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Product market competition and credit risk

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ABSTRACT

This study theoretically and empirically investigates effects of product market competition on credit risk. We first develop a real-options-based structural model in a homogeneous oligopoly and show that credit spreads are *positively* related to the number of firms in an industry. The disparity of firm size in an industry is relevant to both product market competition and credit risk, and we therefore extend the model to an asymmetric duopoly case. In particular, we demonstrate that credit spreads of relatively small (large) firms within an industry are *positively* (*negatively*) related to Herfindahl-Hirschman index, and the relative firm size in an industry is an important determinant of credit risk. The models' implications are empirically scrutinized by a reduced-form hazard model and generally supported. By performing out-of-sample analyses, the results demonstrate that firm size together with the interaction terms between intra-industry firm size dummies and competition intensity can effectively predict default.

1. Introduction

The recent global financial crisis has impacted financial markets around the world, emphasizing the importance of correctly forecasting credit events. The unprecedented scale of corporate defaults has drawn the attention of both academics and practitioners to examine the prediction of defaults and to explore the causes of default clustering. In prior literature, some researchers have indicated that industry characteristics can affect default probabilities. Jorion and Zhang (2007) and Lang and Stulz (1992) documented significant intra-industry contagion effects of bankruptcies through event studies. Jorion and Zhang (2007) empirically showed that intra-industry credit contagion can be captured in credit default swaps (CDS), and further provided evidence that the change in CDS spreads is significantly related to the industry Herfindahl-Hirschman index (HHI). It means that the extent of co-movement in firms' credit quality within an industry can be determined by the intensity of competition, and this in turn explains part of the correlation of credit risk and the phenomenon of clustered defaults. However, the prevailing credit risk models rarely consider this industry effect. This motivates us to fill the gap in the literature by first building a structural model to theoretically illuminate the relationship between industry competition and credit risk, and then empirically exploring the effect of product market competition on credit risk and default prediction.

Since the seminal papers of Merton (1974) and Leland (1994), many structural credit risk models have shown that a firm's capital structure is an important determinant of credit risk. Mauer and Sarkar (2005) and many others clearly demonstrated that a firm's financing and investment decisions are interdependent. Moreover, Grenadier (2002) and Aguerrevere (2009) built real options models to analyze the effect of product market competition on a firm's investment and operational decisions. Accordingly, this paper develops a simple structural model to analyze a firm's optimal operational and financing decisions in a symmetric oligopolistic market and scrutinizes the relationship between product market competition and credit spreads.

Several research works on real options have shown that product market competition has a significant impact on firms' investment and operational decisions (Grenadier, 2002; Aguerrevere, 2009). Recently, Akdogu and Mackay (2012) theoretically and empirically demonstrated that under- and over-investment can be rational when framed in a strategic competitive setting. Research on the effect of competition on other issues of corporate finance has been relatively sparse, but recently more attention has been paid to this issue. For example, Mackay and Phillips (2005) focused on aggregate financial leverage, Grullon and Michaely (2007) investigated payout policy, Giroud and Mueller (2008) explored corporate governance, and Morellec and Nikolov (2009) and Fresard (2010) looked at firms' cash holdings. Valta (2010) examined how the

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intensity of competition affects the cost of bank loans and provides evidence that banks rationally take into account the industry structure and competition when pricing financial contracts. As far as we know, however, no study in the literature addresses the linkage between product market competition and credit risk.

Some real options models use regression approach to test the implications of the models. Since the main subject of the paper is to investigate the influence of product market competition on credit risk, instead of regression analysis, we employ the reduced-form approach. Different from the regression analysis, reduced-form models can further provide estimates of default probabilities, and recent empirical research in this field has greatly improved the accuracy of default forecasting. In addition, structural-form models assume that valuation of any corporate security can be modeled as a contingent claim on the underlying value of the firm, implicitly assuming that firm value contains sufficient information about the probability of bankruptcy, but Bharath and Shumway (2008) indicated that this is unlikely to be the case. They empirically employed a reduced-form hazard model approach and showed that the implied default probability of the Merton model is not a sufficient statistic for default prediction. Therefore, in addition to proposing a theoretical structural model, we empirically analyze the model's implications by the well-known reduced-form approach – the hazard model.

The early reduced-form models for default prediction employ approaches like discriminant analysis (Altman, 1968) or binary response models such as logit and probit regressions (Ohlson, 1980; Zmijewski, 1984). Shumway (2001) argued that these models are inconsistent, because their single-period static features do not adjust period for risk. The hazard model proposed by Shumway (2001) can incorporate time-varying covariates and was later adopted by Chava and Jarrow (2004), Hillegeist et al. (2004), Figlewski et al. (2006), Agarwal and Taffler (2008), and many others. However, most of the prior reduced-form models did not consider the industry effect, with only a few exceptions like Chava and Jarrow (2004) that revealed the importance of introducing industry effects in the hazard rate estimation. Nonetheless, they merely consider variables such as industry dummies and their interaction terms with accounting ratios, which only demonstrate industry differences as well as the degrees of importance of accounting variables for different industries. If default intensities are different across industries with otherwise identical firm-specific characteristics, it is of interest to investigate the determinants behind the industry effect through the perspective of product market competition.[1]

Theoretically, we first build a structural model in a homogeneously oligopolistic industry. We show that credit spreads are *positively* related to the number of firms and the effect is significantly amplified when the firm size is small. The number of firms cannot capture the relative size distribution of the firms in an industry while HHI can. Since the relative firm size in an industry is relevant to both HHI and credit risk, we extend our model to an asymmetric duopolistic industry case, demonstrating that credit spreads of relatively small firms are *positively* related to HHI, while those of relatively large firms are *negatively* related to HHI. The effect of HHI on credit spreads is amplified when the firm size is small, and a firm's relative size in an industry is an important determinant of credit risk. For empirical analysis, we provide evidence supporting our theoretical models' predictions through the reduced-form hazard model. We further perform an out-of-sample default prediction accuracy analysis, incorporating the characteristics of product market competition. The results demonstrate that considering firm size together with interaction terms between the intra-industry firm size dummies and competition intensity can effectively predict default.

The major contributions of our paper are summarized as below. We theoretically and empirically examine the effects of product market competition on credit risk, and further identify that the number of firms and HHI in an industry, measuring different dimensions of market competition, can lead to the opposite impacts. This undoubtedly makes contributions to the literature and practice of pricing, measuring and forecasting credit risk with consideration of market competition.

The remainder of this paper is organized as follows. Section 2 describes our models and hypotheses. Section 3 presents the empirical methodology and data. Section 4 reports the empirical results of the hazard model and the out-of-sample prediction accuracy analysis. Finally, Section 5 draws conclusions.

2. Models and hypotheses

In this section we first develop a structural model that employs the symmetric Cournot-Nash equilibrium in order to model firms' interactions and propose testable hypotheses that demonstrate how credit spreads are related to the number of firms. We then introduce the asymmetric Cournot-Nash equilibrium in a duopoly and propose hypotheses that particularly show the relationships between the two firms' credit spreads and the Herfindahl-Hirschman index (HHI). Finally, we provide numerical illustrations of our models and develop testable hypotheses.

2.1. Homogeneous oligopoly model

For simplicity, all agents are assumed to be risk-neutral and thus all expected cash flows can be discounted at a constant risk-free rate r.[2] Consider a homogeneous oligopolistic industry with n infinitely-lived symmetric firms producing $q(t)$ units of output at total cost $TC(q(t)) = a_0 + a_1q(t)$, where a_0 denotes fixed cost and $a_1q(t)$ is variable costs. Assume that the produced output cannot be stored, i.e. output always equals demand. The industry inversed demand function is thus given by:

$$P(X(t),t) = X(t)Q(t)^{-1/\gamma}, \tag{1}$$

where $Q(t) = \sum_{i=1}^{n} q_i(t)$, γ is elasticity of demand, and $X(t)$ is the industry demand shock governed by $dX(t) = \mu X(t)dt + \sigma X(t)dW(t)$.. We further assume $X(0) = x_0 > 0$ and $r - \mu > 0$. Industry production capacity is exogenously given by K, where each symmetric firm owns capacity $k_i = k = K/n$.

Similar to the set-up of Aguerrevere (2009), at time t, any firm i in the industry makes its optimal production decision $q_i^*(t) = \arg\max_{0 \leqslant q_i(t) \leqslant k} P(t)q_i(t) - TC_i(q_i(t))$, which leads to the symmetric Cournot Nash equilibrium given by:

$$q_i^*(t) = \begin{cases} \frac{1}{n}(X(t)/(a_1A(n,\gamma)))^{\gamma}, & \text{if } X(t) \leqslant SW, \\ k, & \text{if } X(t) \geqslant SW, \end{cases} \tag{2}$$

where $A(n, \gamma) = n\gamma/(n\gamma - 1) \equiv A$ and $SW = a_1AK^{1/\gamma}$. When the industry demand is lower than the switching point SW, the firm will produce below its full capacity (k). On the other hand, the firm will produce at its full capacity when the demand is high enough.[3]

We can now define the firm i's instantaneous after-tax operating net profits as: $\pi_i^*(X(t),K) = (1-\tau)(P(t)q_i^*(t) - TC_i(q_i^*(t)))$.

[1] For example, among others, Duffie et al. (2007), Figlewski et al. (2006), and Duan (2010) incorporated macroeconomic variables into their reduced-form models.

[2] Alternatively, we could assume there is a tradable asset that spans the risks the firms face.

[3] We assume that the firm is unable to adjust its capacity, thereby allowing us to focus on the firm's bankruptcy decision.

According to the symmetric Cournot Nash equilibrium, we have $q_i^*(x,K) = q^*(x,K)$ and $\pi_i^*(x;K) = \pi^*(x;K)$, where $i = 1, 2, \ldots, n$, and thus suppress notation i hereafter. Bringing back the optimal output decision and rearranging terms, we can derive:

$$\pi^*(x;K) = \begin{cases} (1-\tau)\left(\frac{a_1K}{n}\frac{1}{n\gamma-1}\left(\frac{x}{SW}\right)^{\gamma} - a_0\right), & \text{if } x \leqslant SW. \\ (1-\tau)\left(\frac{xK^{1-1/\gamma}}{n} - \left(a_0 + \frac{a_1K}{n}\right)\right), & \text{if } x \geqslant SW. \end{cases} \tag{3}$$

Note that π^* is continuous at the switching point. Eq. (3) shows that when the firm operates at full capacity, its net profit is linear in the industry demand shock, whereas its net profit is non-linear in the shock when it operates below full capacity. This non-linearity demonstrates the firm's operational flexibility, which is affected by other competitors' flexibilities.

To analyze the firm's bankruptcy decisions, we first derive its unlevered firm value, which is related to its recovery value when default occurs. Since the switch point is exogenously given and the firm's abandonment policy is endogenously determined, we consider two possibilities: either switch before abandonment, or abandon before switching. When the abandonment trigger is larger than the switch point $x_A > SW$, our model is exactly the same as the standard Leland style model in which a firm with an unlevered asset value cannot switch its production in the future and each firm always produces at its full capacity. This paper focuses on the case where the abandonment trigger is less than the switch point and hereafter assumes $x_A < SW$. Therefore, we consider the firm's operational flexibility and take the non-linear state-dependence feature into consideration.

The firm's unlevered asset value can be derived as below.[4] For $x_A \leqslant x \leqslant SW$,

$$\begin{aligned} V(x;K) = {} & (1-\tau)\left(\frac{a_1K}{n}\frac{1}{n\gamma-1}\frac{1}{g(\gamma)}\left(\frac{x}{SW}\right)^{\gamma} - \frac{a_0}{r}\right) - (1-\tau) \\ & \times\left(\frac{a_1K}{n}\frac{1}{n\gamma-1}\frac{1}{g(\gamma)}\left(\frac{x_A}{SW}\right)^{\gamma} - \frac{a_0}{r}\right)\left(\frac{x}{x_A}\right)^{\eta_2} + (1-\tau) \\ & \times\left(\left(\frac{1-\eta_2}{\eta_1-\eta_2}\right)\frac{(SW)K^{1-1/\gamma}}{n(r-\mu)} + \left(\frac{\eta_2}{\eta_1-\eta_2}\right)\frac{a_1K}{nr}\right. \\ & \left. -\left(\frac{\gamma-\eta_2}{\eta_1-\eta_2}\right)\frac{a_1K}{n}\frac{1}{n\gamma-1}\frac{1}{g(\gamma)}\right)\left(\frac{x}{SW}\right)^{\eta_1} - (1-\tau) \\ & \times\left(\left(\frac{1-\eta_2}{\eta_1-\eta_2}\right)\frac{(SW)K^{1-1/\gamma}}{n(r-\mu)} + \left(\frac{\eta_2}{\eta_1-\eta_2}\right)\frac{a_1K}{nr}\right. \\ & \left. -\left(\frac{\gamma-\eta_2}{\eta_1-\eta_2}\right)\frac{a_1K}{n}\frac{1}{n\gamma-1}\frac{1}{g(\gamma)}\right)\left(\frac{x_A}{SW}\right)^{\eta_1}\left(\frac{x}{x_A}\right)^{\eta_2}. \end{aligned} \tag{4}$$

For $x \geqslant SW$,

$$\begin{aligned} V(x;K) = {} & (1-\tau)\left(\frac{xK^{1-1/\gamma}}{n(r-\mu)} - \left(\frac{a_0}{r} + \frac{a_1K}{nr}\right)\right) - (1-\tau) \\ & \times\left(\frac{a_1K}{n}\frac{1}{n\gamma-1}\frac{1}{g(\gamma)}\left(\frac{x_A}{SW}\right)^{\gamma} - \frac{a_0}{r}\right)\left(\frac{x}{x_A}\right)^{\eta_2} + (1-\tau) \\ & \times\left(\left(\frac{1-\eta_1}{\eta_1-\eta_2}\right)\frac{(SW)K^{1-1/\gamma}}{n(r-\mu)} + \left(\frac{\eta_1}{\eta_1-\eta_2}\right)\frac{a_1K}{nr}\right. \\ & \left. -\left(\frac{\gamma-\eta_1}{\eta_1-\eta_2}\right)\frac{a_1K}{n}\frac{1}{n\gamma-1}\frac{1}{g(\gamma)}\right)\left(\frac{x}{SW}\right)^{\eta_2} - (1-\tau) \\ & \left(\left(\frac{1-\eta_2}{\eta_1-\eta_2}\right)\frac{(SW)K^{1-1/\gamma}}{n(r-\mu)} + \left(\frac{\eta_2}{\eta_1-\eta_2}\right)\frac{a_1K}{nr}\right. \\ & \left. -\left(\frac{\gamma-\eta_2}{\eta_1-\eta_2}\right)\frac{a_1K}{n}\frac{1}{n\gamma-1}\frac{1}{g(\gamma)}\right)\left(\frac{x_A}{SW}\right)^{\eta_1}\left(\frac{x}{x_A}\right)^{\eta_2}. \end{aligned} \tag{5}$$

The firm's optimal abandonment policy x_A is determined by the smooth-pasting condition: $\lim_{x\downarrow x_A}\frac{\partial V(x;K)}{\partial x} = 0$, where $x_A \in (0, SW)$. The optimal abandonment trigger is numerically solved and is chosen to maximize the unlevered firm value.

