Credit Risk Spillovers and Cash Holdings

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Abstract

This paper examines how credit risk spillovers affect corporate financial flexibility. We construct separate empirical proxies to disentangle the two channels of credit risk spillovers—credit risk contagion (CRC), which increases industry peers' distress likelihood; and product market rivalry (PMR), which strengthens rivals' competitive position. We show that firms facing greater CRC hold more cash, make lower payouts, and must contend with less favorable bank loan terms. In contrast, PMR generally has opposite, albeit weaker, effects. Our findings suggest that credit risk spillovers, especially CRC, play an important role in corporate liquidity management.

JEL Classification Codes: G21, G32, G33

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1 Introduction

In the presence of external financial frictions and credit constraints, firms accumulate cash to better cope with adverse shocks. This precautionary motive is of central importance in understanding the secular trend of corporate cash holdings (Bates, Kahle, and Stulz, 2009). In particular, Acharya, Davydenko, and Strebulaev (2012) document firms building up cash reserves as a buffer against their own deteriorating credit risk. Firms, however, do not operate in isolation and their credit conditions are closely related to the financial soundness of their peers. The recent financial crisis vividly demonstrates how the distress of Lehman Brothers spread out and affected a large number of firms (Fernando, May, and Megginson, 2012; Chakrabarty and Zhang, 2012). Furthermore, studies have long documented significant ex post impact of extreme credit events (e.g., bankruptcies) on the equity returns and credit spreads of other industry participants (Lang and Stulz, 1992; Hertzel, Li, Officer, and Rodgers, 2008; Jorion and Zhang, 2009; Hertzel and Officer, 2012; Boone and Ivanov, 2012). Despite well-documented interconnectedness of corporate credit risk, whether a firm's credit risk exposure to its peers affects its liquidity management remains a largely unexplored question. This paper sets out to fill this gap by systematically analyzing the spillover effects of credit risk on firms' cash holdings and borrowing cost.

A firm's worsening credit risk generates two distinct types of externalities for its peers. The first is the credit risk contagion (CRC) effect, which increases the peer firms' distress likelihood. This could work its way through direct business links across firms, such as those between customers and suppliers (Jarrow and Yu, 2001), or through investors learning and updating beliefs about unobserved states (Das, Duffie, Kapadia, and Saita, 2007; Duffie, Eckner, Horel, and Saita, 2009; Benzoni, Collin-Dufresne, Goldstein, and Helwege, 2015). Moreover, Benmelech and Bergman (2011) articulate a "collateral channel," in which airline bankruptcies reduce the collateral value of solvent airlines and raise the cost of debt across the entire industry.

The second type of externality is the product market rivalry (PMR) effect, which suggests that a firm's financial slump and potential exit may strengthen other industry participants' competitive position. For instance, Lang and Stulz (1992) find that in concentrated industries, the equity value of a firm's competitors would rise following its bankruptcy announcement. Hertzel and Officer (2012) report that the contagion of bankruptcy events, which heightens solvent firms' loan spreads, is mitigated in concentrated industries where a firm's exit often greatly enhances the market power of its rivals.

Given the complexity of peer firms' credit risk externalities, we use an analytic framework to examine a firm's optimal cash holdings in the presence of both CRC and PMR. In the model, the firm faces a tradeoff between deploying its cash for initial investment or saving some of it for a later stage when CRC and PMR come into prominence due to peer firms' financial distress. Comparative statics suggest that the firm would build up liquidity buffers to cope with the adverse CRC effect from the distress of fellow firms. The PMR effect on cash holdings, however, is ambiguous. On one hand, the potential exit of rivals and re-allocation of market share could spur a healthy firm into product market predation, i.e., hoarding cash for future investments. On the other hand, the softened competition due to rivals' slumping could lower the firm's external financing cost, thus reducing its need for precautionary savings.

With the guidance from the analytic framework, we then empirically investigate the impact of CRC and PMR on firms' cash holdings. The empirical identification of the effect of CRC and that of PMR is challenging given their potentially countervailing impacts on cash holdings and the fact that both are stemming from peers' worsening financial situations. We thus turn to the stock market in search of empirical measures that can broadly assess a firm's exposure to credit risk spillover and distinguish the two types of externalities (i.e., CRC and PMR). We proceed in two steps. First, we use PCORR, the partial correlation coefficient between firm-specific stock returns (i.e., after removing the market and industry components), to gauge the extent to which the valuations of two firms are related (Durnev, Morck, and Yeung, 2004; Jorion and Zhang, 2007). A positive PCORR suggests the existence of economic linkages that simultaneously drive the valuations of two "fellow" firms, causing their stock returns to comove. As a result, if one firm enters financial distress, the other firm's stock return and financial health would be adversely affected through the contagion effect. On the other hand, a negative PCORR suggests that the two are "rival" firms, and one is likely to benefit from a negative credit shock to the other through the rivalry effect. Next, for each individual firm, we measure the contagion (rivalry) effect as CRC (PMR)—the positive (negative) PCORR-weighted sum of the expected default probabilities of the firm's industry peers. These two constructs capture a firm's exposure to credit risk spillovers from all of its fellow firms (with PCORR>0) and rival firms (with PCORR<0) separately.[1]

