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Corporate innovation and credit default swap spreads☆

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ABSTRACT

We use patent and credit default swap (CDS) data to examine whether corporate innovation affects credit market valuation. We find that innovation quantity, measured by the number of patents, is negatively associated with CDS spreads. Moreover, the relationship between the quality of innovation and CDS spreads is negative. Both the scientific value (based on patent citations) and economic value (based on stock market reaction) of innovation have a negative effect on CDS spreads, but the effect of economic value is more significant than that of scientific value. Overall, our study suggests that the performance of corporate innovation is reflected in credit market valuation.

1. Introduction

Innovation has long been emphasized as the primary source for economic growth and competitive advantage (Solow, 1957). In this regard, there is considerable literature that examines the effect of corporate innovation on market valuation. Most of these studies focus on the relationship between corporate innovation and stock returns (e.g., Chan et al., 1990; Deng et al., 1999; Eberhart et al., 2004; Lev and Sougiannis, 1996; Pakes, 1985). They suggest that the stock market responds positively to corporate innovation. Indeed, there is also literature on the effect of innovation on credit spreads. Shi (2003) points out the possibility that stock market-based research exaggerates the expected future benefits of innovation, because the uncertainty associated with innovative activities can be positively reflected in stock prices. Thus, he investigates the trade-off between the benefits and uncertainty of innovation from creditors' perspective and finds that R&D investments are positively related to bond spreads. However, Eberhart et al. (2008) use a different measure of R&D intensity and find that the effect of R&D on bond spreads is negative.[1]

We reexamine the relationship between corporate innovation and credit spreads using patent data instead of R&D data. Patents are used as the output measure of a firm's innovation investments, because innovations are usually formally introduced to the public in the form of approved patents.[2] Moreover, they are actively traded in intellectual property markets (Lev, 2001).

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[1] Eberhart et al. (2008) use the ratio of R&D to sales and the ratio of R&D to assets as measures of R&D intensity, whereas Shi (2003) uses the ratio of R&D to the market value of equity. They point out that Shi's (2003) measure is problematic in that the market value of equity reflects the market's expected R&D value.

[2] It should be noted that using patent information for measuring corporate innovation could introduce a selection bias because patent information does not capture the uncertainty associated with innovation. Thus, we repeat our analyses by adding R&D investment as a control variable and obtain nearly identical (unreported) results.

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Francis et al. (2012) note that patents could reduce the information asymmetry between firms and creditors and thus suggest the expected future benefits of innovation. Many studies show that patents are positively associated with firm value (e.g., Griliches, 1981; Hall et al., 2005). Therefore, if credit market participants reflect the innovation activities of firms, a higher quantity of innovation (represented by more patents) will lower credit spreads.

In addition to the quantity of corporate innovation, we consider the quality of innovation by using two measures of patent value. The first measure is the citation-weighted patent counts, which represent the scientific value of patents. This measure is commonly used in existing literature. For example, Hall et al. (2005) show that this measure is positively related to stock market valuations. Gu (2005) and Pandit et al. (2011) use similar measures and find a positive relationship between patent citations and a firm's future earnings. The second measure is the economic value of patents, proposed by Kogan et al. (2017). This measure is based on stock market reactions to patent grants. Kogan et al. (2017) note that although the economic and scientific values of patents are strongly correlated, these two values do not necessarily coincide. Further, they show that their measure for the economic value of patents is more closely related to firm growth than citation-weighted patent counts.

Indeed, Hsu et al. (2015) investigate the effects of patents on credit spreads. They report that firms with more patents have lower bond spreads. However, we use credit default swap (CDS) spreads rather than bond spreads to measure credit spreads. Blanco et al. (2005) show that new information is incorporated into CDS spreads more quickly than into bond spreads and that CDS spreads are more sensitive to changes in a firm's credit quality. This may be because the non-default components in bond spreads that obscure the impact of changes in credit quality.[3] In addition, bond spreads are calculated by subtracting the unknown risk-free interest rate from the bond yield, whereas CDS spreads do not require the specification of the benchmark risk-free yield curve. Thus, we can avoid any additional noise caused by the misspecified model of the risk-free yield curve.

We find that the quantity of innovation, measured by the number of patents, negatively affects CDS spreads. This suggests that the performance of corporate innovation is reflected in credit market valuation. We also show that the effect of innovation quality on CDS spreads is negative. Both the scientific and economic values of patents negatively impact CDS spreads, but the impact of economic value is more significant than that of scientific value. Our results are consistent with Kogan et al. (2017) in that there is additional information about the quality of innovation in the measure of economic value but not in the citation-weighted measure.

