Chapter 8
Effects of Corporate Social Performance on Default Risk: Structural Model-Based Analysis on Japanese Firms

In this chapter, we examine how firms' corporate social performance (CSP) is related to firm default risk. We estimate the default risk of a firm by employing the structural credit risk model first developed by Merton (1974). Using the model, we explain the theoretical linkage between CSP and the probability of default (PD). We find that CSP is positively associated with the PD of financially unconstrained large-capital firms. However, PD among those large-capital firms is extremely low, and CSP exerts little influence over default risk. By contrast, among small-capital firms, CSP is negatively associated with PD. This result implies that a higher degree of CSP alleviates the default risk of small-capital firms. These asymmetric CSP effects on PD can be explained by the difference in risk and profit reduction between large- and small-capital firms. Financially constrained small-capital firms can reduce their PD and cost of debt by improving their CSP, although their corporate social responsibility (CSR) activities are detrimental to the profitability of the firm. Thus, managers of financially unconstrained small-capital firms should pay more attention to CSR activities to enhance trustworthiness in the capital market by mitigating social risk.

8.1 CSP and Expected Default Probability

There has been ongoing debate among researchers as to whether a positive relationship exists between the social and financial risk of firms and whether superior CSP reduces the financial risk of a firm. If firms with superior CSP win the confidence of capital market participants, their continual CSR activities would be rewarded in a form that provides easier access to external funds with lower cost of capital. Thus, CSR is a matter of great importance to managers today. However, as a firm spends its corporate resources, such a belief in support for CSR activities is right in some respects but wrong in others. In this chapter, we empirically show that

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the correlation between CSP and default risk after controlling for firm attributes is positive among large-capital firms and negative among small-capital firms.

We explain the link between CSP and default firm risk based on the structural risk model developed by Merton (1974). In Merton's model, three parameters determine the PD: volatility in the market value of total assets, expected future growth rate of total assets, and current market value of total assets. All these three model parameters are influenced by the CSP level; however, the effects from CSP on these parameters vary. In the case of financially unconstrained large-capital firms, for example, the reduction in total asset volatility and slowing down of the growth rate of total assets negate each other. It is not necessarily the case that CSP is negatively related to default risk.

Once the model to estimate PD is constructed, the credit spread is estimated by employing the valuation model of the defaultable bond, consistent with Jarrow and Turnbull (1995), in which the loss given default (LGD) of an individual firm's debt represents prior knowledge. Because it is difficult to estimate the LGD of Japanese corporate bonds, based on Merton's (1974) model and under the assumption of risk neutrality, we compute the cost of firm debt as the expected bond yield. The results presented in this chapter suggest that the impact of CSP on the cost of debt is no longer negligible for small-capital firms, although it is marginal for large-capital firms.

8.2 Literature Review and Hypothesis Development

8.2.1 CSP and Credit Risk

Several recent studies confirm that CSP is negatively associated with firm market-based risk (Boutin-Dufresne and Savaria 2004; Salama et al. 2011; Mishra and Modi 2013; Gregory et al. 2014). With respect to Japanese data, Suto and Takehara (2015) also find a negative and statistically significant relationship between CSP and the historical volatility of stock returns. Typically, information related to CSP is disseminated into the market price of stocks and bonds.

Suppose that superior CSP reduces the market-based risk. Then, does enhancement of CSP cause a decrease in the cost of capital? This research question represents the starting point for the study presented in this chapter. El Ghoul et al. (2011) demonstrate CSR's effectiveness in reducing the cost of equity capital. Menz (2010) and Goss and Roberts (2011) examine the links between CSR and bank debt and bond markets, respectively; however, the results from these previous studies are inconclusive. These studies suggest that investors and creditors are conscious of the CSR policies and practices of firms in their evaluation of the firms' risk. In addition, Goss and Roberts (2011) find that lenders are indifferent to CSR investments by high-quality borrowers while low-quality borrowers that engage in discretionary CSR spending face higher loan spreads and shorter maturities. Thus, statistical test results might be misleading if we erroneously pool all the data during a sample period by disregarding the difference in firm attributes among sample firms.

In addition, some recent studies examine the relationship between CSP and PD by employing a structural credit risk model. Chang et al. (2013) investigate the relationship between CSP and PD by employing Delianedis and Geske's (2003) credit risk model. For firms listed in Taiwan, the authors find a negative and significant relationship between CSP and PD. Using the data of Japanese public firms, Ajward and Takehara (2014) examine whether superior CSP reduces financial constraints and find that CSP is negatively associated with financial constraints. Because Ajward and Takehara (2014) use the distance to default (DD) as one of the measures of financial constraints, their results indirectly suggest the reduction of default probability by CSR activities.

However, the findings in the earlier studies based on credit risk models are not persuasive because the authors used linear regression analyses to examine the relationship between CSP and PD. As we confirm, the relationship between CSP and PD must be non-linear because the structural credit risk model is developed based on the option pricing model. Linear regression models are not adequate for investigating the effects of CSP on PD.

8.2.2 Hypothesis Development

A brief overview of Merton's (1974) structural risk model should appear in the next section. However, we present it here because the research hypotheses in this chapter are closely related to the structure of Merton's model.

We estimate the Black–Scholes–Merton (BSM) PD (Black and Scholes 1973; Merton 1974) and examine the effect of the CSP level on the model parameters. The BSM probability of bankruptcy (*BSM*) is given as follows.

$$BSM = N\left(-\frac{\ln(V_A/D) + (\mu_A - (\sigma_A^2/2)T)}{\sigma_A\sqrt{T}}\right) \tag{8.1}$$

In Eq. (8.1), there are three parameters: σ_A is total asset volatility, μ_A is the expected growth rate of total assets, and V_A is the market value of total assets. All three variables are unobservable in the stock market, because the total assets of the firm are not tradable in the stock market. We estimate these three parameters in Merton's model based on the estimation method developed by Vassalou and Xing (2004). *N*( ) in Eq. (8.1) denotes the cumulative distribution function of the standard normal distribution, and D and T represent total debt and debt maturity, respectively. Both D and T are constant, and we assume that D equals the book value of debt on the balance sheet and set $T = 1$ (year) as a matter of practical convenience.