To demonstrate the informativeness of the proposed credit risk spillover measures, we first examine whether PCORR, the weight used to aggregate peer default risk, can discern the aforementioned contrasting effects of credit risk spillovers. Specifically, we partition firms into two groups (fellows vs. rivals) based on the sign of their PCORR with an industry peer that subsequently filed for Chapter 11 bankruptcy. We find that non-distressed firms that have a positive pre-event return comovement with the failing firm (i.e., PCORR>0) experience large negative return reactions to the bankruptcy announcement. In contrast, those with a negative pre-event return comovement (PCORR<0) enjoy sizable positive return drifts. These results confirm that the return comovement measured in a normal period (in the absence of peer distress) can inform credit risk spillovers when the peer firms end up in financial distress.[2]

Next, we probe the power of our ex ante PCORR-based spillover measures in predicting corporate failure. Consistent with the very concept of credit risk contagion, we find that a firm's default probability is positively related to its CRC. Economically, a one-standard-

[1] Realistically, the contagion and rivalry effects are likely to simultaneously influence the PCORR between a pair of firms. However, the contagion (rivalry) effect is likely to be more dominant among those with a positive (negative) PCORR. This motivates our choice to calculate the above weighted sum over positive and negative PCORR firms separately.

[2] The major advantage of this method is that it provides an ex ante measurement of the effect of credit risk spillovers. Most of the extant literature on the CRC and PMR effects focus on ex post measurements after bankruptcy occurrences.

deviation increase in CRC is associated with a 10.4 percent rise in the probability of entering financial distress. We also examine how CRC is related to a firm's credit default swap (CDS) premium, a more direct measure of credit risk according to Blanco, Brennan, and Marsh (2005) and Longstaff, Mithal, and Neis (2005). After controlling for conventional credit risk factors, we find that firms with greater CRCs have higher CDS premiums. In contrast, PMR is negatively related to a firm's default risk and CDS premium. Taken together, these results suggest that the spillover proxies are useful in capturing a firm's exposure to distinct externalities generated by its peers' financial distress.

We then examine how credit risk spillovers affect a firm's liquidity management. First, we show that firms with greater exposure to CRC hold more cash. The estimates indicate that a one-standard-deviation increase in CRC boosts the cash-to-assets ratio by two percentage points, a sizable effect compared to the sample average of 14 percent. Moreover, CRC is positively related to the market value of cash holdings. We also show that a greater PMR reduces cash holdings as well as the market value of cash. Therefore, as industry rivals succumb to financial distress, the lower cost of borrowing dominates the predatory motive to hoard cash and gain market share, and consequently alleviates the need for precautionary savings. Consistent with the central importance of the precautionary motive in understanding corporate liquidity management, we find that the impact of CRC outweighs that of PMR in determining cash holdings. Overall, these results indicate that firms build up cash reserves when they are susceptible to credit shocks originating from peers with whom their valuation comoves.

Second, we turn to the effect of credit risk spillovers on corporate payout policy, which is closely related to a firm's liquidity management (Brav, Graham, Harvey, and Michaely, 2005; Hoberg, Phillips, and Prabhala, 2014). If CRC presents a direct threat to a firm's viability, we would expect the firm to reduce payout and retain cash to preserve its financial flexibility. Our results show that CRC indeed reduces a firm's dividend yield and total payout ratio, while PMR allows for a less conservative payout policy. These results paint a coherent picture with the earlier results on cash holdings. Therefore, when facing greater contagion risk, firms preserve liquidity by not only holding more cash, but also cutting back on dividends and share repurchases.