We next assume that each identical firm issues perpetual debt, continuously paying coupon flow C. The debt value can be derived as follows. For $x \geqslant x_D$

$$D(x;K) = \frac{C}{r} - \left(\frac{C}{r} - (1-b)V_i(x_D;K)\right)\left(\frac{x}{x_D}\right)^{\eta_2}, \tag{6}$$

where b is the proportional bankruptcy cost, and thus $(1 - b)$ denotes the recovery rate of the debt if default occurs.

The corresponding equity value can be derived as below. For $x_D \leqslant x \leqslant SW$,

$$\begin{aligned} E(x;K) = {} & (1-\tau)\left(\frac{a_1K}{n}\frac{1}{n\gamma-1}\frac{1}{g(\gamma)}\left(\frac{x}{SW}\right)^{\gamma} - \frac{(a_0+C)}{r}\right) - (1-\tau) \\ & \times\left(\frac{a_1K}{n}\frac{1}{n\gamma-1}\frac{1}{g(\gamma)}\left(\frac{x_D}{SW}\right)^{\gamma} - \frac{(a_0+C)}{r}\right)\left(\frac{x}{x_D}\right)^{\eta_2} + (1-\tau) \\ & \times\left(\left(\frac{1-\eta_2}{\eta_1-\eta_2}\right)\frac{(SW)K^{1-1/\gamma}}{n(r-\mu)} + \left(\frac{\eta_2}{\eta_1-\eta_2}\right)\frac{a_1K}{nr}\right. \\ & \left. -\left(\frac{\gamma-\eta_2}{\eta_1-\eta_2}\right)\frac{a_1K}{n}\frac{1}{n\gamma-1}\frac{1}{g(\gamma)}\right)\left(\frac{x}{SW}\right)^{\eta_1} - (1-\tau) \\ & \times\left(\left(\frac{1-\eta_2}{\eta_1-\eta_2}\right)\frac{(SW)K^{1-1/\gamma}}{n(r-\mu)} + \left(\frac{\eta_2}{\eta_1-\eta_2}\right)\frac{a_1K}{nr}\right. \\ & \left. -\left(\frac{\gamma-\eta_2}{\eta_1-\eta_2}\right)\frac{a_1K}{n}\frac{1}{n\gamma-1}\frac{1}{g(\gamma)}\right)\left(\frac{x_D}{SW}\right)^{\eta_1}\left(\frac{x}{x_D}\right)^{\eta_2}. \end{aligned} \tag{7}$$

For $x \geqslant SW$,

$$\begin{aligned} E(x;K) = {} & (1-\tau)\left(\frac{xK^{1-1/\gamma}}{n(r-\mu)} - \left(\frac{a_0+C}{r} + \frac{a_1K}{nr}\right)\right) - (1-\tau) \\ & \times\left(\frac{a_1K}{n}\frac{1}{n\gamma-1}\frac{1}{g(\gamma)}\left(\frac{x_D}{SW}\right)^{\gamma} - \frac{(a_0+C)}{r}\right)\left(\frac{x}{x_D}\right)^{\eta_2} + (1-\tau) \\ & \times\left(\left(\frac{1-\eta_1}{\eta_1-\eta_2}\right)\frac{(SW)K^{1-1/\gamma}}{n(r-\mu)} + \left(\frac{\eta_1}{\eta_1-\eta_2}\right)\frac{a_1K}{nr}\right. \\ & \left. -\left(\frac{\gamma-\eta_1}{\eta_1-\eta_2}\right)\frac{a_1K}{n}\frac{1}{n\gamma-1}\frac{1}{g(\gamma)}\right)\left(\frac{x}{SW}\right)^{\eta_2} - (1-\tau) \\ & \times\left(\left(\frac{1-\eta_2}{\eta_1-\eta_2}\right)\frac{(SW)K^{1-1/\gamma}}{n(r-\mu)} + \left(\frac{\eta_2}{\eta_1-\eta_2}\right)\frac{a_1K}{nr}\right. \\ & \left. -\left(\frac{\gamma-\eta_2}{\eta_1-\eta_2}\right)\frac{a_1K}{n}\frac{1}{n\gamma-1}\frac{1}{g(\gamma)}\right)\left(\frac{x_D}{SW}\right)^{\eta_1}\left(\frac{x}{x_D}\right)^{\eta_2}. \end{aligned} \tag{8}$$

The equity holder's optimal default decision is determined by the following smooth-pasting condition: $\lim_{x\downarrow x_D}\frac{\partial E(x;K)}{\partial x} = 0$, where $x_D \in (0, SW)$. The optimal bankruptcy trigger can be numerically solved and is chosen to maximize the equity value.

We now define the credit spread of the debt as:

$$CS(x;n,K,x_D^*(n),x_A^*(n)) = \frac{C}{D(x;n,K,x_D^*(n),x_A^*(n))} - r. \tag{9}$$

Eq. (9) shows that credit spreads of debt are linked to the number of firms in an industry, via the recovery value and a firm's optimal abandonment and default policies. We can therefore investigate the effect of the number of firms on credit spreads (credit risk), and the result is provided in the later numerical subsection.

2.2. Asymmetric duopoly model

Using the number of firms in an industry to measure the intensity of product market competition is adequate in an industry having symmetric firms. When employing other measures, such as the Herfin-

[4] In an online appendix, we provide the detailed derivations and explanations of this paper's value functions.

dahl-Hirschman index (HHI) or the four-firm concentration ratio (CR_4), the symmetric oligopolistic assumption is somewhat restricted. We hence extend our model to an asymmetric duopoly model.

We assume that Firm 1 has smaller capacity $k_1 = \kappa K$ while Firm 2 has larger capacity $k_2 = (1-\kappa)K$, where $\kappa \in (0, 0.5)$. This can be explained by stating that Firm 2 was the leader when entering the market, therefore enjoying some first-mover advantages, and builds larger capacity, whereas Firm 1 enters later, is in a disadvantageous position, and thus builds smaller capacity.[5] By doing so, we theoretically capture the effect of relative size on product market competition and on credit risk, which can be empirically examined by using HHI and CR_4 as measures of intensity of product market competition. We assume that the total cost functions of Firms 1 and 2 are given respectively as $TC_1(q_1(t)) = a_0 + 2(1-\kappa)a_1q_1(t)$ and $TC_2(q_2(t)) = a_0 + a_1q_2(t)$. When $\kappa = 0.5$, the two firms' total costs become the same, leading to the case of a symmetric duopoly, which is consistent with the previous section's model. When $\kappa \in (0, 0.5)$, the marginal cost of Firm 1 is larger than that of Firm 2, thereby demonstrating that Firm 1 is in a disadvantageous position.

The asymmetric Cournot Nash equilibrium can be shown as:

$$q_i^*(x;\kappa) = \begin{cases} g_i(\kappa,\gamma)(x/a_1)^{\gamma}, & \text{if } x \leqslant SW_i, \\ k_i, & \text{if } x \geqslant SW_i, \end{cases} \tag{10}$$

where $SW_i = a_1(k_i/g_i(\kappa,\gamma))^{1/\gamma}$, $i = 1, 2$, $g_1 = \frac{1}{1+h}\left((1-\frac{1}{\gamma(1+h))/2(1-\kappa)}\right)^{\gamma}$, $g_2 = \frac{h}{1+h}\left(\left(1-\frac{1}{\gamma(1+h)}\right)/2(1-\kappa)\right)^{\gamma}$, and $h = \frac{1+\gamma(1-2\kappa)}{2(1-\kappa)-\gamma(1-2\kappa)}$.

We now define $\mathrm{HHI}(x;\kappa) \equiv \left(\frac{q_1^*(x;\kappa)}{q_1^*(x;\kappa)+q_2^*(x;\kappa)}\times 100\right)^2 + \left(\frac{q_2^*(x;\kappa)}{q_1^*(x;\kappa)+q_2^*(x;\kappa)}\times 100\right)^2$, and $\mathrm{HHI}(x; 0.5) = 2500$ for any $x > 0$. In this case, there are only two symmetric firms in the market, and 2500 is the lowest bound of HHI, representing the highest competition intensity in a duopoly.

The equilibrium profit functions of the two firms are therefore given by:

$$\pi_1^*(x;K) = \begin{cases} (1-\tau)\left(a_1k_1\left(\frac{2(1-\kappa)}{\gamma(1+h)-1}\right)\left(\frac{x}{SW_1}\right)^{\gamma} - a_0\right), & \text{if } x \leqslant SW_1. \\ (1-\tau)(\kappa x K^{1-1/\gamma} - (a_0 + 2\kappa(1-\kappa)a_1K)), & \text{if } x \geqslant SW_1. \end{cases} \tag{11}$$

and

$$\pi_2^*(x;K) = \begin{cases} (1-\tau)\left(a_1k_2\left(\frac{2(1-\kappa)\gamma(1+h)-\gamma(1+h)+1}{\gamma(1+h)-1}\right)\left(\frac{x}{SW_2}\right)^{\gamma} - a_0\right), & \text{if } x \leqslant SW_2. \\ (1-\tau)((1-\kappa)xK^{1-1/\gamma} - (a_0 + \kappa a_1K)), & \text{if } x \geqslant SW_2. \end{cases} \tag{12}$$

Following the same procedure and employing some similar boundary conditions, we derive all the desired formulae, which are summarized as below. For $x_{A^1} \leqslant x \leqslant SW_1$, the unlevered asset value of Firm 1 is given by

$$\begin{aligned} V_1(x;K) &= (1-\tau)\left(a_1k_1\left(\frac{2(1-\kappa)}{\gamma(1+h)-1}\right)\frac{1}{g(\gamma)}\left(\frac{x}{SW_1}\right)^{\gamma} - \frac{a_0}{r}\right) - (1-\tau) \\ &\times \left(a_1k_1\left(\frac{2(1-\kappa)}{\gamma(1+h)-1}\right)\frac{1}{g(\gamma)}\left(\frac{x_{A^1}}{SW_1}\right)^{\gamma} - \frac{a_0}{r}\right)\left(\frac{x}{x_{A^1}}\right)^{\eta_2} \\ &+ (1-\tau)\Bigg(\left(\frac{1-\eta_2}{\eta_1-\eta_2}\right)\frac{\kappa(SW_1)K^{1-1/\gamma}}{(r-\mu)} + \left(\frac{\eta_2}{\eta_1-\eta_2}\right)\frac{2\kappa(1-\kappa)a_1K}{r} \\ &- \left(\frac{\gamma-\eta_2}{\eta_1-\eta_2}\right)a_1k_1\left(\frac{2(1-\kappa)}{\gamma(1+h)-1}\right)\frac{1}{g(\gamma)}\Bigg)\left(\frac{x}{SW_1}\right)^{\eta_1} \\ &- (1-\tau)\Bigg(\left(\frac{1-\eta_2}{\eta_1-\eta_2}\right)\frac{\kappa(SW_1)K^{1-1/\gamma}}{(r-\mu)} + \left(\frac{\eta_2}{\eta_1-\eta_2}\right)\frac{2\kappa(1-\kappa)a_1K}{r} \\ &- \left(\frac{\gamma-\eta_2}{\eta_1-\eta_2}\right)a_1k_1\left(\frac{2(1-\kappa)}{\gamma(1+h)-1}\right)\frac{1}{g(\gamma)}\Bigg)\left(\frac{x_{A^1}}{SW_1}\right)^{\eta_1}\left(\frac{x}{x_{A^1}}\right)^{\eta_2}. \end{aligned} \tag{13}$$