The rest of this paper is organized as follows: Section 2 explains our empirical approach and the associated data. Section 3 discusses our results. Finally, Section 4 presents concluding remarks.

2. Data and empirical methods

2.1. Data

We obtain CDS data from Markit. We include only CDS spreads with a 5-year maturity, as these contracts are the most popular and liquid in the CDS market (Cao et al., 2010; Ericsson et al., 2009; Wang et al., 2013; Zhang et al., 2009). We further restrict our sample to US dollar-denominated CDS with modified restructuring (MR) for senior unsecured debt.

The innovation variables are constructed from the Google Patent dataset created by Kogan et al. (2017).[4] To measure the quantity of firm-level innovation, we use the number of patents granted to each firm in a year (*Patent*). In addition, we use two measures for the quality of firm-level innovation. The first measure is the number of citation-weighted patents (*Patent_CW*).[5] This measure mainly captures the scientific value of patents. The second measure is the economic value-weighted patent counts (*Patent_EW*) of Kogan et al. (2017), who separate the component related to patent value from the firm's stock return. They then calculate the economic value of each patent as the increase in the firm's market valuation in the three days following the patent announcement.[6] $Patent\_EW_{it}$ is defined as the total economic value of all patents granted to firm i in year t. We scale all innovation variables by total assets because large firms tend to file more patents. We also use sales as a denominator of the innovation variables to ensure the robustness of our results.

We apply several control variables following the previous literature: *Lev* is the ratio of the book value of debt to the sum of the market value of equity and the book value of debt (Ericsson et al., 2009); *Vol* is the annual standard deviation of daily stock returns (Zhang et al., 2009); *ROA* is the ratio of net income to total assets (Zhang et al., 2009); *Div* is the ratio of dividend payout per share to the equity price (Zhang et al., 2009); *RF* is the 5-year Treasury constant maturity rate (Galil et al., 2014); *S&P* is the yearly S&P 500 return (Ericsson et al., 2009); and *Illiquidity* is the difference between the 5-year swap rate and 5-year Treasury constant maturity rate (Wang et al., 2013). We use the Compustat database for financial and accounting data, the Center for Research in Security Prices (CRSP) database for stock market data, and Federal Reserve Economic Data (FRED) for market information.

We merge our CDS data with innovation data and the CRSP/Compustat merged database. We then exclude utilities (SIC codes

[3] Longstaff et al. (2005) find that the most of bond spreads is attributed to the default component, but a significant part is due to illiquidity component. Elton et al. (2001) show that differential taxes between corporate and government bonds account for a larger portion of bond spreads than the default component.

[4] Kogan et al. (2017) collect raw patent data from Google Patents and identify the company (the assignee) to which each patent belongs. This dataset provides annual information on patent assignee names, the number of patents, and the measures of patent quality.

[5] This measure is defined as follows: $Patent\_CW_{it} = \sum_{k \in P_{it}} (1 + \frac{C_k}{\overline{C_k}})$, where P_{it} is the set of patents granted to firm i for year t, C_k is the number of citations received by patent k, and $\overline{C_k}$ is the average number of citations received by the patents that were granted in the same year as patent k.

[6] Kogan et al. (2017) also adjust for the market return, success rate of the patent application, and component of the idiosyncratic return.

Table 1
Summary statistics and correlations.
The following panels show the summary statistics of the variables (Panel A) and correlations of the variables (Panel B). *CDS* is the 5-year CDS spread. *Log(CDS)* is the natural log of *CDS*. *Patent* is the number of patents granted to each firm for a year, scaled by total assets. *Patent_CW* is the number of citation-weighted patents, scaled by total assets. *Patent_EW* is Kogan et al. (2017) economic value-weighted patent counts, scaled by total assets. *Lev* is the ratio of the book value of debt to the sum of the market value of equity and the book value of debt. *Vol* is the annual standard deviation of daily stock returns. *ROA* is the ratio of net income to total assets. *Div* is the ratio of dividend payout per share to the equity price. *RF* is the 5-year Treasury constant maturity rate. *S&P* is the yearly S&P 500 return. *Illiquidity* is the difference between the 5-year swap rate and 5-year Treasury constant maturity rate.