Third, we address the important concern that both the focal firm's cash holdings and the expected default probabilities of the industry peer firms are influenced by common unobservable factors. We draw from the literature on banking industry deregulations to isolate a plausibly exogenous variation in out-of-state peer firms' credit risk, and conduct an instrumental variable (IV) analysis. Specifically, we exploit the lifting of intrastate and interstate banking restrictions in the U.S. during the 1970s through the 1990s. These exogenous regulatory shocks to banking competition provide firms with deeper and cheaper access to bank credit (Klein, 1971; Cetorelli and Strahan, 2006; Rice and Strahan, 2010), thereby reducing their financing constraints and credit risk. The IVs are relevant because they capture exogenous shocks to certain (i.e., out-of-state) peers' default risk due to related banking regulatory changes. Meanwhile, to the extent that out-of-state banking industry deregulations do not directly affect the focal firm's cash holdings, the IVs are exogenous as only out-of-state peers are used in the their construction. Our baseline findings are fully retained when we use this IV-based approach to address the existence of confounding factors that affect both the focal firm's cash holdings and its industry peers' expected default probabilities.

Fourth, we examine the impact of credit risk spillovers from a lender's perspective. Specifically, we analyze how CRC and PMR influence the contracting of bank loans, which serve as the primary source of external financing for firms (Graham, Li, and Qiu, 2008; Chava, Livdan, and Purnanandam, 2009). Our analysis reveals that firms with a greater contagion exposure are charged higher loan spreads and are subject to more restrictive non-price terms, namely shorter maturities, a greater likelihood of collateral requirement, and a more diffused syndicate structure (i.e., a larger number of lenders). These findings suggest that lenders, when designing loan contracts, consider not only a firm's own creditworthiness but also its exposure to contagion risk from its peers. In light of this evidence on lender behavior, it seems that firms act rationally in holding more precautionary cash balance when facing greater CRC. Additionally, we show that a greater PMR lowers the cost of bank loans and relaxes the non-price terms. This confirms our conjecture that the rivalry effect reduces precautionary savings by making it easier for firms to borrow.

For robustness checks, we present several modifications to the definition of our credit risk spillover measures. First, we exploit supply chain information and use the percentage of sales to major customers to substitute for PCORR in the weighted-sum construction of CRC. Second, to allow for the possibility of inter-industry (as opposed to exclusively intra-industry) spillovers, we re-estimate PCORR with an augmented market model and include all firms in the calculation of CRC and PMR.[3] Third, we use more refined industries at the three- and four-digit SIC levels to address the possibility that the relation between cash holdings and our spillover measures is driven by common shocks among subsets of firms within the Fama-French 48 industries. The effects of credit risk spillovers on cash holdings and payout policy remain qualitatively unchanged.

Our study sheds light on a new dimension of firms' precautionary savings motive and contributes to the growing literature on cash holdings. We find that the interdependence of firm-level default likelihood is an important risk factor in determining corporate liquidity management and the cost of borrowing. We empirically distinguish the two contrasting spillover effects of peer financial distress (credit risk contagion vs. product market rivalry), and show that both effects have significant bearing on corporate cash policy.

This paper also enhances our understanding of credit risk spillovers. Previous research has documented a significant ex post contagion effect of bankruptcies. We develop ex ante measures to quantify the externalities produced by peer distress and show that these measures can help explain the likelihood of bankruptcy, the CDS premium, corporate liquidity management, and bank loan contracting. In essence, these results demonstrate that industry peers' financial conditions are an important determinant of how a firm designs its own

[3] Recall that previously, we estimate PCORR with a two-factor model (with market and industry factors) and include only a firm's industry peers (fellows and rivals) in the calculation of its CRC and PMR.

financial policies and how lenders assess its creditworthiness.

Furthermore, our paper is closely related to recent studies that examine how a firm's exposure to market and industry risks affects its cash policy. Acharya, Almeida, and Campello (2013) find that firms with greater aggregate risk exposures (measured by asset betas) hold more cash. They argue that such firms are more likely to demand liquidity when the supply of liquidity is scarce, and hence are charged more by lenders. Similarly, James and Kizilaslan (2014) find that unsecured bank loan spreads are positively related to a firm's industry risk. They argue that firms with larger industry risk exposures are likely to experience greater losses in default due to the potential fire sales by peers during industry downturns. Beyond aggregate and industry risks, our results suggest that lenders may not be able to fully diversify away borrowers' firm-level CRC exposures, and therefore must tailor loan contractual terms accordingly.

The rest of our paper proceeds as follows. Section 2 presents an analytic framework for understanding the impact of credit risk spillovers on corporate cash holdings. Section 3 develops our credit risk spillover measures on both theoretical and empirical grounds and provides evidence of their usefulness. Section 4 discusses the data and the empirical results. Section 5 concludes.