For $x_{A^2} \leqslant x \leqslant SW_2$, the unlevered asset value of Firm 2 is given by

$$\begin{aligned} V_2(x;K) &= (1-\tau)\left(a_1k_2\left(\frac{2(1-\kappa)\gamma(1+h)-\gamma(1+h)+1}{\gamma(1+h)-1}\right)\frac{1}{g(\gamma)}\left(\frac{x}{SW_2}\right)^{\gamma} - \frac{a_0}{r}\right) \\ &- (1-\tau)\left(a_1k_2\left(\frac{2(1-\kappa)\gamma(1+h)-\gamma(1+h)+1}{\gamma(1+h)-1}\right)\frac{1}{g(\gamma)}\left(\frac{x_{A^2}}{SW_2}\right)^{\gamma} - \frac{a_0}{r}\right)\left(\frac{x}{x_{A^2}}\right)^{\eta_2} \\ &+ (1-\tau)\Bigg(\left(\frac{1-\eta_2}{\eta_1-\eta_2}\right)\frac{(1-\kappa)(SW_2)K^{1-1/\gamma}}{(r-\mu)} + \left(\frac{\eta_2}{\eta_1-\eta_2}\right)\frac{\kappa a_1K}{r} - \left(\frac{\gamma-\eta_2}{\eta_1-\eta_2}\right)a_1k_2 \\ &\times \left(\frac{2(1-\kappa)\gamma(1+h)-\gamma(1+h)+1}{\gamma(1+h)-1}\right)\frac{1}{g(\gamma)}\Bigg)\left(\frac{x}{SW_2}\right)^{\eta_1} \\ &- (1-\tau)\Bigg(\left(\frac{1-\eta_2}{\eta_1-\eta_2}\right)\frac{(1-\kappa)(SW_2)K^{1-1/\gamma}}{(r-\mu)} + \left(\frac{\eta_2}{\eta_1-\eta_2}\right)\frac{\kappa a_1K}{r} - \left(\frac{\gamma-\eta_2}{\eta_1-\eta_2}\right)a_1k_2 \\ &\times \left(\frac{2(1-\kappa)\gamma(1+h)-\gamma(1+h)+1}{\gamma(1+h)-1}\right)\frac{1}{g(\gamma)}\Bigg)\left(\frac{x_{A^2}}{SW_2}\right)^{\eta_1}\left(\frac{x}{x_{A^2}}\right)^{\eta_2}. \end{aligned} \tag{14}$$

The two firms' optimal abandonment policies x_{A^i} are determined by the following smooth-pasting conditions: $\lim_{x \downarrow x_{A^i}} \frac{\partial V_i(x;K)}{\partial x} = 0$, where $x_{A^i} \in (0, SW_i), i = 1, 2$. The optimal abandonment triggers are numerically solved and chosen to maximize the two unlevered firms' values separately. For $x_{D^1} \leqslant x \leqslant SW_1$, the equity value of Firm 1 is given by

$$\begin{aligned} E_1(x;K) &= (1-\tau)\left(a_1k_1\left(\frac{2(1-\kappa)}{\gamma(1+h)-1}\right)\frac{1}{g(\gamma)}\left(\frac{x}{SW_1}\right)^{\gamma} - \frac{a_0+C}{r}\right) \\ &- (1-\tau)\left(a_1k_1\left(\frac{2(1-\kappa)}{\gamma(1+h)-1}\right)\frac{1}{g(\gamma)}\left(\frac{x_{D^1}}{SW_1}\right)^{\gamma} - \frac{a_0+C}{r}\right) \\ &\times \left(\frac{x}{x_{D^1}}\right)^{\eta_2} + (1-\tau)\Bigg(\left(\frac{1-\eta_2}{\eta_1-\eta_2}\right)\frac{\kappa(SW_1)K^{1-1/\gamma}}{(r-\mu)} + \left(\frac{\eta_2}{\eta_1-\eta_2}\right)\frac{2\kappa(1-\kappa)a_1K}{r} \\ &- \left(\frac{\gamma-\eta_2}{\eta_1-\eta_2}\right)a_1k_1\left(\frac{2(1-\kappa)}{\gamma(1+h)-1}\right)\frac{1}{g(\gamma)}\Bigg)\left(\frac{x}{SW_1}\right)^{\eta_1} \\ &- (1-\tau)\Bigg(\left(\frac{1-\eta_2}{\eta_1-\eta_2}\right)\frac{\kappa(SW_1)K^{1-1/\gamma}}{(r-\mu)} + \left(\frac{\eta_2}{\eta_1-\eta_2}\right)\frac{2\kappa(1-\kappa)a_1K}{r} \\ &- \left(\frac{\gamma-\eta_2}{\eta_1-\eta_2}\right)a_1k_1\left(\frac{2(1-\kappa)}{\gamma(1+h)-1}\right)\frac{1}{g(\gamma)}\Bigg)\left(\frac{x_{D^1}}{SW_1}\right)^{\eta_1}\left(\frac{x}{x_{D^1}}\right)^{\eta_2}. \end{aligned} \tag{15}$$

For $x_{D^2} \leqslant x \leqslant SW_2$, the equity value of Firm 2 is given by

$$\begin{aligned} E_2(x;K) &= (1-\tau)\Bigg(a_1k_2\left(\frac{2(1-\kappa)\gamma(1+h)-\gamma(1+h)+1}{\gamma(1+h)-1}\right) \\ &\times \frac{1}{g(\gamma)}\left(\frac{x}{SW_2}\right)^{\gamma} - \frac{a_0+C}{r}\Bigg) - (1-\tau) \\ &\times \Bigg(a_1k_2\left(\frac{2(1-\kappa)\gamma(1+h)-\gamma(1+h)+1}{\gamma(1+h)-1}\right) \\ &\times \frac{1}{g(\gamma)}\left(\frac{x_{D^2}}{SW_2}\right)^{\gamma} - \frac{a_0+C}{r}\Bigg)\left(\frac{x}{x_{D^2}}\right)^{\eta_2} + (1-\tau) \\ &\times \Bigg(\left(\frac{1-\eta_2}{\eta_1-\eta_2}\right)\frac{(1-\kappa)(SW_2)K^{1-1/\gamma}}{(r-\mu)} + \left(\frac{\eta_2}{\eta_1-\eta_2}\right)\frac{\kappa a_1K}{r} - \left(\frac{\gamma-\eta_2}{\eta_1-\eta_2}\right)a_1k_2 \\ &\times \left(\frac{2(1-\kappa)\gamma(1+h)-\gamma(1+h)+1}{\gamma(1+h)-1}\right)\frac{1}{g(\gamma)}\Bigg)\left(\frac{x}{SW_2}\right)^{\eta_1} \\ &- (1-\tau)\Bigg(\left(\frac{1-\eta_2}{\eta_1-\eta_2}\right)\frac{(1-\kappa)(SW_2)K^{1-1/\gamma}}{(r-\mu)} + \left(\frac{\eta_2}{\eta_1-\eta_2}\right)\frac{\kappa a_1K}{r} - \left(\frac{\gamma-\eta_2}{\eta_1-\eta_2}\right)a_1k_2 \\ &\times \left(\frac{2(1-\kappa)\gamma(1+h)-\gamma(1+h)+1}{\gamma(1+h)-1}\right)\frac{1}{g(\gamma)}\Bigg)\left(\frac{x_{D^2}}{SW_2}\right)^{\eta_1}\left(\frac{x}{x_{D^2}}\right)^{\eta_2}. \end{aligned} \tag{16}$$

The two equity holders' optimal default decisions are similarly determined by the following smooth-pasting conditions: $\lim_{x \downarrow x_{D^i}} \frac{\partial E_i(x;K)}{\partial x} = 0$, where $x_{D^i} \in (0, SW_i), i = 1, 2$. The optimal bankruptcy triggers also can be numerically solved and are chosen to maximize the two equity values separately.

The debt values and credit spreads are finally derived as below. For $i = 1, 2$

[5] We thank an anonymous referee for valuably suggesting this idea.

$$D_i(x;K) = \frac{C}{r} - \left(\frac{C}{r} - (1-b)V_i(x_{D^i})\right)\left(\frac{x}{x_{D^i}}\right)^{\eta_2}, \tag{17}$$

and

$$CS_i(x;\kappa,K,x^*_{D^i}(\kappa),x^*_{A^i}(\kappa)) = \frac{C}{D_i(x;\kappa,K,x^*_{D^i}(\kappa),x^*_{A^i}(\kappa))} - r. \tag{18}$$

Eq. (18) shows that the credit spreads of debt are linked to the two firms' asymmetry κ, which is relevant to the level of HHI via the recovery value and the two firms' optimal abandonment and default policies. We can therefore investigate the effects of HHI on the two firms' credit spreads, with the results provided in the later subsection.

2.3. Numerical analyses and hypotheses

In this section we conduct numerical analyses to illustrate the effects of product market competition on credit risk and build testable hypotheses along two different dimensions of market competition in our theoretical models: the number of firms and HHI.

With the base-case parameters of $r = 0.06$, $\mu = 0.01$, $\sigma = 0.2$, $\gamma = 1.6$, $n = 10$, $K = 1000$, $\tau = 0.35$, $b = 0.5$, $a_1 = 0.06$, $a_0 = 0.1$, and $C = 0.188$,[6] we first employ the homogeneous oligopoly model to illustrate the effects of the number of firms on credit spreads and then use the asymmetric duopoly model to demonstrate how the Herfinddahl-Hirschman index (HHI) generates different impacts on the credit spreads of large and small firms.

Using our homogeneous oligopoly model, Fig. 1 first demonstrates the effect of the number of firms on credit spreads, showing that as the number of firms in an industry (n) increases (market competition intensifies), credit spreads increase. The reason is that when market competition intensifies, other things being equal, each firm's profits (and thus the unlevered asset value) are diluted by other competitors, thereby increasing the possibility of default as well as credit spreads. Secondly, we observe that credit spreads turn lower as the industry demand increases (firm size becomes larger), which is consistent with the results of standard Leland's style structural models. When industry demand goes up, ceteris paribus, each firm's profits and the unlevered asset value increase, thereby lowering bankruptcy probability as well as credit spreads. The increase of the industry demand leads to the increase of firm size, thereby showing that credit risk is negatively related to the firm's own size.[7] Thirdly, Fig. 1 demonstrates that distances between curves are amplified when industry demand weakens. It clearly shows that the sensitivity of credit spreads to the number of firms in an industry increases as the firm size becomes smaller. In view of Fig. 1, all the above results are robust for changes to various parameters (including industry demand volatility, elasticity, and growth rate), and we respectively summarize the above three results as Hypotheses 1a, 1b and 1c below.

Hypothesis 1a. Credit risk is *positively* related to the number of firms in an industry.

Hypothesis 1b. Credit risk is negatively related to the firm's own size.

Hypothesis 1c. The sensitivity of credit risk to the number of firms in an industry is amplified when the firm's own size becomes smaller.

The above results infer directly that an increase in product market competition intensity (the number of firms in an industry) amplifies a firm's credit risk. Using the number of firms in an industry to measure the intensity of product market competition is only adequate in an industry with similar-size firms, but when firms in an industry have significantly different sizes, the number of firms cannot capture this characteristic. HHI, a commonly accepted measure of market concentration, takes into account not only the number of firms, but also the relative size distribution of the firms in an industry. HHI decreases (representing that competition intensifies) both when the number of firms in an industry increases and as the disparity in size between those firms decreases.

Employing our asymmetric duopoly model and the above base-case parameters, Fig. 2 first demonstrates that the credit spreads of small-capacity Firm 1 decrease, while those of large-capacity Firm 2 increase as HHI decreases (as κ increases, i.e., the asymmetry between the two firms decreases). Our duopoly model fixes the number of firms in a industry to two, and thus HHI purely captures the effect of the disparity in size between the two firms. When HHI is decreasing, the market position of the relatively small Firm 1 improves, whereas that of relatively large Firm 2 gets worse, other things being equal. This is because Firm 1 (2) is in a better (worse) market position in an industry whereby HHI becomes smaller (the asymmetry between the two firms becomes smaller). In particular, we predict that the effect of the concentration ratio on credit spreads for relatively small firms is exactly opposite to that for relatively large firms. As a consequence, when HHI becomes smaller (competition intensifies), Firm 1 (2) suffers smaller (greater) default risk, leading to lower (higher) credit spreads. We therefore propose the following hypotheses to characterize the above result.

Secondly, Fig. 2 illustrates one interesting observation that credit spreads of the relatively small Firm 1 are robustly greater than those of the relatively large Firm 2. The existing credit risk literature often shows that a smaller (own) firm size leads to higher credit risk, but as far as we know, no study investigates how the relative firm size in an industry affects credit risk. Fig. 2 particularly demonstrates that the relatively small Firm 2 suffers a higher credit risk. We give an example to explain the difference between the own and relative firm size arguments. Assume that there are two industries in a market where the first industry contains two firms (Firms A and B) with firm sizes 80 and 20, while the second industry contains two firms (Firms C and D) with firm sizes 8 and 2, respectively. The own size effect suggests that Firm C suffers a higher credit risk than Firm B, other things being equal, whereas the relative size in an industry implies that Firm B suffers greater credit risk than Firm C, other things being equal. As a consequence, the relative firm size in an industry is also an important determinant of credit risk.

Finally, Fig. 2 also demonstrates that distances between curves are significantly amplified as the industry demand weakens. It clearly shows that the sensitivity of credit spreads to HHI in an industry enlarges when the firm size becomes smaller. We summarize all the three results in the following hypotheses.