Panel A: Summary statistics

Variable	Mean	Median	S.D.	p10	p90
CDS (bp)	151.66	74.00	241.73	21.88	355.70
Log(CDS)	4.41	4.30	1.06	3.09	5.87
Patent (%)	0.26	0.00	0.57	0.00	0.97
Patent_CW (%)	0.57	0.00	1.36	0.00	1.86
Patent_EW (%)	4.19	0.00	9.99	0.00	13.00
Lev (%)	27.39	22.80	18.67	7.32	53.67
Vol (%)	5.93	5.71	1.35	4.43	7.69
ROA (%)	1.39	1.39	3.13	−0.16	3.40
Div (%)	0.40	0.32	0.51	0.00	0.92
RF (%)	3.09	3.38	1.19	1.47	4.45
S&P (%)	1.11	1.65	4.29	−6.03	5.74
Illiquidity (%)	0.50	0.44	0.21	0.28	0.83

Panel B: Correlations

	Log(CDS)	*Patent*	*Patent_CW*	*Patent_EW*	*Lev*	*Vol*	*ROA*	*Div*	*RF*	*S&P*	*Illiquidity*
Log(CDS)	1.00										
Patent	−0.19	1.00									
Patent_CW	−0.18	0.95	1.00								
Patent_EW	−0.28	0.61	0.62	1.00							
Lev	0.60	−0.19	−0.20	−0.29	1.00						
Vol	0.67	−0.03	−0.01	−0.03	0.40	1.00					
ROA	−0.29	0.04	0.05	0.12	−0.36	−0.27	1.00				
Div	−0.06	0.00	−0.03	0.02	0.07	−0.11	−0.01	1.00			
RF	−0.40	0.13	0.12	0.12	−0.13	−0.35	0.03	−0.15	1.00		
S&P	−0.22	0.06	0.05	0.11	0.03	−0.06	0.00	0.00	0.26	1.00	
Illiquidity	0.16	0.05	0.05	0.04	−0.02	0.18	−0.01	0.01	0.16	−0.54	1.00

from 4900 to 4949) and financial firms (SIC codes from 6000 to 6999). We also winsorize all variables at the 1% level to reduce the influence of outliers. Finally, we eliminate observations from which any of the required variables are missing. The resulting sample consists of 2861 firm-year observations from 2000 to 2010.[7]

2.2. Methodology

We examine the impact of our key corporate innovation variables on CDS spreads using the following ordinary least squares (OLS) regressions:

$$\begin{aligned}
&\text{(A) } Log(CDS_{it+1}) = \beta_0 + \beta_1 Patent_{it} + \alpha_j D_j + \alpha_t D_t + \varepsilon_{it};\\
&\text{(B) } Log(CDS_{it+1}) = \beta_0 + \beta_1 Patent_{it} + \gamma' X_{it} + \alpha_j D_j + \alpha_t D_t + \varepsilon_{it};\\
&\text{(C) } Log(CDS_{it+1}) = \beta_0 + \beta_1 Patent_CW_{it} + \alpha_j D_j + \alpha_t D_t + \varepsilon_{it};\\
&\text{(D) } Log(CDS_{it+1}) = \beta_0 + \beta_1 Patent_CW_{it} + \gamma' X_{it} + \alpha_j D_j + \alpha_t D_t + \varepsilon_{it};\\
&\text{(E) } Log(CDS_{it+1}) = \beta_0 + \beta_1 Patent_EW_{it} + \alpha_j D_j + \alpha_t D_t + \varepsilon_{it};\\
&\text{(F) } Log(CDS_{it+1}) = \beta_0 + \beta_1 Patent_EW_{it} + \gamma' X_{it} + \alpha_j D_j + \alpha_t D_t + \varepsilon_{it}.
\end{aligned}$$

Regressions (A) and (B) test the effect of innovation quantity on CDS spreads. Regression (A) shows whether the number of patents (i.e., *Patent*) is negatively associated with CDS spreads (i.e., $\beta_1 < 0$), which would indicate that credit market participants value the performance of corporate innovation. Regression (B) checks whether our result in (A) remains intact even after controlling for other variables known to be related to CDS spreads. X_{it} represents a set of control variables discussed in Section 2.1. D_j and D_t are industry and year fixed effects, respectively.

In regressions (C), (D), (E), and (F), we examine the relationship between innovation quality and CDS spreads. Regressions (C) and (D) test whether the number of citation-weighted patents (i.e., *Patent_CW*) is negatively associated with CDS spreads (i.e.,

[7] The years are chosen based on the availability of our CDS and innovation data.

Table 2
Effects of innovation quantity on CDS spreads.