2 Analytic Framework

Peers' worsening credit risk generates two types of externalities, namely, credit risk contagion (CRC) and product market rivalry (PMR), which have distinct implications on corporate liquidity management. In this section, we use a simple analytic framework to illustrate the effects of credit risk spillovers on a firm's cash holdings from its fellow firms and rival firms. The model extends Bloom, Schankerman, and Van Reenen (2013, BSV hereafter)'s two-stage model into three stages. The key setup in Stages 1 and 2 is similar to BSV's. The new feature of our model is that, in Stage 0, the firm needs to determine its cash holdings—how much to save for investment in Stage 1 and how much to invest right away in Stage 0. We then develop testable hypotheses about the differential impacts of CRC and PMR on corporate cash policy.

2.1 The Setup

As in BSV, there are three firms, j, τ and m. Firms j and τ are fellow firms that share common economic linkages (e.g., interlocking boards, strategic alliance partners, customer-supplier relationship, and so on). Firms j and m are rival firms competing in the same product market.

Stage 0. Firm j is endowed with cash W^j and assets in place A^j. It can save cash C^j and invest the rest $I^j = W^j - C^j$ in a project that yields a payoff $F(I^j)$ in Stage 2, where F is non-decreasing and concave.

Stage 1. Firm j produces output k^j with its own spending r^j, where $k^j = \phi(r^j)$ and the production function ϕ is non-decreasing and concave. Firm j's spending r^j is supported by its cash reserve C^j from Stage 0 and external borrowing capacity B^j:

$$r^j = C^j + B^j.$$

The external borrowing capacity of firm j is determined by its assets in place A^j and credit risk q^j:

$$B^j = \left(1 - q^j\right) A^j,$$

where $1 - q^j$ can be interpreted as the loan-to-value ratio, which declines with the firm's credit risk. We assume that firm j's credit risk q^j is affected by its fellow firm τ's credit risk q^τ and its rival firm m's output k^m, that is, $q^j \equiv q^j(q^\tau, k^m) = q^j[q^\tau, k^m(q^m)]$. The credit risk contagion effect says that the fellow firm τ's credit risk will increase firm j's credit risk, i.e., $q_1^j(q^\tau, k^m) > 0$. The product market rivalry effect says that the rival firm m's output will increase firm j's competitive pressure and hence its credit risk, i.e., $q_2^j(q^\tau, k^m) > 0$.

Stage 2. Firm j's investment in Stage 0 yields a payoff $F(I^j)$. Moreover, the product market competition between firm j and firm m yields a reduced-form profit function for firm j, $\Pi(k^j, k^m)$, which depends on their output levels, k^j and k^m, where $\Pi_1 > 0$ and $\Pi_2 < 0$.

This simple three-stage setup articulates the tradeoff firm j faces—using its cash for initial investment when credit risk contagion and product market rivalry are not important, or saving some of it for a later stage when both elements come into prominence.

2.2 Comparative Statics

In Stage 0, firm j's optimization problem is to choose its cash reserve C^j that maximizes its total profit from investments in Stages 0 and 1:

$$\max_{C^j} F\left(I^j\right) + \Pi\left(k^j, k^m\right) - I^j - r^j, \tag{1}$$

$$\begin{aligned} \text{s.t. } I^j &= W^j - C^j, \\ r^j &= C^j + B^j, \\ B^j &= \left(1 - q^j\right) A^j, \\ k^j &= \phi\left(r^j\right), \end{aligned}$$

which is equivalent to:

$$\max_{C^j} F\left(W^j - C^j\right) + \Pi\left\{\phi\left[C^j + \left(1 - q^j\right) A^j\right], k^m\right\} - W^j - B^j. \tag{2}$$

The optimal cash reserve C^{j*} satisfies the following first-order condition:

$$F_1\left(W^j - C^j\right) = \Pi_1\left\{\phi\left[C^j + \left(1 - q^j\right) A^j\right], k^m\right\}\phi_1. \tag{3}$$

The left hand side term of equation (3) is the benefit of one additional dollar of cash invested in the project in Stage 0. The right hand side shows the benefit of moving one additional dollar of cash to Stage 1 to be used in output production then. At the optimal level, C^{j*}, the marginal benefit of investing in the project in Stage 0 equals that of saving cash for the investment in Stage 1.

Comparative statics demonstrate the impact of credit risk contagion and product market rivalry on firm j's cash holdings as follows:

$$\frac{\partial C^{j*}}{\partial q^\tau} = \frac{\Pi_{11}\phi_1^2 A^j q_1^j\left(q^\tau, k^m\right)}{H}, \tag{4}$$

and

$$\frac{\partial C^{j*}}{\partial q^m} = \frac{-\Pi_{12}\phi_1 + \Pi_{11}\phi_1^2 q_2^j\left(q^\tau, k^m\right)}{H} k_1^m\left(q^m\right), \tag{5}$$

where $H = F_{11} + \Pi_{11}\phi_1^2 < 0$ by the second order condition.

