(-0.610)
Power Distance	-0.010**	-0.002
	(-2.370)	(-0.843)
Masculinity	-0.001	-0.006*
	(-0.684)	(-2.110)
GDP Growth	0.005	0.006
	(0.466)	(0.536)
Common Law	0.277**	-0.124*
	(2.946)	(-2.022)

	(1)	(2)
Political Risk	-0.022**	0.019
	(-2.496)	(1.582)
Socioeconomic Risk	-0.003	-0.083
	(-0.156)	(-1.324)
Banking Crisis	0.016	-0.016
	(0.497)	(-0.210)
Private Credit / GDP	-0.001*	-0.001
	(-2.157)	(-0.655)
Long-Term Orientation	0.001	-0.002
	(0.894)	(-1.172)
Government Effectiveness	0.250**	-0.071
	(2.258)	(-0.491)
Constant	2.187**	0.572
	(2.333)	(0.922)
Year Fixed Effects	YES	YES
Clustered Errors	YES	YES
Observations	159	82
R-squared	0.403	0.266

CHAPTER 6 CONCLUSION

Credit ratings play a central role in disseminating credit information to market participants and shaping a firm's financing and capital structure. Substantial literature has emerged to investigate the economic implications and determinants of credit ratings. Notably absent from this literature is the exploration of the determinants of soft information in credit ratings. The scarcity of research in this area is particularly surprising because recent evidence suggests that global rating standards change over time, and a firm with consistent fundamentals may receive different ratings, indicating the potential role of soft information in credit ratings. Our study contributes to filling this important gap. Using Hofstede's (2001) four cultural dimensions (uncertainty avoidance, collectivism, power distance, and masculinity) to capture the national culture, our regression results suggest a positive (negative) association between uncertainty avoidance (power distance) and soft information in credit ratings. Importantly, this result holds even after controlling for country institutional factors such as the legal origin, political, financial, and economic factors. Furthermore, we observe that this new evidence is discernible primarily in developed countries. This study, nonetheless, admits some limitations. Firstly, the soft information proxy in this study is a statistical measure (unexplained variance in credit rating model) that is prone to misspecification and measurement errors that can result in biased prediction. Hence, one should take caution in interpreting the findings of this study and future research may focus on developing a more fundamental proxy for soft information. Secondly, rating agencies typically incorporate private information as well which our study could not account for. The lower explanatory power of the model suggests that there is a large proportion of unexplained dimensions in credit rating soft information, possibly including private information, leaving the area wide open for further research.

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APPENDIX A

TABLE A.1 FULL LIST OF THE NUMERICAL RATING CONVERSION

Rating	Numerical Rating
AAA	1
AA+	2
AA	3
AApi	3
AA-	4
AA-pi	4
A+	5
A+pi	5
A	6
Api	6
A-	7
A-/NR	7
BBB+	8
BBB+pi	8
BBB	9
BBBpi	9
BBB/NR	9

Rating	Numerical Rating
BBB-	10
BBB-pi	10
BB+	11
BB+pi	11
BB	12
BBpi	12
BB-	13
BB-pi	13
B+	14
B+pi	14
B	15
Bpi	15
B-	16
CCC+	17
CCC	18
CCC-	19
CC	20
C	21

TABLE A.2 DEFINITION AND SOURCE OF FIRM-LEVEL VARIABLES

Variable	Definition	Source
Rating	Numerical score of S&P firm long-term issuer level credit rating on the following scale: AAA = 1, ……, C = 21.	S&P Capital IQ database
Tangibility	Property, plant, & equipment (PPENT) scaled by total assets (AT)	Compustat Global database
Capital expenditures ratio	Capital expenditures (CAPX) scaled by total assets (AT).	Compustat Global database
Cash ratio	Cash and short-term investments (CHE) scaled by total assets (AT)	Compustat Global database
Debt to cash flow ratio	Long-term debt (DLTT) plus debt in current liabilities (DLC), all scaled by operating income before depreciation (OIBDP).	Compustat Global database
Interest coverage ratio	Operating income before depreciation (OIBDP) scaled by interest expense (XINT).	Compustat Global database
Total debt ratio	Long-term debt (DLTT) plus debt in current liabilities (DLC), all scaled by total assets (AT)	Compustat Global database
Convertible debt ratio	Convertible debt (DCVT) scaled by total assets (AT), where DCVT is set equal to zero if it is missing.	Compustat Global database
Operating margin	Operating income before depreciation (OIBDP) scaled by sales (SALE).	Compustat Global database

Variable	Definition	Source
Rent ratio	Rental expense (XRENT) scaled by total assets (AT).	Compustat Global database
Firm size	Natural logarithm of total assets (AT) measured in constant 2010 dollars.	Compustat Global database
Operating margin volatility	Rolling standard deviation of the five most recent observations of operating margin, with a minimum of two observations.	Compustat Global database
Bound firm dummy	A dummy variable indicating whether a firm has a rating at or above its country's sovereign rating	S&P Capital IQ database