Hypothesis 2a. The credit risk of a relatively small (large) firm is *positively* (*negatively*) related to HHI.

Hypothesis 2b. Relatively small firms in an industry suffer a higher credit risk than relatively large firms.

Hypothesis 2c. The sensitivity of credit risk of relatively small firms to HHI in an industry is higher than that of relatively large firms to HHI.

[6] Most of the parameters are chosen from Aguerrevere (2009) and Leland (1994) except for a_0 and C, which are unique to our model. Since a_0 is fixed costs, related to a firm's operating leverage, and C is the coupon payment, related to a firm's financial leverage, we choose these two parameters to match the medians of operating and financial leverages of our sample firms (2.35 and 0.48, respectively). Our empirical section details the samples. The operating leverage is defined as the ratio of revenues minus variable costs to the revenues minus fixed and variable costs, while financial leverage is defined as the debt to asset ratio.

[7] The inference that higher industry demand induces a larger firm size is similar to Morellec and Nikolov (2009).

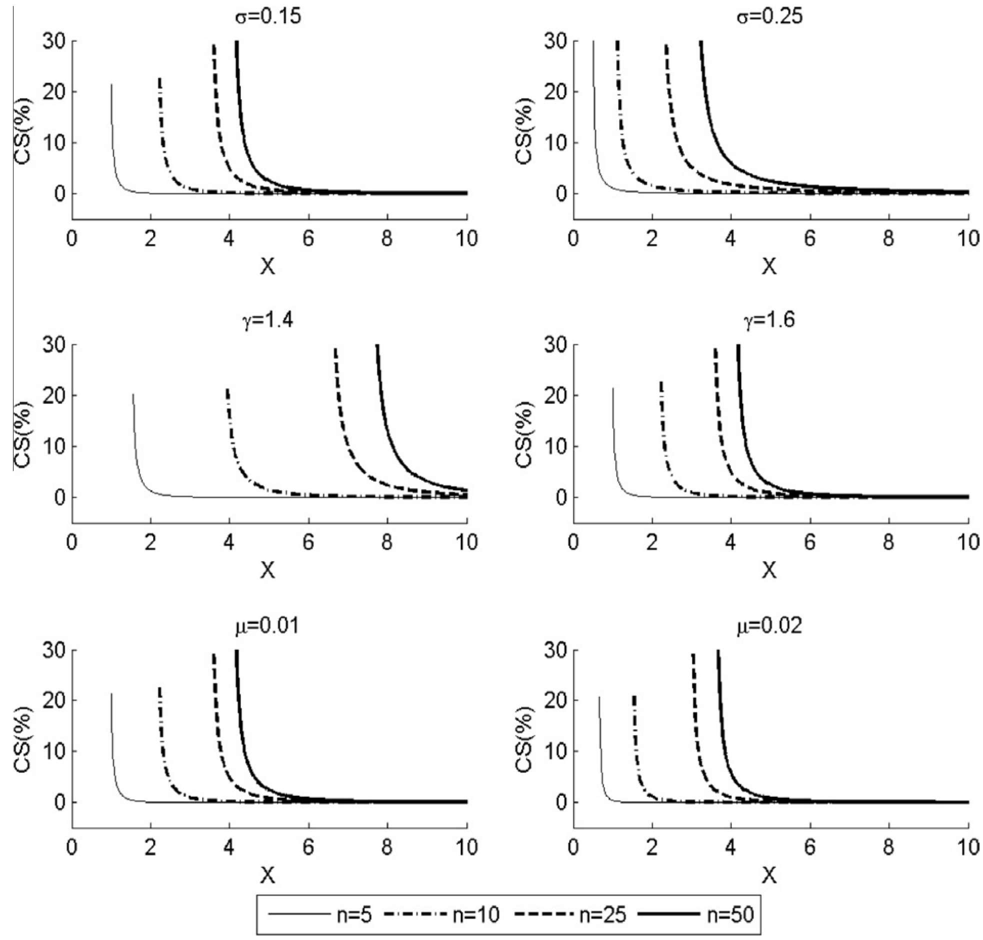

Fig. 1. Effect of the number of firms on credit spreads. This figure shows the effects of the number of firms in an industry on credit spreads (*CS*) under various settings of return volatilities of demand shocks (σ), industry demand price elasticity (γ), and expected growth return of demand shocks (μ). Here, *X* is the industry demand shock and *n* is the number of firms in industry. Other parameters are the same as the base-case parameters.

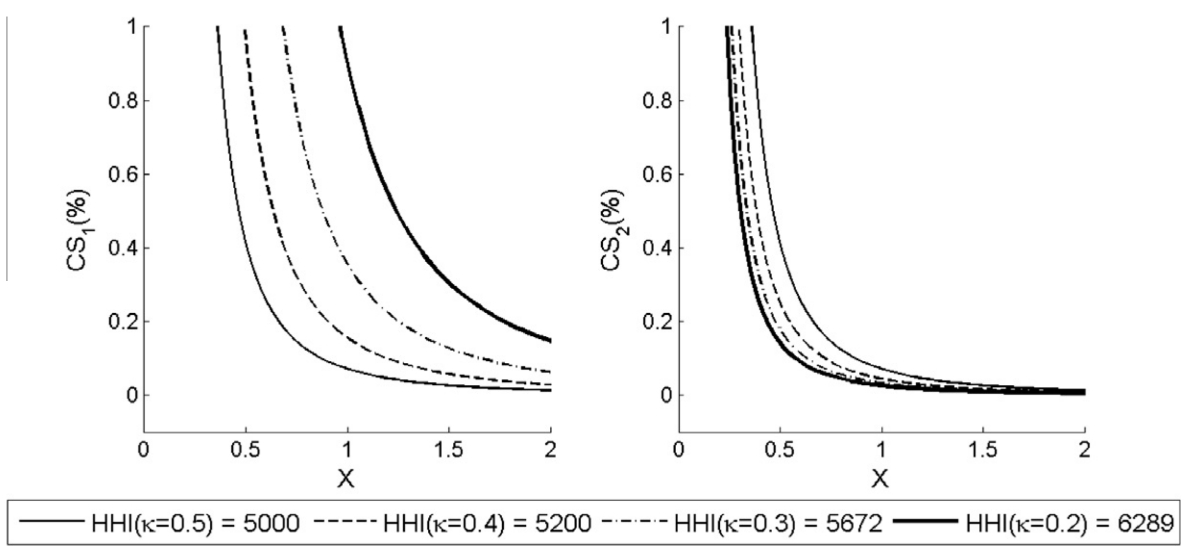

Fig. 2. Effect of Herfindahl-Hirschman Index on Credit Spreads. This figure shows the effects of Herfindahl-Hirschman Index (HHI) on credit spreads. The left panel denotes the credit spreads of the relatively smaller firm 1 (CS_1), while the right panel denotes those of the relatively larger firm 2 (CS_2). Here, *X* is the industry demand shock and HHI is the sales-based HHI defined as $\mathrm{HHI}(\kappa) \equiv \left(\frac{q_1^*(X;\kappa)}{q_1^*(X;\kappa)+q_2^*(X;\kappa)} \times 100\right)^2 + \left(\frac{q_2^*(X;\kappa)}{q_1^*(X;\kappa)+q_2^*(X;\kappa)} \times 100\right)^2$, which is calculated at $X = 40$ for $\kappa = 0.5, 0.4, 0.3$, and 0.2. Other parameters are the same as the base-case parameters.

In a brief summary, we predict that a larger number of firms in an industry (more competitive) leads to a higher credit risk. Nevertheless, the relatively small (large) firms suffer from lower (higher) credit risk when HHI is lower in an industry (more competitive). The identification that the number of firms and HHI in an industry, measuring different dimension of market competition generate different impacts on credit risk is essentially important when we explore the relation between competition and credit risk or predicting default.

3. Methodology and data

3.1. Empirical methodology

The empirical performance of credit risk models in pricing risky debts and analyzing credit spreads is generally unsatisfactory, because the illiquid corporate bond market hinders theoretical models from accurately pricing risky debts. However, predicting the credit quality of a corporate security could be a good application, because it is less affected by additional factors such as liquidity, tax differences, and recovery rates. Recently, some researchers have used credit default swap (CDS) spreads as a direct measure of credit quality. Nonetheless, comprehensive and a long history of CDS data is not available, especially for small companies that are crucial for our study.[8] Therefore, we use equity data for empirical analysis. The advantage of using stock market data is good quality and availability of return data for long periods. However, calibration of our theoretical models using equity data is practically infeasible due to the complexity of our structural models. Accordingly, we explore the effect of product market competition on default intensity, which can be estimated through reduced-form models and is closely related to credit spreads in our theoretical models. In addition, reduced-form models by construction can also incorporate other accounting and financial information to control for factors that may affect default intensity.

In the framework of reduced-form modeling, the default of firm i is described by default time τ_i, and the default time can be modeled through its stochastic intensity λ_i. If the firm is alive at time t, then the intensity at time t for firm i satisfies:

$$\lambda_i(t) = \lim_{\Delta t \to 0} \frac{P(t < \tau_i \leqslant t + \Delta t | \tau_i \geqslant t, F_t)}{\Delta t}.$$

In a word, the default probability within a small time period Δt after t is close to $\lambda_i(t)\Delta t$, where $\lambda_i(t)$ depends on information available at time t as represented by F_t. This information contains all intensities of firms and all default histories up to time t. Under the reduced-form setting, modeling the default probability for firm i thus reduces to modeling its default intensity $\lambda_i(t)$. As a bond credit spread may be affected by factors such as liquidity unrelated to credit quality, we use default probability as the measure of credit quality in our empirical study.

To analyze the impact of product market competition on default intensity, we adopt the popular Cox proportional hazard model, which has been used by Bharath and Shumway (2008), Hillegeist et al. (2004), and many others in empirical studies. Proportional hazard models assume that the probability of default at time t, conditional on survival until time t, is $\lambda(t) = \varphi(t)[\exp(x(t)'\beta)]$, where $\phi(t)$ is the "baseline" hazard rate and the term $\exp(x(t)'\beta)$ allows the expected time to default to vary across firms, according to covariate $x(t)$. The baseline hazard rate $\phi(t)$ is common to all firms and the Cox proportional hazard model does not impose any structure on $\phi(t)$. Cox's partial likelihood estimator provides estimates of β, and the details of estimation can be seen in Cox and Oakes (1984).

3.2. Data

In the spirit of the broad definition of bankruptcy by Brockman and Turtle (2003) and Dichev (1998), our default samples are defined as firms that are delisted due to bankruptcy, liquidation, or poor performance. This is because many firms were delisted from the stock exchange for reasons other than liquidation, bankruptcy or merger/acquisition. A significant portion of firms are delisted due to poor performance or failure to meet exchange listing requirements. Specifically, a firm is considered as "performance delisted" by Brockman and Turtle (2003) if it is given a CRSP delisting code with the first digit of 4 (liquidation), or between 550 and 591 (poor performance).

We regard these performance-related delistings as companies under financial distress and use these firms as default samples to perform our empirical tests. This is because delisting from a stock exchange can trigger a credit rating downgrade by rating agencies and drastically reduce the value of corporate bonds, leading to a substantial increase in credit spreads. Sometimes when a firm is delisted, its creditors can withdraw lines of credit. Both downgrade and credit line withdrawal make it more expensive for a financially distressed company to raise capital for operations, which further increases its default risk. Moreover, a company in bad shape does not necessarily file for bankruptcy around the date of delisting for various reasons. After delisting from the exchange, a firm can be either acquired by another firm or file for bankruptcy several years later.

Government intervention, as witnessed during the recent global financial tsunami, has a direct impact in reducing the number of bankruptcy filings (Duan, 2010). The most extreme example can be Fannie Mae and Freddie Mac. They are government agencies and have extremely low probabilities of filing for bankruptcy. Nonetheless, they still were delisted for failing to meet the requirements set forth by the stock exchange.[9] Shareholders of these firms suffered huge losses due to financial distress from delisting. Thus, default risk and hazard rate estimation should not be tied only to events of bankruptcy filings. Overall, the broad definition of bankruptcy (or financial distress) can be of equal importance to bankruptcy prediction.

Since the sample size of defaults is relatively small, our sampling period is from January 1985 to December 2009. Table 1 summarizes defaulting and other-exit firms by the major industry categories. Other-exit firms are those delisted due to merger or acquisition. The majority of delisted firms are manufacturing and service companies. Table 2 reports the number and the percentage (over active firms) of defaulting and other-exit samples over the years. One can find that the number and proportion of non-financial delisted companies during the subprime-mortgage crisis are less than those during the burst of Dotcom-bubble between 2001 and 2003. This is somewhat unanticipated in terms of severity for the two economic downturns. Government intervention clearly, to some degree, reduces the number of firms forced out of the market. Therefore, examining the effect of product market competition on performance delisted firms rather than bankruptcy can effectively increase the sample size of default firms and reduce the potential bias of default events in the hazard model.

[8] For example, Ericsson et al. (2009), Das et al. (2009), and Tang and Yan (2010) conducted analyses of credit spreads using CDS data. However, the total number of sample firms in the above-mentioned studies is very small (less than 300) compared with ours (around 15,000). We also perform our analyses using bond yield spreads from TRACE transactions data, but they are still subject to the similar sample selection bias problem. Most of the sample bonds are issued by relatively larger firms in industry.