The quantity defined in the next Eq. (8.2), which appears in parentheses in Eq. (8.1), is called DD.

$$DD = \frac{\ln(V_A/D) + (\mu_A - (\sigma_A^2/2)T)}{\sigma_A\sqrt{T}} \tag{8.2}$$

This measure indicates the default risk of a firm at the corporate level. Default is assumed to occur when the ratio of total assets to debt (V_A/D) is less than 1 (or its log value is negative), indicating that the DD measure informs the number of standard deviations that the log of this ratio is required to deviate from the mean for default to take place. Accordingly, higher DD values indicate that the PD is lower while lower DD values indicate a higher risk of default.

We assume that each of the three parameters, σ_A, $\mu_{A,}$ and V_A, is a linear function of CSP and firm attribute variables. We determine the adequacy of this linearity assumption by employing the portfolio formation method in the next section. It should also be noted that we control firm size by employing the size dummy variables. We assume that a linear relationship exists even after controlling firm size.

How is the level of CSP associated with the parameters? First, we expect that CSR activities mitigate the firm's financial risk and reduce total asset volatility. Previous studies support this expectation (Boutin-Dufresne and Savaria 2004; Salama et al. 2011; Gregory et al. 2014; Mishra and Modi 2013). Therefore, we posit Hypothesis 1 in this chapter as follows.

Hypothesis 1. Within equal-sized firms, CSP is negatively associated with total asset volatility.

Even if CSR activities reduce total asset volatility, they also reduce the expected growth rate of total assets. To improve the degree of CSP, firms must allocate their limited financial and managerial resources to CSR activities. However, CSR activities are detrimental to the short-term profitability of the firm.[1] Accordingly, we propose the following Hypothesis 2.

Hypothesis 2. Within equal-sized firms, CSP is negatively associated with the expected growth rate of total assets.

The total assets to debt ratio, V_A/D, appears as the first term of the numerator of DD defined in Eq. (8.2). Let V_E denote the market value of equity, then $V_A/D = 1 + V_E/D$ by definition. In Merton's model, the market value of equity V_E is assumed equal to the call option premium, which is written in the market value of total assets V_A, as in Eq. (8.3).

[1]CSR activities might enhance the long-term profitability of the firm, but this is not the focus of this study, in which we discuss default within a relatively short term. It is difficult to assume that firms can reduce asset volatility without lowering the growth rate of assets in the short term.

$$
\begin{aligned}
V_E &= V_A N(d_1) - X e^{-r_f t} N(d_2), \\
d_1 &= \frac{\ln(V_A/D) + (\mu_A + (\sigma_A^2/2)T)}{\sigma_A \sqrt{T}}, \\
d_2 &= d_1 - \sigma_A \sqrt{T}.
\end{aligned}
\tag{8.3}
$$

When volatility σ_A is a decreasing function of CSP, and drift term μ_A is not an increasing function of CSP, V_E must be a decreasing function of CSP, because the *vega,* which is defined as the call option's sensitivity to changes in volatility σ_A, is positive in the case of (8.3). Thus, when both Hypothesis 1 and 2 are simultaneously supported, the following Hypothesis 3 is automatically supported.

Hypothesis 3. Within equal-sized firms, CSP is negatively associated with the ratio of assets to debt.

As we confirm it in the next section, the correlation coefficient between CSP and DD is positive, which implies that CSP is negatively associated with PD. However, Ajward and Takehara (2014) note that the relationship between CSP and DD is different among size-ranked decile portfolios. The behavior of financially constrained and unconstrained firms is inferred to differ in terms of CSP. If firm size can be regarded as a good proxy for financial constraint (Fazzari et al. 1988), then the relationship between CSP and PD among large-capital firms must be different from the relationship between CSP and PD among small-capital firms.

Therefore, we expect that financially unconstrained large-capital firms can invest more in CSR activities to enhance their CSP, which will largely reduce total asset volatility. However, investment in CSR activities reduces the market value of total assets and the expected growth rate of total assets in the short term. As a result, CSR activities increase default risk. Accordingly, we propose Hypothesis 4 as follows.

Hypothesis 4. Among financially unconstrained firms, CSP is positively associated with PD.

By contrast, for financially constrained small-capital firms, we do not expect a flat (or slightly positive) relationship between CSP and PD. As noted by Guariglia (2008), small-capital firms are particularly susceptible to information asymmetry effects and, overall, face financial constraints. Because financially constrained firms do not have excess free cash flows and have difficulty in accessing external funds, small-capital firms mitigate their financial constraints through their CSR activities. Based on this inference, Hypothesis 5 is posited as follows.

Hypothesis 5. Among financially constrained firms, CSP is negatively associated with PD.

8.3 Results from the Portfolio Formation Approach

8.3.1 CSP Measure, Parameter Estimates, and Control Variables

The composite CSP measure used in this chapter is the same one used throughout this book. The sample period in this chapter is from 2007 to 2016. Table 8.1 classifies the listed companies into three groups for the observed period: companies listed on the First Section of the Tokyo Stock Exchange (TSE), those listed on the Second Section of the TSE, and those listed on other stock exchanges.[2] The number of firm-year samples is smallest at 743 in 2007 and largest at 1,066 in 2016. The total number of samples in the observation period (2007–2016) is 8,634.

To estimate the three parameters in Merton's model, σ_A, $\mu_{A,}$ and V_A, we employ the method developed by Vassalou and Xing (2004), in which market value of equity, historical volatility of daily stock returns, and average realized return of daily stock returns are necessary as initial inputs. We compute these input variables using the NIKKEI NEEDS Database.

When constructing the regression model to investigate the relationship between the CSP score and the three parameters in Merton's model, we control firm size, dependency on a bank, and maturity of debt.

The most important variable we include in the regression model is the natural logarithm of market value of equity (lnMV), which is regarded as a measure of firm size. There are two reasons to pay particular attention to the market value of equity. First, previous studies find that size is positive and strongly associated with CSP and negatively associated with PD. Accordingly, we must control firm size when we ascertain the intrinsic relationship between CSP and PD. Second, in studies that examine the financial constraints of firms using Tobin's q model (Fazzari et al. 1988; Hoshi et al. 1991), firm size is considered a measure of financial constraint. Large-capital firms are assumed to be financially unconstrained, and small-capital firms are more financially constrained in reverse.