This table shows the effect of innovation quantity on CDS spreads by presenting the estimation results of the regressions. The dependent variable is the natural log of the 5-year CDS spread, *Log(CDS)*. The independent variables are the measures of innovation quantity, and a set of control variables defined in Table 1 (i.e., *Lev, Vol, ROA, Div, RF, S&P*, and *Illiquidity*). The measures of innovation quantity are *Patent* (columns (1) and (2)) and $Patent_{sales}$ (columns (3) and (4)): *Patent* is the number of patents, scaled by total assets; $Patent_{sales}$ is the number of patents, scaled by sales. All independent variables are scaled to unit standard deviation. Intercepts are not reported. The standard errors are adjusted for clustering at the firm level. The numbers in parentheses represent t-statistics. The symbols ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	Patents to total assets		Patents to sales	
	(1)	(2)	(3)	(4)
Patent	−0.156***	−0.073***		
	(−3.90)	(−3.87)		
$Patent_{sales}$			−0.146***	−0.081***
			(−3.27)	(−3.74)
Lev		0.433***		0.434***
		(13.81)		(13.86)
Vol		0.535***		0.536***
		(16.17)		(16.27)
ROA		−0.035**		−0.035**
		(−2.16)		(−2.16)
Div		−0.059*		−0.059*
		(−1.95)		(−1.95)
RF		0.001		0.004
		(0.01)		(0.06)
S&P		−0.075***		−0.075***
		(−3.27)		(−3.27)
Illiquidity		0.100**		0.100**
		(2.09)		(2.05)
Adjusted R-Squared	0.29	0.70	0.29	0.70
Observations	2861	2861	2861	2861
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes

$\beta_1 < 0$), which would indicate that the scientific value of innovation is reflected in credit market valuation. Moreover, we use the number of economic-value weighted patents (i.e., *Patent_EW*) in regressions (E) and (F) to examine whether the economic value of innovation has a significant impact on CDS spreads. More importantly, these regressions enable us to compare the effect of the innovation's economic value on CDS spreads with the effect of scientific value. The control variables are the same as those in regression (B).

3. Results

3.1. Sample statistics

Panel A of Table 1 displays the summary statistics for the sample and reports the means, medians, standard deviations, 10th percentiles, and 90th percentiles of the variables. The mean for *CDS* is 151.66 basis points (bp), with a median of 74.00 bp, indicating that the 5-year CDS spread is heavily skewed to the right. To alleviate the degree of skewness, we use the natural log of the 5-year CDS spreads (*Log(CDS)*) in our analysis. The mean for *Log(CDS)* is 4.41, with a median of 4.30.

All innovation variables (*Patent, Patent_CW*, and *Patent_EW*) are distributed across a wide range. For example, the mean for *Patent* is 0.26%, with a higher standard deviation of 0.57%. Moreover, the 90th percentile for *Patent* is 0.97% and the 10th percentile is 0.00%. In a similar pattern, the means (standard deviations) for *Patent_CW* and *Patent_EW* are 0.57% (1.36%) and 4.19% (9.99%), respectively.

Panel A of Table 1 also shows the summary statistics of control variables. The means (standard deviations) for *Lev, Vol, ROA, Div, RF, S&P*, and *Illiquidity* are 27.39% (18.67%), 5.93% (1.35%), 1.39% (3.13%), 0.40% (0.51%), 3.09% (1.19%), 1.11% (4.29%), and 0.50% (0.21%), respectively.

Panel B of Table 1 displays the correlations of the variables. All the innovation variables are negatively correlated with CDS spreads. Among them, *Patent_EW* is the most significantly correlated (−0.28). We also find that the correlation between *Patent_CW* and *Patent_EW* is 0.62, indicating that these two variables have a positive correlation but do not necessarily coincide. In addition, consistent with previous studies, CDS spreads are positively correlated with *Lev, Vol*, and *Illiquidity* and negatively correlated with *ROA, Div, RF*, and *S&P*.

Table 3

Effects of innovation quality on CDS spreads.