[9] Fannie Mae and Freddie Mac were delisted from NYSE on July 7, 2010 with final trading prices of \$0.25 and \$0.34, respectively. They were delisted by NYSE, because they could no longer meet the standard for NYSE continued listing – a minimum price of \$1 per share.

Table 1
Summary of default firms and other exit firms by industry category. This table reports the number of default firms and other exits over the years from 1985 to 2009. Percent is the percentage of default (other exit) firms in a given industry category over the total number of default (or other exit) firms.

Industry category	SIC code	Class	Number of default firms	Percent (%)	Number of other exit firms	Percent (%)
1	<1000	Agriculture, forestry, and fisheries	30	0.49	26	0.31
2	1000 to less than 1500	Mineral industries	434	7.05	427	5.02
3	1500 to less than 1800	Construction	107	1.74	72	0.85
4	2000 to less than 4000	Manufacturing	2228	36.20	2923	34.38
5	4000 to less than 4900	Transportation and Communications	365	5.93	539	6.34
6	4900 to less than 5000	Utilities	82	1.33	231	2.72
7	5000 to less than 5200	Wholesale trade	304	4.94	262	3.08
8	5200 to less than 6000	Retail trade	457	7.42	501	5.89
9	6000 to less than 6800	Finance, insurance, and real estate	680	11.05	1838	21.62
10	7000 to less than 9000	Services	1257	20.42	1650	19.40
11	9100 to less than 10,000	Public administration	211	3.43	34	0.40
Total			6155	100	8503	100

Table 2
Summary of default firms and other exit firms over the sample period. This table reports the number of default firms and other exit firms for each year during the sample period from 1985 to 2009. Percent is the percentage of default firms and other exit firms over active firms in that year. Financial versus non-financial companies are reported separately.

Year	Active non-financial		Default non-financial		Other exit non-financial		Active financial		Default financial		Other exit financial	
	Num	Percent (%)	Num	Percent (%)	Num	Percent (%)	Num	Percent (%)	Num	Percent (%)	Num	Percent (%)
1985	4237	91.43	185	3.99	212	4.57	567	91.60	20	3.23	32	5.17
1986	4299	90.09	245	5.13	228	4.78	615	92.48	19	2.86	31	4.66
1987	4564	92.37	166	3.36	211	4.27	722	94.88	13	1.71	26	3.42
1988	4512	89.76	219	4.36	296	5.89	724	91.18	35	4.41	35	4.41
1989	4409	91.10	209	4.32	222	4.59	703	91.78	36	4.70	27	3.52
1990	4404	92.04	235	4.91	146	3.05	711	93.68	25	3.29	23	3.03
1991	4363	92.77	248	5.27	92	1.96	740	93.55	35	4.42	16	2.02
1992	4531	92.24	302	6.15	79	1.61	747	92.34	39	4.82	23	2.84
1993	4836	95.37	134	2.64	101	1.99	827	94.84	16	1.83	29	3.33
1994	5321	94.16	164	2.90	166	2.94	1395	94.51	21	1.42	60	4.07
1995	5467	93.07	194	3.30	213	3.63	1444	90.82	31	1.95	115	7.23
1996	5922	93.26	148	2.33	280	4.41	1427	89.92	19	1.20	141	8.88
1997	6142	91.75	218	3.26	334	4.99	1385	88.90	21	1.35	152	9.76
1998	6048	88.65	357	5.23	417	6.11	1350	87.15	47	3.03	152	9.81
1999	5606	87.35	345	5.38	467	7.28	1359	90.54	27	1.80	115	7.66
2000	5525	88.30	274	4.38	458	7.32	1379	89.95	32	2.09	122	7.96
2001	5136	86.93	426	7.21	346	5.86	1310	90.66	29	2.01	106	7.34
2002	4738	89.51	355	6.71	200	3.78	1269	92.63	35	2.55	66	4.82
2003	4360	90.21	248	5.13	225	4.66	1242	93.03	20	1.50	73	5.47
2004	4281	93.35	100	2.18	205	4.47	1199	90.42	23	1.73	104	7.84
2005	4199	91.84	126	2.76	247	5.40	1230	93.75	23	1.75	59	4.50
2006	4189	92.57	61	1.35	275	6.08	1212	92.03	12	0.91	93	7.06
2007	4063	90.07	49	1.09	399	8.85	1182	91.77	9	0.70	97	7.53
2008	3969	91.62	168	3.88	195	4.50	1142	91.58	42	3.37	63	5.05
2009	3404	84.05	217	5.36	429	10.59	1022	88.18	51	4.40	86	7.42
Total			5393		6443				680		1846	

An important empirical issue for product market competition research is industry classification. This study, for robustness, conducts all the tests for both Fama–French 49-Industry and 3-digit SIC level classifications.[10] The 4-digit SIC definition is not examined in our study, because it is too fine and thus too many industries under this specification comprise only one or two firms.[11] Furthermore, some of the four-digit codes may fail to define sound economic markets as pointed out by Clarke (1989) and Kahle and Walking (1996).[12]

Following literature, we exclude all firms with SIC codes starting with 6 (financial firms) and with first two digits being 49 (utilities). In the Fama–French 49-Industry classification, we exclude firms classified as utilities (Fama–French Industry Code 31), financial companies (Industry Code 45 to 48), and firms that cannot be well-classified by Fama and French (Industry Code 49). Figs. 3 and 4 show the frequency of median monthly number of firms per industry under Fama–French 49 and 3-digit SIC industry classifications, respectively. The median number of firms in an industry with a 3-digit SIC industry classification is generally far fewer than that under the Fama–French classification. One can observe that even under the 3-digit SIC industry classification, there are 85 industries with fewer than 5 firms and 134 industries with less than 10 firms, confirming the difficulty in using 4-digit SIC classification for empirical tests. In sum, excluding financial and utility companies, there are a total of 44 industries in the Fama/French classification and 245 industries in the 3-digit SIC classification.

Equity prices are collected from CRSP, and financial statement information is retrieved from Compustat. Our sampling period is from January 1985 to December 2009. The quarterly accounting information is from 1984 to 2009, because some firms under financial distress stopped filing financial reports a long time before they were delisted from the stock exchanges. Following prior literature, we lag all accounting information by 3 months due to reporting

[10] We classify all the companies to 49 industries according to Kenneth French's website. (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html)

[11] For the 4-digit SIC definition, 145 out of 440 industries have 2 or less companies. A total of 255 industries have fewer than 5 firms.

[12] Some researchers exclude firms with four-digit SIC codes ending with "0" and "9".

delay. If the accounting variable is missing, we substitute it with the most recent or closest observation prior to it.

4. Empirical results

4.1. Covariates

4.1.1. Variables of major interests

4.1.1.1. The intensity of competition. We first summarize the most widely used measures of product market competition. Variables for intensity of competition are taken from papers in prior literature, including Morellec and Nikolov (2009), Valta (2010), and Gasper and Masa (2006), among others.

1. *Natural logarithm of the number of firms per industry (Ln_N)*: The number of firms in an industry may affect the ability of a firm to influence price. In a perfectly competitive market, firms are just price takers, while the firm can decide prices in the case of a monopoly. In practice, most industries are somewhere in-between these two cases. Following Morellec and Nikolov (2009), we use the logarithm of the number of firms.
2. *Herfindahl-Hirschman Index (HHI)*: HHI is the sum of the squared fractions of all individual firms' market share. A higher value of HHI means a more concentrated industry.[13]
3. *Four-firm concentration ratio (CR_4)*: This measure is computed as the combined market share of the four largest firms over the aggregate sales volume in each industry. Similar to HHI, higher values of CR_4 imply more concentrated industries.

4.1.1.2. Relative size of firms within an industry. Our numerical analyses in Section 2.3 indicate that the intensity of competition in terms of HHI and the relative firm size (relatively small versus relatively large firms) can jointly affect credit spreads, and therefore we introduce the following dummy variables for the relative size of firms in an industry and their interaction with three different competition varaibles.

1. *Relative size dummies (Relative_size_S and Relative_size_M)*: To isolate the effect of the relative size of firms from market capitalization (firm's own size in the finance literature), we use dummy variables to divide the samples of each industry into three groups. In accordance with the variables of market competition, we use a firm's sales volume to represent its relative size in a given industry.[14] Thus, firms are sorted into three groups – Small, Medium, and Big – by using 30 percentile and 70 percentile of sales volume within the given industry as the cutoff points. Note that a firm can have a large market capitalization even as it belongs to the Small relative size group (thus, Relative_size_S = 1) due to its relatively small sales volume as compared to other companies in an industry. That is, firms with large own size can be classified into the Small relative size group.

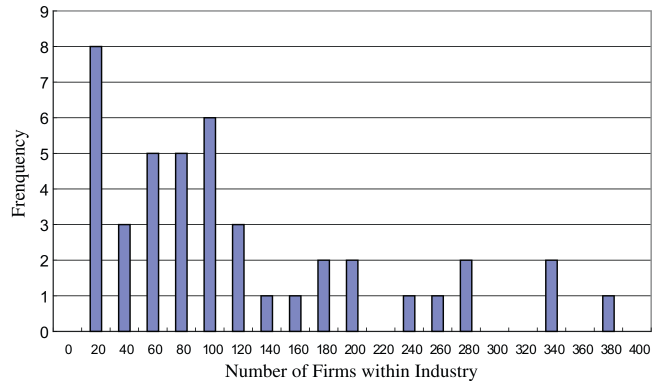

Fig. 3. Number of Firms within an Industry under the Fama–French 49-Industry Classification. This figure presents the median of the monthly sample number of firms in an industry during the sample period from 1985 to 2009.

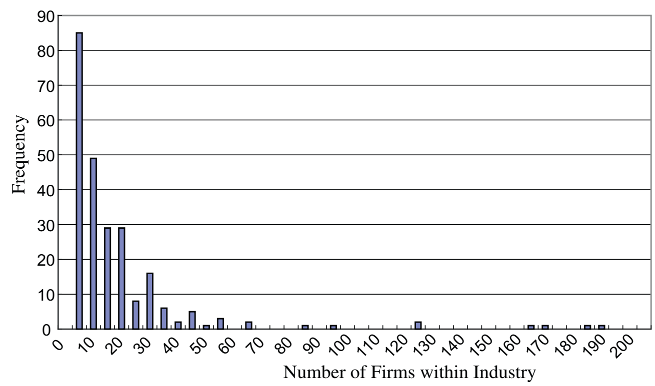

Fig. 4. Number of firms within an industry under the 3-digit SIC industry classification. This figure presents the median of the monthly sample number of firms in an industry during the sample period from 1985 to 2009. There are two 3-digit SIC level industries not presented in this frequency plot, because the median number of firms is over 200. The first industry with the first 3-digit SIC code of 283 includes companies related to medicinal chemicals, pharmaceutical, and biological products. The second industry with the first 3-digit SIC code of 737 includes computer programming, data processing, and prepackaged software companies.

2. *SIC_DN5*: This dummy variable is set to 1 for industries with less than five companies. When SIC_DN5 is equal to 1, Relative_size_S and Relative_size_M are set to zero. A plausible cutoff choice is five companies for two reasons. First, the computation of the four-firm concentration ratio loses its meaning for industries with less than five firms. Second, it seems unreasonable to divide firms into three groups for such a small industry.

4.1.1.3. Firm's own size.

1. *Firm's own size (FirmSize)*: In the numerical analysis of Section 2.3, it is apparent that firm's own size can play a crucial role in determining credit spreads. When firm's own size is large, credit spreads tend to be very small. Following the extant literature, firm's own size is defined as the logarithm of each firm's equity value, computed as stock price times shares outstanding, divided by the total market value of NYSE/AMEX to make the size stationary. Note that firm's own size is not new in the reduced-form literature. Therefore, we have no intention to claim that FirmSize is a measure completely resulting from product market competition; instead, from another perspective it provides economic interpretation of the effect of a firm's own size on default risk.

[13] Note that the recent research by Ali et al. (2009) indicates that the Census HHI is better for capturing actual industry competition than measures that are obtained based on Compustat firms. The Census HHI is based on data from both public and private firms in an industry, and HHI is computed by summing the squares of the sales of individual companies for the 50 largest firms or all the companies in the industry, whichever is lower. However, the U.S. Census Bureau only reports these indices for manufacturing firms every five years. Therefore, due to the very low frequency disadvantage of the Census HHI data, we decide to use HHI computed from public firms in our monthly analysis.

[14] We also conduct an analysis by using market equity as the criterion of relative size dummy. The results are very similar to those using sales as the measure of relative size.

Table 3
Summary statistics of independent variables under the Fama–French 49 Industry Classification. This table reports descriptive statistics of firm-month samples from 1986 to 2009. Ln_N is the natural logarithm of the number of firms per industry; HHI is the Herfindahl-Hirschman Index; CR_4 is the four-firm concentration ratio. Figures in parentheses indicate the number of firms (N) in an industry; S, M, and B denote the relative size groups by respectively dividing each industry into 3 subgroups of small, medium, and big firms. Thirty percentile and seventy percentile of sales volume in the given industry are used as cutoffs; FirmSize is defined as the logarithm of each firm's equity value divided by the total market equity of NYSE/AMEX. π_{Merton} is the firm's implied default probability calculated from the Merton model; Exret_y is the firm's trailing 1-year excess stock return; Idio_Risk is idiosyncratic risk; NI/TA is the ratio of net income to total assets; TL/TL is the ratio of total liabilities to total assets.