There are three more control variables in the regression models. First, we employ the book-to-market (B/M) ratio as a measure of firm financial distress. Second, based on the findings of Arikawa and Miyajima (2005), the debt choice of Japanese firms is effected by the main bank relationship. We include dependency on bank (BankD), which is defined as "bank loans payable" to "interest-bearing debt" in the set of explanatory variables. The last control variable we use is the weight of current liability to debt (WCL), which is defined as "interest-bearing debt classified as current debt" to "total amount of interest-bearing debt." Goss and Roberts (2011) find that low-quality borrowers who engage in discretionary CSR spending face shorter maturities. We expect that Japanese banks do not provide credit lines with

[2] According to Suto and Takehara (2015), the average response rate to Toyo Keizai's CSR questionnaire survey for 2007–2011 is 29.7%.

Table 8.1 Number of samples

	TSE first section	TSE second section	Other exchanges/sections	Total
2007	535	58	141	743
2008	535	63	142	750
2009	546	53	153	766
2010	557	57	161	789
2011	575	56	145	787
2012	593	55	145	805
2013	648	85	134	880
2014	722	94	159	988
2015	800	104	147	1,060
2016	779	115	154	1,066
Total	6,290	740	1,481	8,634

The sample period is from 2007 to 2016, and the total number of firm-year observations is 8,634. Firms that did not respond to the questionnaire survey and financial firms are excluded from the sample

Table 8.2 Descriptive statistics

	Mean	S.D.	25th percentile	Median	75th percentile
CSP	0.234	1.738	−1.200	0.353	1.761
DD	3.208	2.310	1.762	2.890	4.229
σ_A (%)	21.384	13.535	11.925	18.202	27.231
μ_A (%)	1.891	28.590	−10.655	−0.342	11.311
lnV_A/D	0.669	0.525	0.299	0.518	0.888
lnMV	10.650	2.055	9.046	10.523	12.143
B/M (%)	109.049	78.924	56.212	90.811	139.788
BankD (%)	60.977	25.660	42.732	59.961	81.517
WCL (%)	52.848	28.666	30.481	49.639	75.054

CSP CSP score, *DD* Distance to default, σ_A Volatility of total assets in %, μ_A Drift of total assets in %, lnV_A/D Log(market value of total assets/debt), lnMV Natural logarithm of market value of equity (in million JPY), *B/M* Book-to-market ratio in %, *BankD* Dependency on bank in %, *WCL* Weight of current liabilities to interest-bearing debt in %. V_A, $\mu_{A,}$ and σ_A are estimated by the method developed by Vassalou and Xing (2004)

longer maturity to firms with lower CSP. The primary data source for these control variables is the NIKKEI NEEDS database provided by Nikkei Media Incorporated.

Descriptive statistics are reported in Table 8.2. The mean of the CSP score is 0.234. Although the CSP index constructed in Suto and Takehara (2015) has a continuous uniform distribution in the interval (−3, 3), excluding financial firms from the sample makes the average CSP slightly larger than 0. The mean of DD is 3.208, which means that average PD within the next year is 0.067% [= $N(-3.208)$]. The 25th percentile of DD is 1.762, which is equivalent to PD at 3.93%

[= $N(-1.762)$]. As a whole, the average default risk of Japanese listed firms is sufficiently low, although default risk is relatively high in a substantial portion of firms.

The mean of total asset volatility (σ_A) is 21.38% per annum, which is at a reasonable level. By contrast, the mean of the expected growth rate of total assets (μ_A) is relatively low at 1.891% per annum. This might be affected by the long-term recession in Japan and the global financial crisis in 2008. The mean of $\ln V_A/D$ is 0.669, which means that the market value of total assets to debt ratio (V_A/D) equals 1.952.

For the control variables, the natural logarithm of the market value of equity (lnMV) is 10.650. Thus, the average size of firms in the sample is approximately 42 billion. The means for dependency on bank (BankD) and weight of current liabilities (WCL) are 60.977 and 52.848%, respectively.

Table 8.3 shows the Pearson and Spearman correlations among variables and provides a glance into the relationship between CSP and PD. However, the research hypotheses in this chapter cannot be validated based on these correlation numbers, because the relationship is based on the period controlling for firms' attributes. The Pearson correlation between the CSP score and DD is 0.107. Therefore, the higher is the degree of CSP, the lower is the PD; this finding is similar to that obtained in Chang et al. (2013). CSP is positively associated with $\ln V_A/D$ and $\mu_{A,}$ which seems not to support Hypothesis 2 and 3 at first glance. On the other hand, CSP is negatively associated with asset volatility and is consistent with Hypothesis 1.

What cannot be overlooked in Table 8.3 is that CSP is very strongly correlated with firm size. The Pearson (Spearman) correlation between CSP and lnMV is 0.671 (0.684). Thus, we have to control for firm size when we investigate the pure impact of CSP on PD.

8.3.2 Portfolio Formation to Check Linearity

When we employ linear regression analyses in the empirical study, we implicitly assume a linear relationship between the independent variables and the dependent variable. However, Eq. (8.2) shows that the relationship between CSP and DD must be non-linear. Therefore, we relax the assumption and assume a linear relationship between CSP, and three parameters appear in Eq. (8.2). In addition, a positive and very strong relationship between CSP and firm size and a linearity assumption should be confirmed after controlling the size effects.

As a preliminary check of the linearity between CSP and parameters in Eq. (8.2), we construct two types of ranked portfolios. The first is CSP-ranked quintile portfolios. At the end of September of each year t = 2007, …, 2016, all sample firms are ranked by their CSP score and divided into five groups. For each group, we construct an equal-weighted portfolio and buy and hold the portfolio until the end of September of year t + 1. Using this portfolio, we check the linearity between CSP and other variables. The second ranked portfolio comprises 25 size and

Table 8.3 Pearson and Spearman correlations among variables

	CSP	DD	σ_A	μ_A	$\ln V_A/D$	lnMV	B/M	BankD	WCL
CSP	1.000	0.139	0.019	0.009	0.124	0.684	−0.268	−0.068	−0.185
DD	0.107	1.000	−0.060	0.496	0.514	0.308	−0.294	0.013	−0.032
σ_A	−0.066	−0.111	1.000	0.109	0.670	0.186	−0.425	0.076	0.025
μ_A	0.008	0.372	0.218	1.000	0.058	0.103	−0.272	−0.041	−0.023
$\ln V_A/D$	0.086	0.534	0.579	0.125	1.000	0.348	−0.460	0.098	0.009
lnMV	0.671	0.265	0.066	0.101	0.313	1.000	−0.539	−0.131	−0.302
B/M	−0.263	−0.279	−0.329	−0.228	−0.388	−0.504	1.000	0.093	0.162
BankD	−0.060	0.010	0.071	−0.038	0.090	−0.135	0.092	1.000	0.812
WCL	−0.167	−0.010	0.060	−0.015	0.053	−0.290	0.157	0.827	1.000