This table shows the effect of innovation quality on CDS spreads. The dependent variable is the natural log of the 5-year CDS spread, *Log(CDS)*. The independent variables are the measures of innovation quality, and a set of control variables defined in Table 1 (i.e., *Lev, Vol, ROA, Div, RF, S&P*, and *Illiquidity*). The measures of innovation quality are *Patent_CW* (columns (1) and (2)), $Patent\_CW_{sales}$ (column (3)), *Patent_EW* (columns (4) and (5)), and $Patent\_EW_{sales}$ (column (6)): *Patent_CW* is the number of citation-weighted patents, scaled by total assets; $Patent\_CW_{sales}$ is the number of citation-weighted patents, scaled by sales; *Patent_EW* is Kogan et al. (2017) economic value-weighted patent counts, scaled by total assets; $Patent\_EW_{sales}$ is Kogan et al. (2017) economic value-weighted patent counts, scaled by sales. All independent variables are scaled to unit standard deviation. Intercepts are not reported. The standard errors are adjusted for clustering at the firm level. The numbers in parentheses represent t-statistics. The symbols ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	Scientific value of innovation			Economic value of innovation		
	(1)	(2)	(3)	(4)	(5)	(6)
Patent_CW	−0.147***	−0.070***				
	(−3.87)	(−3.86)				
$Patent\_CW_{sales}$			−0.072***			
			(−3.23)			
Patent_EW				−0.279***	−0.138***	
				(−8.77)	(−7.84)	
$Patent\_EW_{sales}$						−0.147***
						(−7.16)
Lev		0.432***	0.434***		0.406***	0.409***
		(13.81)	(13.84)		(12.81)	(12.97)
Vol		0.537***	0.538***		0.548***	0.550***
		(16.23)	(16.24)		(16.85)	(16.92)
ROA		−0.033**	−0.034**		−0.026*	−0.029*
		(−2.10)	(−2.10)		(−1.71)	(−1.86)
Div		−0.060**	−0.061**		−0.049*	−0.048
		(−1.98)	(−1.99)		(−1.66)	(−1.63)
RF		0.005	0.007		0.005	0.005
		(0.08)	(0.11)		(0.08)	(0.07)
S&P		−0.075***	−0.075***		−0.071***	−0.071***
		(−3.30)	(−3.31)		(−3.09)	(−3.12)
Illiquidity		0.099**	0.097**		0.090*	0.088*
		(2.05)	(2.01)		(1.88)	(1.80)
Adjusted R-Squared	0.29	0.70	0.70	0.33	0.71	0.71
Observations	2861	2861	2861	2861	2861	2861
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

3.2. Effects of corporate innovation on CDS spreads

In this section, we demonstrate the effects of corporate innovation on CDS spreads. First, Table 2 shows the extent to which the quantity of innovation affects CDS spreads. In column (1), the result of performing regression (A) shows that the coefficient estimate for *Patent* is significantly negative (coefficient = −0.156, $t = -3.90$), indicating that greater innovation output leads to lower CDS spreads. Further, we estimate regression (B) to check whether the negative relationship between innovation quantity and CDS spreads remains intact even after including other control variables. The regression results appear in column (2). We find that the effect of *Patent* on CDS spreads is still significant (coefficient = −0.073, $t = -3.87$), although the coefficient declines in comparison to the result in column (1). The economic magnitude is also substantial: A one standard-deviation increase in innovation quantity is associated with a decline of 7.3% in the CDS spread. In columns (3) and (4), we scale the number of patents by sales instead of total assets. We obtain results similar to those shown in columns (1) and (2). Therefore, we find evidence that the performance of corporate innovation is reflected in credit market valuation.

Table 3 shows the impact of innovation quality on CDS spreads by using two measures of patent value (i.e., *Patent_CW* and *Patent_EW*). Columns (1), (2), and (3) are estimated using *Patent_CW*. In columns (1) and (2), we estimate regressions (C) and (D), respectively. We find that the coefficients for *Patent_CW* in columns (1) and (2) are −0.147 and −0.070, respectively, and are negatively significant at the 1% level. This finding suggests that the scientific value of innovation is negatively associated with CDS spreads. The other specification through column (3) shows a similar result.[8]

In addition, we investigate the extent to which the economic value of innovation affects CDS spreads by estimating regressions (E) and (F). As shown in columns (4) and (5), the coefficients for *Patent_EW* are −0.279 and −0.138, respectively, and are statistically significant at the 1% level. This finding suggests that the economic value of innovation is also negatively related to CDS spreads. This negative relationship is robust to the other specification in column (6). More importantly, we find that the effect of *Patent_EW* on CDS spreads ($t = -7.84$ in column (5)) is more significant than that of *Patent_CW* ($t = -3.86$ in column (2)). Further, the difference in economic magnitude is about double: A one standard-deviation increase in *Patent_CW* is associated with a decline of 7.0% in the CDS

[8] As in Table 2, we use sales as a denominator of the innovation variable.

spread (in column (2)), but a one standard-deviation increase in *Patent_EW* is associated with a decline of 13.8% in the CDS spread (in column (5)). These results are consistent with Kogan et al. (2017) in that *Patent_EW* contains significant information in addition to *Patent_CW*.

4. Conclusion

This study uses patent and CDS data to examine the relationship between corporate innovation and credit spreads. We provide evidence that innovation quantity, measured by the number of patents, is negatively related to CDS spreads. We also find that the relationship between innovation quality and CDS spreads is negative. Both the scientific and economic values of patents negatively impact CDS spreads, but the economic value has a more significant impact than scientific value. In short, our study highlights a beneficial effect of corporate innovation on market valuation.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2018.12.030.

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