Variable	Status	N_Obs	Mean		Median		Standard deviation	
Ln_N (N)	Non-default	1,398,995	5.1195	(215.7383)	5.2311	(187)	0.7824	(146.2770)
	Default	5161	5.1714	(229.9702)	5.2958	(200)	0.7854	(164.7853)
CR_4	Non-default	1,398,995	0.4592		0.4159		0.1659	
	Default	5161	0.4712		0.4381		0.1690	
HHI	Non-default	1,398,995	0.1014		0.0664		0.0982	
	Default	5161	0.1093		0.0722		0.1076	
Ln_N_S (N_S)	Non-default	409,855	5.1034	(213.6932)	5.2204	(185)	0.7955	(146.2522)
	Default	3603	5.1746	(229.2784)	5.2832	(197)	0.7788	(162.3743)
Ln_N_M (N_M)	Non-default	563,726	5.1198	(215.7018)	5.2364	(188)	0.7820	(146.0622)
	Default	1221	5.1706	(230.6675)	5.3566	(212)	0.7903	(164.5213)
Ln_N_B (N_B)	Non-default	425,045	5.1347	(217.7501)	5.2523	(191)	0.7700	(146.5855)
	Default	337	5.1409	(235.0920)	5.1761	(177)	0.8383	(190.0354)
HHI_S	Non-default	409,855	0.1020		0.0668		0.0986	
	Default	3603	0.1121		0.0729		0.1104	
HHI_M	Non-default	563,726	0.1013		0.0663		0.0984	
	Default	1221	0.1042		0.0705		0.1022	
HHI_B	Non-default	425,045	0.1009		0.0663		0.0975	
	Default	337	0.0978		0.0686		0.0947	
CR_4_S	Non-default	409,855	0.4609		0.4175		0.1668	
	Default	3603	0.4757		0.4399		0.1715	
CR_4_M	Non-default	563,726	0.4589		0.4154		0.1660	
	Default	1221	0.4626		0.4293		0.1642	
CR_4_B	Non-default	425,045	0.4580		0.4151		0.1649	
	Default	337	0.4538		0.4366		0.1576	
FirmSize	Non-default	1,398,995	−10.9495		−11.0666		2.0839	
	Default	5161	−14.4030		−14.4984		1.4501	
π_{Merton}	Non-default	1,398,995	0.1417		0.0015		0.2634	
	Default	5161	0.7263		0.8962		0.3340	
Exret_y	Non-default	1,398,995	0.0164		−0.0202		0.6754	
	Default	5161	−0.7700		−0.8090		1.1140	
Idio_Risk	Non-default	1,398,995	0.1542		0.1248		0.1314	
	Default	5161	0.3024		0.2599		0.2223	
NI/TA	Non-default	1,398,794	−0.0185		0.0074		0.2885	
	Default	5161	−0.2286		−0.0747		2.4553	
TL/TA	Non-default	1,398,995	0.4899		0.4791		0.4759	
	Default	5161	0.9325		0.7713		2.7018	

4.1.2. Control variables

We include the following firm-specific covariates widely used in the prior literature.

1. The firm's implied default probability from the Merton model (π_{Merton}): π_{Merton} is derived from the Merton (1974) model, and $N(-DTD)$ represents a company's bankruptcy probability, where $N(.)$ is the standard normal cumulative distribution function and DTD (Distance to Default) is regarded as a volatility-adjusted measure of leverage. Merton's model is widely adopted in both industry (see Crosbie and Bohn, 2003) and academics (see Duffie et al., 2007; and Bharath and Shumway, 2008). Here, π_{Merton} is estimated on a monthly basis using the preceding 1-year daily equity values. Our method for computing π_{Merton} is based on the iterated procedure used by Vassalou and Xing (2004) and Bharath and Shumway (2008). The online Appendix gives a detailed description of its computation.
2. The firm's trailing 1-year excess stock return (Exret_y): Following Shumway (2001) and others, we measure each firm's trailing 1-year excess return in month t as the return of the firm minus the value-weighted market return. Each firm's trailing 1-year returns are calculated by cumulating monthly returns. Market returns are obtained from Kenneth French's website.
3. Idiosyncratic risk (Idio_Risk): The 1-year idiosyncratic volatility is calculated by regressing the monthly stock return on the market return over the preceding 12 months.
4. The ratio of net income to total assets (NI/TA).
5. The ratio of total liabilities to total assets (TL/TL).

We note that there are still many other variables that have been used for reduced-form models in the literature, such as trailing 1-year return on the S&P 500 index, 3-month U.S. Treasury rate, real GDP growth, the cash to total assets ratio, and the market-to-book ratio. Control variables included in our study are by no means comprehensive. Nonetheless, the main purpose of this paper is to investigate how product market competition can affect default risk. To ease any possible estimation difficulty, we tentatively leave those variables for future studies.[15]

[15] In an unreported study, we also include two widely used macro variables (Duffie et al., 2007) in our test – the trailing one-year return on the S&P 500 index and the three-month U.S. Treasury rate (CMT rate in percentage terms). The coefficients of these two covariates are both positively significant as in prior studies. We also incorporate two firm-specific variables – the cash to total assets ratio and the market-to-book ratio – in empirical tests. The inclusion of these covariates does not distinctively affect the levels of significance of other variables. However, there is no improvement of out-of-sample prediction capability by including these two macro variables or two firm-specific variables mentioned above. Since they do not make up the major interest of this paper, we do not report the results so as to conserve space.

Table 4
Hazard model estimates under the Fama–French 49-Industry Classification. This table reports estimates of several Cox proportional hazard models with time-varying covariates. The sample period is from 1986 to 2009 and there are 1398,995 firm-month samples and 5161 defaults in the sample. p-Values are in parentheses, below the estimates. Variables of product market competition are defined as follows: Ln_N is the natural logarithm of the number of firms in an industry; Relative_size_S and Relative_size_M are relative size dummies of small and medium firms, respectively. Thirty percentile and seventy percentile of sales volume in the given industry are used as cutoffs; FirmSize is defined as the logarithm of each firm's equity value divided by the total market equity of NYSE/AMEX. Five firm-specific control variables are as follows: π_{Merton} is the firm's implied default probability from the Merton model; Exret_y is the firm's trailing 1-year excess stock return; Idio_Risk is idiosyncratic risk; NI/TA is the ratio of net income to total assets; TL/TL is the ratio of total liabilities to total assets.

Parameter		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Panel A. Hazard model estimates of the number of firms per industry (Ln_N)										
Ln_N	Coefficient	0.2103	0.0378	−0.0157					0.0292	−0.0069
	p-Value	(<.0001)	(0.0301)	(0.3675)					(0.0935)	(0.6917)
Ln_N* Relative_size_S	Coefficient				0.2748	0.1044				
	p-Value				(<.0001)	(<.0001)				
Ln_N* Relative_size_M	Coefficient				0.1002	0.0256				
	p-Value				(<.0001)	(0.0126)				
Relative_size_S	Coefficient						1.7620	0.7313	1.7618	0.7306
	p-Value						(<.0001)	(<.0001)	(<.0001)	(<.0001)
Relative_size_M	Coefficient						0.8012	0.2876	0.8019	0.2871
	p-Value						(<.0001)	(<.0001)	(<.0001)	(<.0001)
FirmSize	Coefficient			−0.4928		−0.4306		−0.4238		−0.4241
	p-Value			(<.0001)		(<.0001)		(<.0001)		(<.0001)
π_{Merton}	Coefficient		2.7992	1.6610	2.9108	1.8849	2.8830	1.9180	2.8900	1.9161
	p-Value		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Exret_y	Coefficient		−1.1729	−0.9046	−1.0099	−0.8773	−1.0284	−0.8788	−1.0231	−0.8795
	p-Value		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Idio_Risk	Coefficient		4.2602	3.3208	3.6360	3.2013	3.6842	3.1978	3.6668	3.2001
	p-Value		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
NI/TA	Coefficient		−0.0644	−0.0417	−0.0448	−0.0339	−0.0550	−0.0389	−0.0539	−0.0392
	p-Value		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
TL/TA	Coefficient		0.0163	0.0212	0.0199	0.0224	0.0150	0.0203	0.0155	0.0202
	p-Value		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)

Table 3 reports descriptive statistics of firm-month variables under Fama–French 49-industry classification. As we expect, the number of firms in the industry (Ln_N or N) for default samples is higher than that of non-default samples. However, the default group has higher average concentration ratios, HHI, and CR_4, indicating more concentrated and less competitive industries. This may at first look puzzling, but when the effect of the relative size of firms in an industry also comes into play, relatively small firms in a more concentrated industry (with high HHI and CR_4) could even be more easily driven out of the market than equally small firms in a less concentrated industry (with low HHI and CR_4). This can make firms in the default group have a higher HHI (CR_4) than the non-default samples, which is confirmed by observing the HHI (CR_4) of sales-ordered subgroups. In Panel A of Table 3 for the default samples, the average HHIs of small, medium, and big relative size subgroups are 0.1121, 0.1042, and 0.0978, respectively. The decreasing trend of concentration ratios conforms to our conjecture that HHI is indeed negatively associated with the relative size of firms. The results of CR_4s are similar and present the same pattern. In addition, we find that the number of default firms in small, medium, and big size groups are 3603, 1221, and 337, respectively. It appears that default firms are relatively small firms in their respective industries. The average FirmSize, measured as a firm's market equity, of companies in the default group is much smaller than that for the non-default group.[16] All control variables are in line with results in the literature – π_{Merton}, idiosyncratic risk and TL/TA are larger, while NI/TA and trailing 1-year excess return are smaller for the default samples.

4.2. Empirical results of the hazard model

We present our empirical results under the Fama–French 49-industry classification in Section 4.2 and leave the results under the 3-digit SIC classification to robustness analysis in Section 4.3. Before reporting our empirical results, we first briefly discuss our variables constructed in the previous section. Since the firm's size can be characterized in terms of the firm's own value or its relative size in an industry, empirically we use a firm's equity value (FirmSize) as a proxy for firm's own size and employ the relative order of the firm's market share in an industry (Relative size dummies; Relative_size_S and Relative_size_M) to represent the relative size of the firm. Relative size dummies (Relative_size_S and Relative_size_M), computed as the relative order of market shares, measure the degree of ''the relative market power'' or ''relative competitive position'' within an industry. Relative size dummies can effectively measure firms' relative size distribution in a given industry.

We report estimates of the hazard model under the Fama–French 49-Industry classification in Tables 4 and 5. Table 4 presents the results for the logarithm of the number of firms per industry (Ln_N), and Table 5 reports those for HHI and CR_4. From Hypothesis 1a, the number of firms in an industry (Ln_N) is expected to be positively related to the hazard rate since a higher Ln_N indicates higher competition intensity, which implies distressed firms should have higher probabilities of default in more competitive industries. Model 1 of Table 4 shows the coefficient of Ln_N is positive and significantly explains default intensity. This is consistent with Hypothesis 1a that credit risk is are positively related to the number of firms in an industry.

Fig. 1 also demonstrates the importance of the effects of a firm's own size on credit spreads. Credit spreads are much more sensitive to competition intensity when firm's own size is small. It is only when the firm's own size is small enough that the credit spread does increase remarkably in terms of economic magnitude. It implies that other uncontrolled firm characteristics can hinder us from uncovering the real relationship between product market competition and credit risk. Accordingly, in addition to competition related variables, the five control variables of firm

[16] Note that the average of firm size is negative, because it is the logarithm of a small fraction of the total NYSE/AMEX market equity value.

Table 5
Hazard model estimates under the Fama–French 49-Industry Classification. This table reports estimates of several Cox proportional hazard models with time-varying covariates. The sample period is from 1986 to 2009 and there are 1398,995 firm-month samples and 5161 defaults in the sample. *p*-Values are in parentheses, below the estimates. Variables of product market competition are defined as follows: HHI is the Herfindahl-Hirschman Index; CR_4 is the four-firm concentration ratio; Relative_size_S and Relative_size_M are relative size dummies of small and medium firms, respectively. Thirty percentile and seventy percentile of sales volume in the given industry are used as cutoffs; FirmSize is defined as the logarithm of each firm's equity value divided by the total market equity of NYSE/AMEX. Five firm-specific control variables are as follows: π_{Merton} is the firm's implied default probability from the Merton model; Exret_y is the firm's trailing 1-year excess stock return; Idio_Risk is idiosyncratic risk; NI/TA is the ratio of net income to total assets; TL/TL is the ratio of total liabilities to total assets.