CSP CSP score, *DD* Distance to default, σ_A Volatility of total assets in %, μ_A Drift of total assets in %, $\ln V_A/D$ Log(market value of total assets/debt), lnMV Natural logarithm of market value of equity (in million JPY), *B/M* Book-to-market ratio in %, *BankD* Dependency on bank in %, *WCL* Weight of current liabilities to interest-bearing debt in %. V_A, μ_A, and σ_A are estimated by the method developed by Vassalou and Xing (2004)

Numbers shown in the lower-left triangular matrix are Pearson correlations, and numbers in the upper-right triangular matrix are Spearman rank correlations

CSP-ranked portfolios. In the first step, firms are ranked based on their market value of equity at the end of September, and we construct size-ranked quintile portfolios. In the second stage, each quintile portfolio size is further subdivided into five groups based on their CSP score. As a result, we obtain size and CSP-ranked 25 (=5 × 5) portfolios. By introducing sequential two-stage sort by size and CSP, we can check the linearity after controlling firms' size.

The 25 size and CSP-ranked portfolios are used to examine the relationship between CSP and PD among firms of similar size. Thus, we construct these 25 size and CSP-ranked portfolios to test Hypothesis 1–5 in a different way.

8.3.3 Relationship Between CSP and Probability of Default

The attributes of CSP-ranked quintile portfolios are shown in Table 8.4. First, DD (PD) is positively (negatively) associated with CSP, although the relationship is not linear. Second, among the three parameters in Eq. (8.2) that define DD, the differences between P1 (highest CSP portfolio) and P5 (lowest CSP portfolio) are significant both for total asset volatility (σ_A) and total asset-to-debt ratio ($\ln V_A/D$). As for the drift, we cannot observe a monotone tendency and, in addition, the difference between P1 and P5 is not statistically significant. By contrast, for the four control variables, the monotone increasing (or decreasing) relationship between CSP and these control variables and the differences (P1–P5) are statistically significant at the 1% level without exception.

Table 8.4 Composite CSP-ranked five portfolios

CSP rank	P1 (High)	P2	P3	P4	P5 (Low)	Diff.	p-value
CSP	2.516	1.488	0.352	−0.893	−2.295	4.811	0.000
DD	3.441	3.518	3.155	3.091	2.834	0.607	0.000
σ_A	20.933	20.858	20.246	21.516	23.366	−2.432	0.000
μ_A	1.301	3.127	1.747	1.522	1.760	−0.460	0.640
$\ln V_A/D$	0.730	0.734	0.630	0.630	0.622	0.108	0.000
lnMV	12.772	11.689	10.295	9.407	9.083	3.689	0.000
B/M	75.449	90.380	123.355	126.619	129.497	−54.049	0.000
BankD	56.910	60.865	63.038	62.209	61.874	−4.963	0.000
WCL	42.884	50.197	56.885	57.692	56.602	−13.718	0.000

CSP CSP score, *DD* Distance to default, σ_A volatility of total assets in %, μ_A Drift of total assets in %, $\ln V_A/D$ Log(market value of total assets/debt), lnMV Natural logarithm of market value of equity (in million JPY), *B/M* Book-to-market ratio in %, *BankD* Dependency on bank in %, *WCL* Weight of current liabilities to interest-bearing debt in %. V_A, $\mu_{A,}$ and σ_A are estimated by the method developed by Vassalou and Xing (2004)

In each year t = 2007, …, 2016, we rank the sample firms based on their CSP score and construct quintile portfolios. P1 (P5) is the highest (lowest) CSP portfolio. "Diff." denotes the difference in variables in each row between P1 and P5 (P1–P5) and p-value denotes the probability value from the paired t-test where the null hypothesis "Diff." equals 0

Table 8.5 shows the attributes of the 25 size and CSP-ranked portfolios. Panel A shows the average CSP score during the sample period (2007–2016). As explained in Sect. 3.1, the CSP index used in this book has a continuous uniform distribution between −3 and 3, and there is a large dispersion between CSP1 (highest degree of CSP) and CSP5 (lowest degree of CSP).

We discuss the linearity between CSP and parameters in the Merton's credit risk model based on the figures shown in panels B, C, and D of Table 8.5. Panels B and D of Table 8.5 and Figs. 8.1 and 8.3 confirm that the relationships between CSP and volatility and relationship between CSP and $\ln V_A/D$ are almost linear in all the size quintile portfolios (labeled MV1 through MV5 in Figs. 8.1, 8.2, 8.3 and 8.4). Because the differences between CSP1 and CSP5 are negative and statistically significant in most cases, both volatility and $\ln V_A/D$ are negatively associated with CSP. Therefore, Hypothesis 1 and 3 are supported. With respect to the drift term μ_A (i.e., expected growth rate of total assets), we cannot find a monotone decreasing relationship with CSP in Fig. 8.2. In panel B of Table 8.5, the differences (CSP1–CSP5) are significant at the 5% level in MV2 and MV4. In panel C of Table 8.5, however, the signs of the differences between CSP1 and CSP5 are all negative and cannot occur by chance. Thus, we have only weak evidence to support Hypothesis 2.

Finally, for the first three size quintiles (MV1, MV2, and MV3) in Fig. 8.4, there is a negative relationship between CSP and DD, which means CSR activities increase the default risk of those large-cap firms. In panel E of Table 8.5 the difference in DD between CSP1 and CSP5 is negative and statistically significant at the 5% level. This finding suggests that among financially unconstrained large-capital firms, CSP is positively associated with PD. This finding supports Hypothesis 4. On the other hand, the difference turns positive at 0.165 in the smallest capital stock portfolio (MV5). Although the difference is not statistically significant, the positive difference between P1 and P5 is supportive of Hypothesis 5. Among small-capital firms that are financially constrained, CSP is negatively associated with PD.

8.4 Results from Regression Analyses

8.4.1 Regression Models

We conduct regression analyses to check the robustness of the findings obtained using the portfolio formation method explained in Sect. 3.3.