Parameter		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Panel A. Hazard model estimates of the Herfindahl-Hirschman Index (HHI)										
HHI	Coefficient	1.2110	1.1534	0.9580					1.1389	0.9807
	p-Value	(<.0001)	(<.0001)	(<.0001)					(<.0001)	(<.0001)
HHI* Relative_size_S	Coefficient				3.1464	1.7992				
	p-Value				(<.0001)	(<.0001)				
HHI* Relative_size_M	Coefficient				−1.2378	−0.3944				
	p-Value				(<.0001)	(0.0893)				
Relative_size_S	Coefficient						1.7620	0.7313	1.7616	0.7347
	p-Value						(<.0001)	(<.0001)	(<.0001)	(<.0001)
Relative_size_M	Coefficient						0.8012	0.2876	0.7998	0.2876
	p-Value						(<.0001)	(<.0001)	(<.0001)	(<.0001)
FirmSize	Coefficient			−0.4916		−0.4635		−0.4238		−0.4225
	p-Value			(<.0001)		(<.0001)		(<.0001)		(<.0001)
π_{Merton}	Coefficient		2.7864	1.6709	2.8287	1.7675	2.8830	1.9180	2.8824	1.9247
	p-Value		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Exret_y	Coefficient		−1.1810	−0.9014	−1.1310	−0.8935	−1.0284	−0.8788	−1.0296	−0.8780
	p-Value		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Idio_Risk	Coefficient		4.2889	3.3118	4.0981	3.2734	3.6842	3.1978	3.6905	3.1964
	p-Value		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
NI/TA	Coefficient		−0.0660	−0.0418	−0.0631	−0.0412	−0.0550	−0.0389	−0.0557	−0.0397
	p-Value		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
TL/TA	Coefficient		0.0152	0.0211	0.0140	0.0203	0.0150	0.0203	0.0145	0.0199
	p-Value		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Panel B. Hazard model estimates of the four-firm concentration ratio (CR_4)										
CR_4	Coefficient	0.6963	0.7142	0.5981					0.7473	0.6238
	p-Value	(<.0001)	(<.0001)	(<.0001)					(<.0001)	(<.0001)
CR_4 * Relative_size_S	Coefficient				2.2134	1.1143				
	p-Value				(<.0001)	(<.0001)				
CR_4 * Relative_size_M	Coefficient				0.4180	0.2340				
	p-Value				(<.0001)	(0.0067)				
Relative_size_S	Coefficient						1.7620	0.7313	1.7662	0.7383
	p-Value						(<.0001)	(<.0001)	(<.0001)	(<.0001)
Relative_size_M	Coefficient						0.8012	0.2876	0.8031	0.2894
	p-Value						(<.0001)	(<.0001)	(<.0001)	(<.0001)
FirmSize	Coefficient			−0.4907		−0.4313		−0.4238		−0.4211
	p-Value			(<.0001)		(<.0001)		(<.0001)		(<.0001)
π_{Merton}	Coefficient		2.7881	1.6730	2.8908	1.8914	2.8830	1.9180	2.8885	1.9299
	p-Value		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Exret_y	Coefficient		−1.1816	−0.9026	−1.0630	−0.8829	−1.0284	−0.8788	−1.0292	−0.8786
	p-Value		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Idio_Risk	Coefficient		4.2878	3.3132	3.8193	3.2157	3.6842	3.1978	3.6851	3.1953
	p-Value		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
NI/TA	Coefficient		−0.0651	−0.0410	−0.0566	−0.0392	−0.0550	−0.0389	−0.0547	−0.0390
	p-Value		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
TL/TA	Coefficient		0.0144	0.0204	0.0108	0.0184	0.0150	0.0203	0.0136	0.0191
	p-Value		(<.0001)	(<.0001)	(0.0002)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)

characteristics (π_{Merton}, Exret_y, Idio_Risk, NI/TA, and TL/TA) are included in the following hazard models (Models 2–9).

The results of Models 2 and 3 in Table 4 support Hypothesis 1b and confirm the importance of firm's own size to the hazard rate. The coefficients of FirmSize are significantly negatively related to default intensity, controlling for the five firm characteristics. Although the negative relationship between credit risk (default probabilities) and firms' equity value (FirmSize) is not the exclusive prediction of our theoretical models, we provide theory-based explanations through the effect of product market competition.[17] The signs of the five control variables are in line with previous empirical studies and are all statistically significant.

The results of Models 4 and 5 confirm our Hypothesis 1c that the sensitivity of credit risk to the number of firms in an industry is amplified when the firm size becomes smaller. Ln_N*Relative_size_S and Ln_N*Relative_size_S are both significantly positively related to hazard rates, and the economic significances of the interaction terms between Ln_N and Relative_size_S are larger than those for Relative_size_M. For example, in Model 5, the coefficient of Ln_N*Relative_size_S is 0.1044 and this is around four times the magnitude of 0.0256, the coefficient of Ln_N*Relative_size_M. These results are consistent with Hypothesis 1c, which suggests that credit spreads are much more sensitive to the intensity of competition when firm size is smaller. Note that

[17] As mentioned previously, we do not intend to claim that FirmSize is a measure resulting completely from the effect of competition; rather, we wish to provide theory-based explanations and empirical tests in our study.

unlike the insignificant coefficient of Ln_N in Model 3, the interaction terms between Ln_N and Relative_size_S in Model 5 is positively significant in explaining the credit risk (hazard rate) even when one controls for five firm-specific characteristics and FirmSize. This again confirms the higher sensitive of Ln_N for smaller firms compared to that of larger firms.

We next present the empirical results of Hypotheses 2a, 2b, and 2c in Table 5. We examine two widely-used variables measuring concentration of an industry, HHI and CR_4, in the literature. For the purpose of comparison, we present variables in the same way as Table 4. The support of Hypothesis 2a can be found in Models 4 and 5 of Table 5. In Panel A (B), HHI*Relative_size_S (CR_4*Relative_size_S) is significantly positively related to hazard rates, indicating that the credit risk (hazard rate) of relatively small firms are positively related to HHI (CR_4). The results confirm our Hypothesis 2a and suggest that the firms' relative size distribution within the industry does influence the effect of competition intensity on firms' credit risk. The economic interpretation of Hypothesis 2a can be as the following. Relatively small firms in a highly concentrated industry (with high HHI and CR_4) can be driven out of the market more easily than equally small firms in a less concentrated industry (with low HHI and CR_4), thereby making the default likelihood of some relatively small firms in high HHI (CR_4) industries be even higher compared to those in low HHI (CR_4) industries.

For further illustration, consider two five-firm industries. Ind_1: Three firms have a market share of 30% each and the other two have 5% each; Ind_2: The market shares of five firms are all equal to 20%. To facilitate the comparison, we present HHI and CR_4 using the decimal number format hereafter. The HHI and CR_4 of Ind_1 are clearly higher (HHI: 0.275 in Ind_1 versus 0.2 in Ind_2; CR_4: 0.95 in Ind_1 versus 0.8 in Ind_2). However, the conventional wisdom is that those two firms in Ind_1 with 5% market shares are more likely to be forced out of the market compared with the firms in Ind_2. This demonstrates a sensible "positive" relationship between default intensity of the relatively small firms and HHI. In this paper, CR_4 is similar to HHI and has the same problem in interpreting the relationship between the hazard rate and competition intensity. Therefore, it raises the need to account for the relative firm size within an industry to overcome the problem of diverseness of firm size.

Hypothesis 2b is a novel prediction, suggesting that default risk should increase with a decrease in the relative size of firms in an industry. In Models 6–7, the coefficient of the dummy variable Relative_size_S is expected to be positive and larger than the coefficient of Relative_size_M. Our results of Models 6–7 strongly support Hypothesis 2b. The relative size dummies exhibit a strong positive relationship with default intensity. In addition, the coefficients of Relative_size_S are much larger than those of Relative_size_M, implying that default probabilities decrease with an increase in relative firm sizes in an industry. The statistical significance of the results is also robust to the inclusion of firm's own size (FirmSize), suggesting that relative size dummies indeed capture the degrees of "relative market power" or "relative competitive position" within an industry which are not fully reflected by the firm's own size. Cross comparing Models 6 and 7 to Models 8 and 9, it appears that the explanatory power of the relative size dummies is not affected by the inclusion of competition variables.[18]

To gain support for Hypothesis 2c, one needs to examine the coefficients of the interaction terms between HHI (CR_4) and relative size dummies in Models 4 and 5. In Panels A and B, the economic and statistical significances of interaction terms of the relatively small firms within an industry (Relative_size_S) are both larger than those of the medium firms (Relative_size_M). For example, in Models 4 and 5, the coefficients of CR_4*Relative_size_S are around five times the magnitude of CR_4*Relative_size_M (2.2134 versus 0.4180 in Model 4; and 1.1143 versus 0.2340 in Model 5). These results are consistent with Hypothesis 2c, which suggests that credit risks are much more sensitive to the concentration ratio (HHI and CR_4) when a firm's relative size compared to other firms in the same industry is smaller.

Finally, we turn back to the results of Models 1–3 in Table 5. The positive relation between HHI (CR_4) and default intensity suggests that credit risk is lower for industries with low concentration ratios (less concentrated). However, less concentrated industries are usually been interpreted as being more competitive with a large number of companies in the industry. This simple reasoning suggests exactly opposite signs of HHI (CR_4) and Ln_N, thus making the results of our Models 1–3 seem a little puzzling – the coefficients of HHI (CR_4) in Table 5 exhibit the same positive signs as those of Ln_N in Table 4. As we have already shown in our theoretical models and empirical results, the interpretation of HHI (CR_4) may not be so obvious across different industries due to its ability to capture the disparity of firm size in a given industry. In the real world, firms in an industryhave different sizes and Hypothesis 2a indicates that effects of HHI (CR_4) on firms' credit risk can be opposite for relatively small and relatively large firms in an industry. As a consequence, due to the higher sensitivity of credit risk for smaller firms compared to lower sensitivity for larger firms (previous finding of Hypothesis 2c), the relationship between default intensity and HHI (CR_4) can be dominated by the impact of the small firms in high HHI (CR_4) industries, thereby yielding a positive relationship between HHI (CR_4) and default intensity.

4.3. Robustness analysis

For robustness, we also conduct all the tests under the 3-digit SIC level classification, because an important empirical issue for product market competition research is industry classification. Most of the results by the 3-digit SIC code in Table 6 are very similar to those in Tables 4 and 5 in terms of statistical significance. Therefore, it appears that our results regarding the effect of product market competition on credit risk are robust and not particularly sensitive to the choice of industry classification in the hazard model.[19]

In summary, our empirical findings regarding the effect of product market competition on credit risk are robust to the choice of industry classification. In general, the hypotheses are supported by empirical tests. Consequently, the variables of product market competition can substantially influence default probabilities of companies.

4.4. Out-of-sample prediction accuracy analysis

Following the literature, we conduct an out-of-sample predication accuracy analysis incorporating factors related to product market competition. We adopt the method of Receiver Operating Characteristic (ROC) and accuracy ratio (AR) proposed by Moody's, which is also widely used by academics. A detailed description of AR computation can be found in Crosbie and Bohn (2003) and Vassalou and Xing (2004).

To perform the out-of-sample test, for each month we first classify all firms into two groups: an estimation group and an

[18] In Models 8 and 9 of Tables 4 and 5, we wish to disentangle the explanatory power of competition variables and relative-size dummies. From the results in Models 8 and 9, one finds that the results of HHI and CR_4 are very similar to those in Models 2 and 3, while the explanatory power of Ln_N further deteriorates when relative-size dummies are added.

[19] We do not report estimates of the control variables to conserve space. Unreported results of the control variables show that NI/TA is no longer significant in explaining the hazard rate under this finer industry classification.

Table 6

Robustness analysis: Hazard model estimates under the 3-digit SIC industry classification. This table reports estimates of several Cox proportional hazard models with time-varying covariates. The sample period is from 1986 to 2009 and there are 1420,779 firm-month samples and 5398 defaults in the sample. p-Values are in parentheses, below the estimates. Variables of product market competition are defined as follows: Ln_N is the natural logarithm of the number of firms in a given industry; HHI is the Herfindahl-Hirschman Index; CR_4 is the four-firm concentration ratio; Relative_size_S and Relative_size_M are relative size dummies of small and medium firms, respectively. Thirty percentile and seventy percentile of sales volume in the given industry are used as cutoffs; FirmSize is defined as the logarithm of each firm's equity value divided by the total market equity of NYSE/AMEX. Five firm-specific control variables are as follows: π_{Merton} is the firm's implied default probability from the Merton model; Exret_y is the firm's trailing 1-year excess stock return; Idio_Risk is idiosyncratic risk; NI/TA is the ratio of net income to total assets; TL/TL is the ratio of total liabilities to total assets. We do not report estimates of control variables to conserve space.