We assume that a linear relationship exists between CSP and each of the three parameters, V_A, μ_A, and σ_A. Then, let V_{jt}, μ_{jt}, and σ_{jt} denote the estimated market value of total assets, drift term, and the volatility of firm j in year t. The key explanatory variable is CSP_{jt}, the CSP score of firm j in year t, and we include $BankD_{jt}$ and WCL_{jt} as control variables. BankD is introduced in Chap. 6 while

Table 8.5 Size and CSP-ranked 25 portfolios

CSP rank	CSP1 (High)	CSP2	CSP3	CSP4	CSP5 (Low)	Diff.	p-value
Panel A. Difference in CSP score							
MV1 (Large)	2.895	2.603	2.168	1.657	0.236	2.659	0.000
MV2	2.585	2.011	1.392	0.584	−1.291	3.876	0.000
MV3	2.040	1.092	0.335	−0.615	−1.975	4.015	0.000
MV4	1.254	0.130	−0.684	−1.591	−2.530	3.783	0.000
MV5 (Small)	0.375	−0.710	−1.402	−2.054	−2.694	3.069	0.000
Panel B. Difference in volatility of total assets (σ_A)							
MV1 (Large)	20.121	20.883	23.616	24.231	25.113	−4.992	0.000
MV2	20.744	20.992	22.400	24.285	26.259	−5.515	0.000
MV3	17.776	19.660	21.619	22.465	23.992	−6.215	0.000
MV4	15.730	16.934	18.196	22.594	22.527	−6.797	0.000
MV5 (Small)	17.593	19.632	22.157	23.002	22.187	−4.595	0.000
Panel C. Difference in drift term of total assets (μ_A)							
MV1 (Large)	1.556	1.667	4.771	6.268	5.898	−4.342	0.039
MV2	0.145	1.607	4.580	6.252	8.101	−7.956	0.001
MV3	−0.557	2.105	3.525	3.570	5.140	−5.697	0.012
MV4	−1.192	−1.151	1.070	0.880	4.626	−5.819	0.006
MV5 (Small)	−2.979	−2.166	−0.558	−3.827	−2.017	−0.962	0.625
Panel D. Difference in $\ln V_A/D$							
MV1 (Large)	0.672	0.732	0.929	1.023	1.061	−0.390	0.000
MV2	0.693	0.725	0.761	0.868	0.927	−0.234	0.000
MV3	0.542	0.618	0.670	0.672	0.772	−0.230	0.000
MV4	0.472	0.491	0.532	0.702	0.632	−0.160	0.000
MV5 (Small)	0.386	0.455	0.514	0.470	0.415	−0.029	0.267
Panel E. Difference in distance to default							
MV1 (Large)	3.312	3.481	4.105	4.129	4.228	−0.916	0.000
MV2	3.236	3.373	3.569	3.751	3.703	−0.467	0.003
MV3	3.079	3.296	3.369	3.131	3.530	−0.451	0.025
MV4	3.083	2.884	3.030	3.377	3.207	−0.124	0.478
MV5 (Small)	2.252	2.477	2.479	2.036	2.087	0.165	0.230

In each year $t = 2007, \ldots, 2016$, firms are first ranked by their market value of equity, and size-ranked quintile portfolios are constructed. Then, firms in each of these size-ranked quintile portfolios are further divided into five groups based on their CSP score. As a result, we obtain size and CSP-ranked 25(=5 × 5) portfolios. "Diff." denotes the difference in variables in each row between CSP1 and CSP5 (CSP1 to CSP5), and p-value denotes the probability value from the paired t-test where the null hypothesis "Diff." equals 0

WCL is newly introduced in this chapter to control the duration of debt in the regression analysis.

The base model we introduce is the model with size and year fixed effects. $DSize_{i,j}$ is a size dummy variable, which equals 1 if sample j belongs to the i-th size