Parameter		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Panel A. Hazard model estimates of the number of firms per industry (Ln_N)										
Ln_N	Coefficient	0.0836	0.0141	−0.0142					0.0178	−0.0120
	p-Value	(<.0001)	(0.1427)	(0.1343)					(0.0861)	(0.2434)
Ln_N* Relative_size_S	Coefficient				0.2231	0.0716				
	p-Value				(<.0001)	(<.0001)				
Ln_N* Relative_size_M	Coefficient				0.0224	−0.0239				
	p-Value				(0.0192)	(0.0156)				
Ln_N*SIC_DN5	Coefficient				0.2458	0.0441				
	p-Value				(0.0011)	(0.5632)				
Relative_size_S	Coefficient						1.7402	0.7250	1.7422	0.7221
	p-Value						(<.0001)	(<.0001)	(<.0001)	(<.0001)
Relative_size_M	Coefficient						0.7977	0.2753	0.7984	0.2746
	p-Value						(<.0001)	(<.0001)	(<.0001)	(<.0001)
SIC_DN5	Coefficient						1.0048	0.4176	1.0573	0.3801
	p-Value						(<.0001)	(<.0001)	(<.0001)	(<.0001)
FirmSize	Coefficient			−0.4955		−0.4492				−0.4331
	p-Value			(<.0001)		(<.0001)				(<.0001)
Panel B. Hazard model estimates of the Herfindahl-Hirschman Index (HHI)										
HHI	Coefficient	0.4427	0.5420	0.4695					0.8296	0.7059
	p-Value	(<.0001)	(<.0001)	(<.0001)					(<.0001)	(<.0001)
HHI* Relative_size_S	Coefficient				2.4432	1.3097				
	p-Value				(<.0001)	(<.0001)				
HHI* Relative_size_M	Coefficient				−0.3260	−0.0291				
	p-Value				(0.0238)	(0.8335)				
HHI*SIC_DN5	Coefficient				0.1279	0.0906				
	p-Value				(0.2627)	(0.4216)				
Relative_size_S	Coefficient						1.7402	0.7250	1.7373	0.7237
	p-Value						(<.0001)	(<.0001)	(<.0001)	(<.0001)
Relative_size_M	Coefficient						0.7977	0.2753	0.7994	0.2739
	p-Value						(<.0001)	(<.0001)	(<.0001)	(<.0001)
SIC_DN5	Coefficient						1.0048	0.4176	0.6092	0.0654
	p-Value						(<.0001)	(<.0001)	(<.0001)	(0.5384)
FirmSize	Coefficient			−0.4942		−0.4655		−0.4320		−0.4308
	p-Value			(<.0001)		(<.0001)		(<.0001)		(<.0001)
Panel C. Hazard model estimates of the four-firm concentration ratio (CR_4)										
CR_4	Coefficient	0.4098	0.5522	0.5532					0.6460	0.6209
	p-Value	(<.0001)	(<.0001)	(<.0001)					(<.0001)	(<.0001)
CR_4 * Relative_size_S	Coefficient				1.7809	0.9144				
	p-Value				(<.0001)	(<.0001)				
CR_4 * Relative_size_M	Coefficient				0.5099	0.3130				
	p-Value				(<.0001)	(<.0001)				
CR_4 *SIC_DN5	Coefficient				0.5481	0.3275				
	p-Value				(<.0001)	(0.0002)				
Relative_size_S	Coefficient						1.7402	0.7250	1.7381	0.7207
	p-Value						(<.0001)	(<.0001)	(<.0001)	(<.0001)
Relative_size_M	Coefficient						0.7977	0.2753	0.8020	0.2781
	p-Value						(<.0001)	(<.0001)	(<.0001)	(<.0001)
SIC_DN5	Coefficient						1.0048	0.4176	0.7902	0.2065
	p-Value						(<.0001)	(<.0001)	(<.0001)	0.0387
FirmSize	Coefficient			−0.4950		−0.4410		−0.4320		−0.4325
	p-Value			(<.0001)		(<.0001)		(<.0001)		(<.0001)

evaluation group. Following the standard empirical methodology to test prediction performance, we employ coefficients estimated from the estimation group to compute default probabilities of each firm in the evaluation group. To ensure there are enough samples for properly "training" the model, we use all monthly samples from 1986 to 1999 for model estimation and conduct the out-of-sample prediction starting from January 2000 by a moving-window approach. In other words, we re-estimate the hazard model each month with all data available up to that time and take the coefficients obtained to calculate predicted default probabilities for all firms in that month. For instance, we compute default probabilities of all firms in January 2000 based on the estimated hazard model coefficients using data from 1986 to December 1999. We next calculate firms' default probabilities in February 2000 based on

Table 7
Accuracy ratios under the Fama–French 49-Industry Classification. All models include five firm-specific variables: π_{Merton}, exret_y, Idio_Risk, NI/TA, and TL/TA. Two benchmark models are used to contrast the AR of each model – one includes only 5 firm-specific variables (Model 5) and the other incorporates an additional variable FirmSize (Model 10). Relative_Size_D represents two relative size dummies (Relative_size_S and Relative_size_M). We use all monthly samples from 1986 to 1999 for model estimation and conduct out-of-sample predictions from 2000/1 to 2009/12. There are 1398,995 firm-month samples and 5161 defaults in the sample.

Model	Variables of competition	ROC Area	Contrast Estimate	Model 5 *p*-Value	Contrast Estimate	Model 10 *p*-Value
Panel A. 3-Month prediction						
1	Ln_N * Relative_Size_D	0.8624	0.0214	<.0001	−0.0168	<.0001
2	CR_4 * Relative_Size_D	0.8535	0.0125	<.0001	−0.0257	<.0001
3	HHI * Relative_Size_D	0.8454	0.0044	<.0001	−0.0338	<.0001
4	Relative_Size_D	0.8631	0.0222	<.0001	−0.0161	<.0001
5		0.8410			−0.0382	<.0001
6	Ln_N * Relative_Size_D + FirmSize	0.8814	0.0404	<.0001	0.0022	<.0001
7	CR_4 * Relative_Size_D + FirmSize	0.8788	0.0378	<.0001	−0.0005	0.1095
8	HHI * Relative_Size_D + FirmSize	0.8787	0.0377	<.0001	−0.0006	0.0008
9	Relative_Size_D + FirmSize	0.8806	0.0396	<.0001	0.0014	0.0007
10	FirmSize	0.8792	0.0382	<.0001		
Panel B. 6-Month prediction						
1	Ln_N * Relative_Size_D	0.8417	0.0241	<.0001	−0.0164	<.0001
2	CR_4 * Relative_Size_D	0.8315	0.0139	<.0001	−0.0266	<.0001
3	HHI * Relative_Size_D	0.8226	0.0050	<.0001	−0.0354	<.0001
4	Relative_Size_D	0.8425	0.0248	<.0001	−0.0156	<.0001
5		0.8176			−0.0404	<.0001
6	Ln_N * Relative_Size_D + FirmSize	0.8613	0.0437	<.0001	0.0032	<.0001
7	CR_4 * Relative_Size_D + FirmSize	0.8582	0.0405	<.0001	0.0001	0.7102
8	HHI * Relative_Size_D + FirmSize	0.8577	0.0401	<.0001	−0.0003	0.0083
9	Relative_Size_D + FirmSize	0.8604	0.0428	<.0001	0.0023	<.0001
10	FirmSize	0.8581	0.0404	<.0001		
Panel C. 12-Month prediction						
1	Ln_N * Relative_Size_D	0.7951	0.0305	<.0001	−0.0178	<.0001
2	CR_4 * Relative_Size_D	0.7822	0.0176	<.0001	−0.0308	<.0001
3	HHI * Relative_Size_D	0.7709	0.0062	<.0001	−0.0421	<.0001
4	Relative_Size_D	0.7970	0.0324	<.0001	−0.0160	<.0001
5		0.7646			−0.0484	<.0001
6	Ln_N * Relative_Size_D + FirmSize	0.8179	0.0532	<.0001	0.0049	<.0001
7	CR_4 * Relative_Size_D + FirmSize	0.8139	0.0492	<.0001	0.0009	<.0001
8	HHI * Relative_Size_D + FirmSize	0.8128	0.0482	<.0001	−0.0002	0.0835
9	Relative_Size_D + FirmSize	0.8174	0.0528	<.0001	0.0045	<.0001
10	FirmSize	0.8130	0.0484	<.0001		

Variable * Relative_Size_D denotes the interaction terms between variables of intensity of competition and the relative size dummies.

coefficients obtained using data from 1986 to January 2000. These default probabilities are then used as input for 3-month, 6-month, and 1-year out-of-sample prediction analyses.

Table 7 reports accuracy ratios of three different prediction horizons under the Fama–French 49-industry classification. In addition to industry competition variables, all models in the AR test include five firm-specific variables: π_{Merton}, exret_y, Idio_Risk, NI/TA, and TL/TA. Two benchmark models are used to contrast the AR of each model: one includes only five firm-specific variables (Model 5) and the other incorporates an additional variable FirmSize (Model 10). Relative_Size_D represents two relative size dummies (Relative_size_S and Relative_size_M) in Table 7. Variable*Relative_Size_D denotes the interaction terms between variables of competition and the relative size dummies.

First we look at the results for the 3-month prediction of Models 1–5 in Panel A of Table 7. Comparing the effect of competition variables, Model 4's adding of the relative size dummies (AR = 0.8631) is the best performing model, followed by Model 1 incorporating the interaction terms between relative size dummies and number of firms per industry (Ln_N) (AR = 0.8624), Model 2 introducing interactions with CR_4 (AR = 0.8535), Model 3 adding interaction terms with HHI (AR = 0.8454), and Model 5 with only five control variables (AR = 0.8812). It is apparent that considering the variables of product market competition indeed enhances out-of-sample prediction accuracy. Similar results are also obtained from the 6-month and 12-month predictions in Panels B and C of Table 7.

We next incorporate FirmSize into the AR test in Models 6 to 10. The improvement in AR of Model 10 by adding FirmSize alone, compared with Model 5, is substantial and can be up to around 4% for different prediction horizons. One also observes that when FirmSize is considered, contributions from other competition variables to AR largely decrease, compared with Model 10. While Models 6 and 9 still improve their ARs over the benchmark Model 10, the interaction terms of relative size and CR_4 (Model 7) and of HHI (Model 8) surprisingly do not add any prediction power to the out-of-sample AR test. The reason why FirmSize largely improves the performance of AR and reduces the power of other variables could be due to its reflection of industry competition in many aspects. Since it is well-known in the literature that a firm's default probability (or the likelihood of financial distress) is highly related to its profitability and the ability to pay off its debts, the joint effect of aggregate industry demand and intra-industry competitiveness should be the most crucial factor in determining credit spreads. Profits and firm values are the consequence of product market competition and are collectively reflected in FirmSize, a firm's market capitalization. The results of the AR test in Table 7 thus confirm the importance of this joint effect.

The relative competitiveness and its interaction with competition intensity are of second-order importance, once we put Firm-

Size into default probability computation. Therefore, while variables of product market competition in Table 7 are all statistically significant in explaining default intensity in the hazard model test, they can only marginally enhance prediction capability in addition to a firm's own size. Another finding in Table 7 is that the prediction capability of Model 9 adding the relative size dummies now falls behind Model 6, which incorporates interaction terms between the relative size dummies and the number of firms per industry (Ln_N). This may be attributed to the closer relationship between FirmSize and the relative size dummies compared with the interaction terms of the relative size dummies and Ln_N.

Finally, the accuracy ratio analysis is similar under the 3-digit SIC industry classification and is reported in an online Appendix. The order of predictive capabilities of almost all models is in line with the Fama–French 49-industry classification.[20] In sum, our out-of-sample prediction accuracy analysis shows that the variables of product market competition effectively influence default probabilities and are useful in predicting future defaults.

5. Conclusion

Prior studies of Jorion and Zhang (2007) and Chava and Jarrow (2004) have documented that industry characteristics can affect default risk. However, most prevailing credit risk models do not consider the industry effect. This study thus theoretically and empirically investigates the effect of product market competition on credit risk. The main results of our paper can be summarized as follows.

This paper theoretically and empirically examines the effects of product market competition on credit risk. We first consider the case of symmetric firms in a homogeneous oligopoly and show that credit spreads are *positively* related to the number of firms in an industry. When the firm's own size is small, the sensitivity of the above effect is amplified and the firm's credit risk increases. To clearly identify that the number of firms and HHI are the two different dimensions of market competition in an industry, we further extend the model to the case of asymmetric firms in a duopoly. We demonstrate that credit spreads of relatively small firms are *positively* related to HHI and those of relatively large firms are *negatively* related to HHI. In addition, relatively small firms in an industry suffer a higher credit risk than relatively large firms, and the sensitivity of credit risk of relatively small firms to HHI in an industry is higher than that of relatively large firms to HHI.

The reduced-form hazard model is then employed to empirically investigate our models' predictions. Controlling for firm characteristics, the estimates of the hazard model confirm that:

(1) Default intensity is significantly *positively* related to the number of firms in an industry, whereas default intensity of relatively smaller (large) firms is significantly *positively* (*negatively*) related to the concentration ratio (HHI and four-firm concentration ratio), thereby supporting our predictions and showing that the number of firms and concentration ratio leads to different impacts on credit risk for relatively small firms in an industry.
(2) The firm size (using market equity as proxy) is significantly negatively related to hazard rate, whereas the relative firm size dummy in an industry, accounting for heterogeneity of firms, has significant power to explain default intensity, thereby supporting our predictions and demonstrating that not only a firm's own size, but also the relative firm size in an industry is crucial to default risk.
(3) By introducing the interaction terms between competition intensity and relative firm size dummies, credit risk is found to be much more sensitive to the number of firms and HHI in an industry when the firm size is small, thus supporting our predictions.

We also perform an out-of-sample default prediction by using accuracy ratio tests. The results show that relative market power and its interaction with competition intensity are important to default prediction. In particular, we find that considering firm size together with the interaction terms between the relative size dummy and the number of firms in the industry most effectively predicts default. As a result, incorporating variables related to product market competition can enhance the out-of-sample prediction performance of reduced-form models.

In addition to the prevailing macro factors and firm-specific characteristics, our study raises some important issues for considering product market competition as an industry effect. Our findings have important implications for default correlation and credit contagion, thereby being applicable to portfolio credit risk models. Moreover, our models contribute to the literature linking the cross section of equity returns to credit spreads and product market competition (e.g., Lyandres and Watanabe, 2011). Finally, aside from the academic importance, for practitioners, default intensities are a necessary input to credit derivative pricing models.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jbankfin.2012.09.001.

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[20] A notable difference is that all models perform better under the Fama-French 49-industry than the 3-digit SIC industry classification, for an average difference of 1.5% in AR. Two possible reasons for higher ARs of the Fama-French 49-industry industry classification are: (1) the coarser definition of the Fama-French 49-industry industry classification; and (2) exclusion of some firms that are hard to classify by Fama and French (Industry Code 49) since the competition effect of these firms is not expected to be substantial.

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