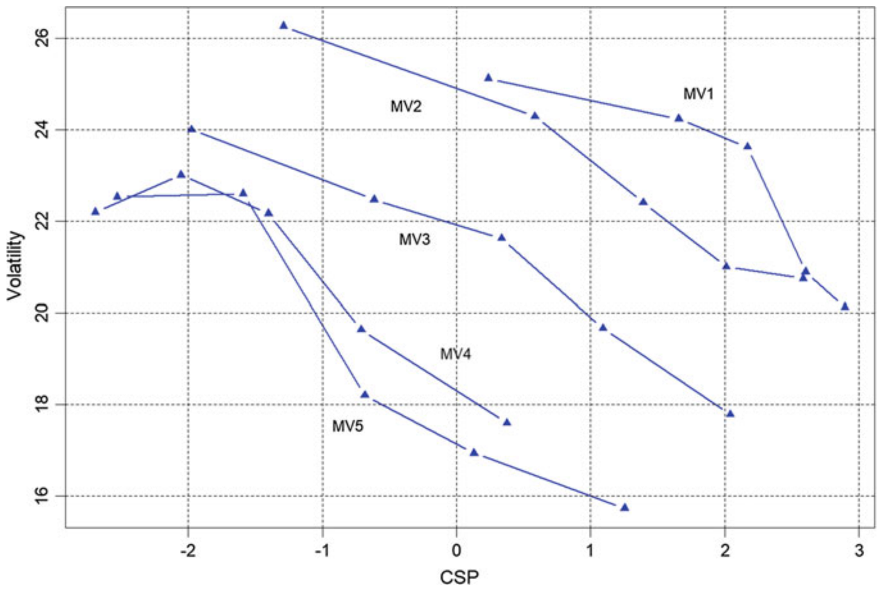

Fig. 8.1 Volatility of 25 size-CSP ranked portfolios

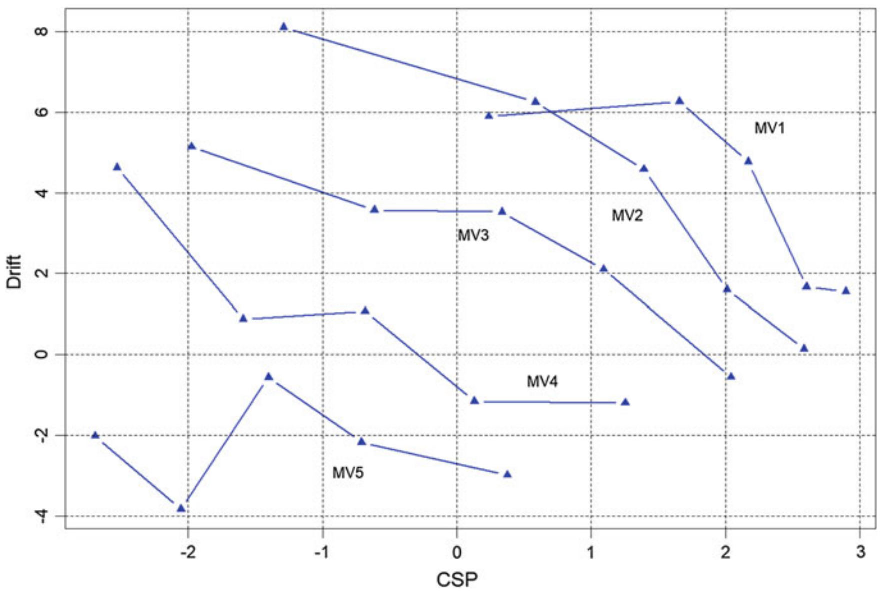

Fig. 8.2 Drift term of total asset (μ_A) of 25 size-CSP ranked portfolios

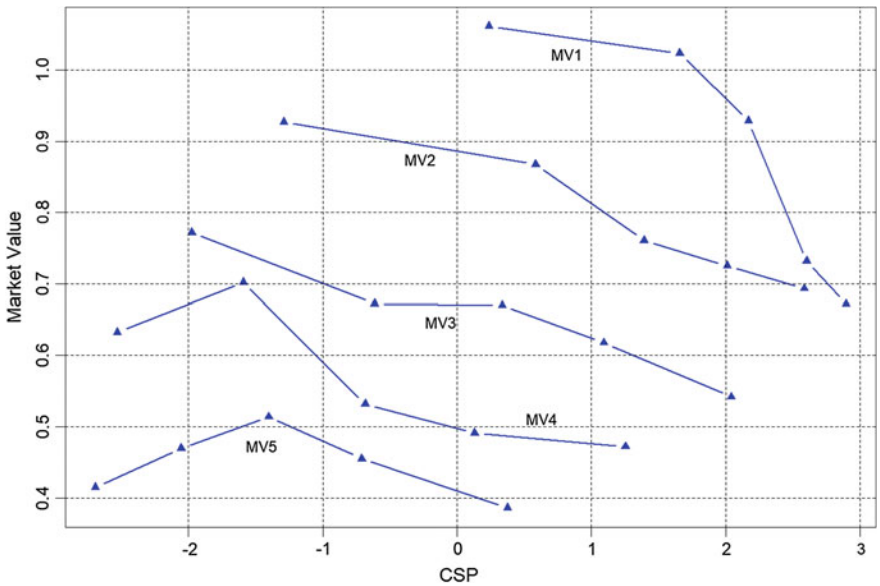

Fig. 8.3 Market value to total assets ($\ln VA/D$) of 25 size-CSP ranked portfolios

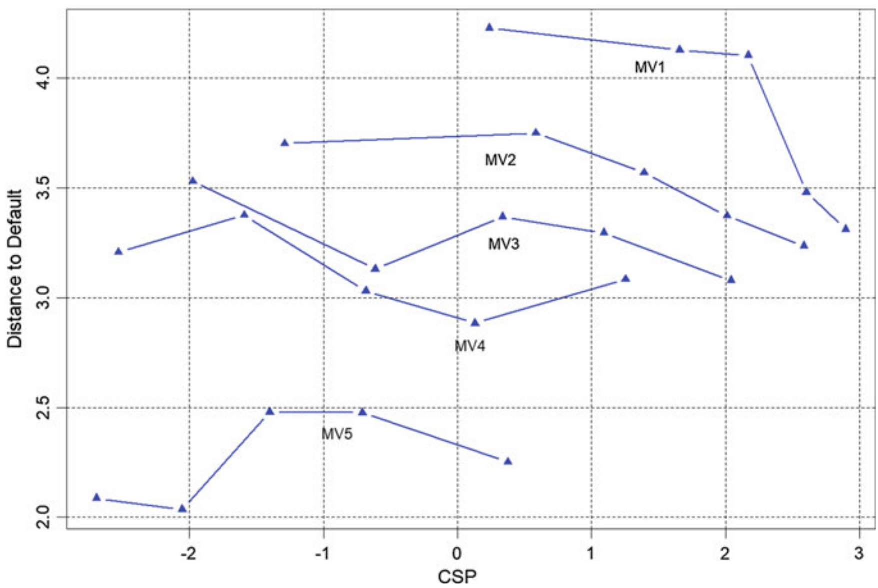

Fig. 8.4 Distance to default of 25 size-CSP ranked portfolios

quintile and 0 otherwise. $DYear_{i,j}$ are the dummy variables for each year (i.e., $t = 2007, \ldots, 2014$, and 2015). Using these notations, the regression model is given as follows:

$$\begin{aligned} y_{jt} = {} & \alpha + \beta_1 CSP_{jt} + \beta_2 BM_{jt} + \beta_3 BankD_{jt} + \beta_4 WCL_{jt} \\ & + \sum_{i=1}^{4} \delta_i DSize_{i+1,j} + \sum_{t=1}^{9} \eta_t DYear_{t+2006,j} + \varepsilon_{jt}. \end{aligned} \tag{8.4}$$

In Model (8.4), the dependent variable y_{jt} is one of the three parameters in Merton's model, that is, σ_A, μ_A, or V_A.

Although our base model (8.4) is a fixed effects model, there is no guarantee that we can pool all firm-year samples disregarding the difference between size quintile and structural change across years. Therefore, we introduce a simpler regression model (8.5) in which size dummy and year dummy are excluded.

$$y_{jt} = \alpha + \beta_1 CSP_{jt} + \beta_2 BM_{jt} + \beta_3 BankD_{jt} + \beta_4 WCL_{jt} + \varepsilon_{jt}. \tag{8.5}$$

We run a regression analysis (8.5) for each size quintile and each year to examine the cross-sectional and time-series change in slope coefficients.

8.4.2 *Findings from Regression Analyses*

The results we obtain by employing a two-stage portfolio formation method support our research Hypothesis 1, 3, 4, and 5. Hypothesis 2 is weakly supported. We examine Hypothesis 1–3 using the regression analyses in which we control dependency on bank and maturity of debt and check the robustness of our previous findings.

Table 8.6 shows the regression slopes and their corresponding probability values in model (8.4). Regression slopes for σ_A, $\mu_{A,}$ and V_A are −1.207, −0.798, and −0.042, respectively. They are all negative and significant at least at the 1% level. Thus, they support Hypotheses 1–3.

Next, in each size quintile and in each year $t = 2007, \ldots, 2016$, we run regression analysis and verify Hypothesis 1–3 allowing the inter-size-quintile and time-series change of regression slope for CSP. For each of the three parameters, we run the regression analysis 50 times (size quintile × 10 years). Table 8.7 shows the regression slopes for CSP (β_1 in (8.5)) and their significance.[3]

Panel A of Table 8.7 shows the results for asset volatility. The slope coefficient for CSP is negative in almost every case, and in 15 out of 50 cases, it is statistically

[3]The slopes for other control variables are not reported because of space constraints. They are available from the authors upon request.

Table 8.6 Results of pooled regression analysis

Dependent variable	σ_A	(p-value)	μ_A	(p-value)	$\ln V_A/D$	(p-value)
Intercept	26.718	0.000	4.253	0.000	0.919	0.000
CSP	−1.207	0.000	−0.798	0.000	−0.042	0.000
B/M	−0.056	0.000	−0.053	0.000	−0.002	0.000
BankD	0.020	0.009	−0.065	0.000	0.001	0.000
WCL	0.030	0.000	0.065	0.000	0.002	0.000
MV2	0.069	0.835	0.185	0.800	−0.086	0.000
MV3	−2.017	0.000	−0.790	0.330	−0.231	0.000
MV4	−4.402	0.000	−2.163	0.018	−0.336	0.000
MV5	−3.155	0.000	−2.821	0.006	−0.409	0.000
D07	−3.046	0.000	−3.840	0.000	−0.027	0.190
D08	3.143	0.000	−21.324	0.000	−0.082	0.000
D09	6.197	0.000	2.087	0.022	−0.116	0.000
D10	−2.991	0.000	0.069	0.932	−0.108	0.000
D11	−1.044	0.026	5.801	0.000	−0.123	0.000
D12	−4.676	0.000	5.408	0.000	−0.132	0.000
D13	1.078	0.031	31.116	0.000	−0.138	0.000
D14	−4.428	0.000	13.083	0.000	−0.038	0.045
D14	−0.823	0.065	6.136	0.000	0.004	0.817
Adjusted R^2	0.235		0.313		0.227	

CSP CSP score, *B/M* Book-to-market ratio, *BankD* Dependency on bank, *WCL* Weight of current liabilities to interest-bearing debt, MV2, …, MV5 Size dummy variables, D07, …, D15 Year dummy variables, σ_A Volatility of total assets in%, μ_A Drift of total assets in %, $\ln V_A/D$ Log (market value of total assets/debt). Columns labeled p-value to the immediate right of the dependent variables are probability values of slope coefficients. Standard errors are corrected by White's (1982) method

significant at the 10% level. From the findings in Tables 8.5, 8.6, and 8.7, we conclude that a higher degree of CSP is negatively associated with total asset volatility.

Next, for the drift term of total assets, the slope coefficient is negative in 36 cases and positive in 14 cases. In three cases, the regression slope for CSP is positive and significant at the 10% level. In addition, even among same size quintile portfolios, the signs of slopes are positive in some years but negative in others. We infer that the relationship between CSP and asset growth rates is unstable across years and depends on economic conditions to some extent.

Finally, the $\ln V_A/D$ slopes for CSP shown in Panel C of Table 8.7 are negative in most cases. This tendency again supports Hypothesis 3, and the spending on CSR activities might reduce the total asset value of the firm.

Table 8.7 Summary of year-by-year regression analysis

Year	MV1 (Large)	MV2	MV3	MV4	MV5 (Small)
Panel A. Dependent variable = Volatility of total assets (σ_A)					
2007	−0.060	−0.037	−0.035	−0.001	0.011
2008	−0.039	−0.068***	−0.017	0.001	−0.003
2009	−0.052*	−0.008	−0.036	−0.018	0.026
2010	−0.022	−0.056	−0.010	−0.014	0.010
2011	−0.056*	−0.027	−0.006	0.002	0.006
2012	−0.117**	−0.013	−0.036*	0.007	−0.021
2013	−0.103**	−0.007	−0.020	−0.050**	0.001
2014	−0.215***	−0.041	−0.030	−0.052***	−0.004
2015	−0.135***	−0.038*	−0.032	−0.058***	0.006
2016	−0.149***	−0.031	−0.061***	−0.038**	0.006
Panel B. Dependent variable = Drift of total assets (μ_A)					
2007	1.799	−1.638	1.587	−0.695	−1.285
2008	−1.514	1.375	1.158	−1.339	1.819
2009	−0.946	−0.730	−4.597***	−0.447	−0.806
2010	1.923*	2.120**	0.337	−0.092	−1.727**
2011	−2.305**	−1.630*	−0.236	0.238	−1.832***
2012	−0.243	−1.725	−0.528	−0.763	−1.734**
2013	−0.257	−2.518**	−0.702	−1.966	−2.741**
2014	−2.789*	−0.509	−0.863	0.800	2.406**
2015	−6.365***	−2.883**	0.057	0.222	−0.641
2016	−0.292	−1.856**	−0.877	−0.653	1.206
Panel C. Dependent variable = Natural logarithm of total assets to debt (ln V_A/D)					
2007	−1.370***	−1.038**	−0.684	−0.308	−0.436
2008	−0.272	−2.294***	−1.132**	−0.037	−2.352**
2009	−1.829**	−0.986	−1.181	−0.652	−1.257
2010	0.100	−0.870*	−0.623*	−0.781	−0.817
2011	−0.896	−0.261	−0.327	−1.117*	−2.724**
2012	−0.591	−1.105**	−0.379	−0.377	−2.181***
2013	−0.996	−0.847*	−0.803	−2.947	−1.974
2014	−3.891***	−1.551***	−1.482***	−1.727	0.354
2015	−3.068***	−0.944	−0.945**	−1.083**	−0.074
2016	−2.076***	−0.406	−1.742***	−1.196**	−0.292

***Significant at 1% level; **Significant at 5% level; *Significant at 10% level

8.5 Effects of CSP on Recovery Rate and Credit Spreads

We confirm that CSP is negatively associated with both volatility and V_A/D in the previous section. On the other hand, the relationship between CSP and expected growth rate of assets (μ_A) remains unclear. Thus, from this point forward, we assume that drift μ_A equals the risk-free interest rate r_f.[4] In this case, under the risk-neutral measure, we compute a recovery rate of debt and credit spreads based on Merton's (1974) model.

Two new variables, L and d, are defined as follows:[5]

$$L = \frac{e^{-r_f T} D}{V_A},\ d = \frac{1}{\sigma_A \sqrt{T}} \left(\ln\left(\frac{1}{L}\right) + \frac{1}{2}\sigma_A^2 T \right) \tag{8.6}$$

The recovery rate (*RR*) and credit spread (*SPR*) are given by the following Eqs. (8.7) and (8.8).[6]

$$RR = e^{r_f T} \left(\frac{V_A}{D}\right) \left(\frac{N(-d)}{N\left(-d + \sigma_A \sqrt{T}\right)} \right) \tag{8.7}$$

$$SPR = -\frac{1}{T} \ln\left(N(d - \sigma_A \sqrt{T}) + \frac{1}{L} N(-d) \right) \tag{8.8}$$

Using the regression slopes for model (8.5), we compute σ_A, $\ln V_A/D$, and DD in each year and each size quintile. Then, based on Eqs. (8.7) and (8.8), we estimate the recovery rate (=1 − LGD) and credit spreads of the 25 size and CSP-ranked portfolios.[7]

Table 8.8 shows the DD, PD, recovery rate, and credit spreads of size and CSP-ranked portfolios. First, for the largest-capital firms (MV1), PD and credit spreads remain low. Although the CSP is positively correlated with PD, the effects of CSP on default risk are invisibly small.

Second, as a characteristic common to all size quintiles, the recovery rate is a monotone increasing function of CSP reflecting the negative association between CSP and total asset volatility. In size quintiles except MV1, CSP is negatively associated with estimated credit spreads.

Finally, for the smallest-capital firms (MV5), PD is high at 5.549% in the lowest CSP portfolio (CSP5) while it is low at 2.653% in the highest CSP portfolio (CSP1). In addition, credit spread in CSP5 is 56.009 basis points, which is approximately seven times larger than the credit spread in CSP1 (6.784 basis point).

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[4]In cases in which it is difficult to obtain the estimate of drift with precision, practitioners often set the drift equal to 0 when they compute risk measures. This accepted practice and the low risk-free interest rate in our observation period warrants our assumption that $\mu_A = r_f$.

[5]These notations are from Sundaram and Das (2011).

[6]Recall that the LGD is a percentage of principal debt and interest on a debt that will not be recovered if a borrower defaults. Since the recovery rate (*RR*) is defined as 1 − LGD, it is the proportion of principal debt and interest that can be recovered expressed as a percentage of the debt instrument's face value.

[7]To simplify the discussion, we set the risk-free interest rate at 2% and assume that it is constant during our sample period.

Table 8.8 Probability of default, recovery rate, and credit spreads of 25 size-CSP ranked portfolios

		CSP1 (High)	CSP2	CSP3	CSP4	CSP5 (Low)
MV1 (Large)	Distance to default	3.596	3.734	3.975	4.024	4.170
	Probability of default (%)	0.016	0.009	0.004	0.003	0.002
	Recovery rate (%)	94.846	94.744	94.647	94.654	94.430
	Credit spread (in BP)	2.169	2.044	1.707	1.432	1.448
MV2	Distance to default	3.386	3.337	3.466	3.488	3.627
	Probability of default (%)	0.035	0.042	0.026	0.024	0.014
	Recovery rate (%)	94.803	94.737	94.293	94.007	93.482
	Credit spread (in BP)	1.453	1.745	2.351	2.422	2.992
MV3	Distance to default	3.022	2.988	2.999	3.003	3.048
	Probability of default (%)	0.126	0.140	0.136	0.134	0.115
	Recovery rate (%)	94.958	94.705	94.510	94.230	93.616
	Credit spread (in BP)	2.996	2.926	2.897	3.180	3.305
MV4	Distance-to-default	2.771	2.660	2.689	2.700	2.702
	Probability of default (%)	0.279	0.391	0.359	0.346	0.345
	Recovery rate (%)	95.658	95.175	94.754	94.132	93.973
	Credit spread (in BP)	3.291	4.232	5.902	5.684	8.081
MV5 (Small)	Distance to default	1.934	1.764	1.718	1.618	1.594
	Probability of default(%)	2.653	3.890	4.287	5.288	5.549
	Recovery rate (%)	94.660	93.315	92.633	92.233	91.727
	Credit spread (in BP)	6.784	18.259	30.040	39.281	56.009

In the United States market, Goss and Roberts (2011) find that lenders are indifferent to CSR investments by high-quality borrowers, while low-quality borrowers that engage in discretionary CSR spending face higher loan spreads. The numerical example in Table 8.8 is consistent with our empirical results. The mixed effects of CSP on the default risk are explained by the structural credit risk model. As we confirmed in this chapter, CSR activities are detrimental to the default risk of financially unconstrained large capital firms although the PD of these firms is very low. On the other hand, for financially constrained small-capital firms, CSR activities mitigate the default risk.

8.6 Conclusion

This chapter examines how CSP is related to firm default risk. We estimate PD using the structural credit risk model first developed by Merton (1974). Based on this model, we explain the linkage between CSP and default risk. We find that CSP is negatively and linearly associated with total asset volatility. This implies that CSR activities reduce the financial risk of the firm. CSP is, in general, negatively associated with the expected growth rate of total assets, although the relationship is unstable and not linear. Expenditure on CSR activities lowers the short-term profitability of the firm. As for the market value of total assets, CSP has a negative linear association. Because risk reduction lowers the default risk and the other two parameters, the expected growth rate and market value of total assets work in opposite directions, and CSP can either decrease or increase the default risk of the firm. We find that CSP is positively associated with default risk among financially unconstrained large-capital firms. By contrast, among small-capital firms, CSP is negatively associated with default risk. Thus, a higher degree of CSP alleviates the default risk of small-capital firms.

Under the risk neutrality assumption that the expected growth rate of total assets equals the risk-free interest rate, we estimate the recovery rate and expected bond yield hypothetically issued by firms. For large-capital firms, the difference in credit spreads among CSP-ranked quintile portfolios is less than 3 basis points. However, the difference is more than 50 basis points for small-capital firms. Thus, the managers of small-capital firms that might be financially constrained must be more conscious of CSR to instill confidence in lenders by mitigating social risk if their desire is to reduce the cost of debt.

Because the CSP index used in this book is constructed based on the results of a questionnaire survey, only firms who responded to the survey are included in the sample set. For firms that did not respond to the survey, we do not confirm the magnitude of credit spreads either empirically or theoretically. This problem is left for future research.

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