2.3 Hypotheses

Shown in equation (4), $\frac{\partial C^{j*}}{\partial q^\tau}$ is positive given $q_1^j\left(q^\tau, k^m\right) > 0$ and $\Pi_{11} < 0$. In other words, firm j will increase its cash reserve in response to an increase in its fellow firm τ's credit risk. The intuition is that when firm τ's credit risk increases, the effect spills over to firm j and reduces its loan-to-value ratio. As a result, the marginal benefit of cash rises and firm j will increase its cash holdings. This is essentially the precautionary savings motive applied to an increase in credit risk through the contagion channel. Therefore, we hypothesize that cash holdings are positively associated with CRC.

Turning to the spillover effect of PMR, equation (5) shows that the sign of $\frac{\partial C^{j*}}{\partial q^m}$ is determined by the two components in the numerator (since both $k_1^m\left(q^m\right)$ and H are negative), $-\Pi_{12}\phi_1$ and $\Pi_{11}\phi_1^2 q_2^j\left(q^\tau, k^m\right)$. The first component $-\Pi_{12}\phi_1 > 0$ captures a predatory channel: when the rival firm m's output decreases, it raises firm j's marginal profit of investment when they are strategic substitutes ($\Pi_{12} < 0$), and firm j will hold more cash to fund Stage 1 investment. In other words, a firm will increase its cash holdings in order to take advantage when rivals reduce output due to financial distress.

The second component $\Pi_{11}\phi_1^2 q_2^j\left(q^\tau, k^m\right) < 0$ captures a market rivalry channel: when the rival firm m's output decreases, it reduces the competitive pressure facing firm j, and firm j's credit risk declines ($q_2^j\left(q^\tau, k^m\right) > 0$) and its loan-to-value ratio rises as a result, leading to a lower marginal benefit of cash. Since the predatory channel and the market rivalry channel have opposite effects on cash holdings, the sign of $\frac{\partial C^{j*}}{\partial q^m}$ is formally ambiguous. The impact of PMR on cash policy thus demands further empirical investigation.

3 Measuring Credit Risk Spillovers

In this section, we lay out a general framework for calculating a firm's exposure to credit risk spillover. We then motivate our empirical construct by quantifying the spillover effect through a specific firm linkage—the customer-supplier relationship. In light of the limitations of the spillover proxy derived from a specific economic linkage, we then propose a novel measure that aims to capture a firm's overall exposure to externalities originating from industry peers' potential default.

3.1 Methodological Considerations

We begin with a reduced-form representation of a firm's default intensity, also called its default hazard rate (Lando, 1998; Duffie and Singleton, 1999), and extended to a setting of counterparty risk by Jarrow and Yu (2001) and Yu (2007):

$$\lambda_{it} = \left(\alpha_i + \beta_i^{'} X_t + \sum_{j \neq i} \gamma_{ij} N_{jt} \right) (1 - N_{it}) \,. \tag{6}$$

The default intensity λ_{it} has an intuitive interpretation as the default probability per unit time for firm i at time t, and is associated with the point process N_{it} that starts at zero and jumps to one at firm i's time of default.[4] In other words, we have:

$$\lambda_{it} = \lim_{s \to t+} E_t \left(\frac{N_{is} - N_{it}}{s - t} \right) . \tag{7}$$

The first part of this specification, $\alpha_i + \beta_i^{'} X_t$, where X_t is a set of common factors, can be considered as the firm's own contribution toward its default risk.[5] The second part, $\sum_{j \neq i} \gamma_{ij} N_{jt}$, summarizes the spillover effect from the financial distress of the firm's peers. Essentially, γ_{ij} represents the increase in firm i's default intensity when firm j is defaulting.

By the definition of general stochastic intensities for point processes (Brémaud, 1981),

[4] The default intensity takes the value of zero after the firm has defaulted.

[5] The set of common factors could include market and industry factors. We could also easily include a firm-specific contribution to the default intensity (Duffee, 1999).

this spillover effect has an expected value of:

$$E\left(\sum_{j\neq i}\gamma_{ij}N_{jt}\right) = E\left(\int_0^t \sum_{j\neq i}\gamma_{ij}\lambda_{js}ds\right). \tag{8}$$

Therefore, we can consider $\sum_{j\neq i}\gamma_{ij}\lambda_{jt}$ as the basis for the construction of our time-varying spillover measures.

While we can proxy λ_{jt} with one of several time-varying corporate default risk measures, it is less straightforward to find good proxies of γ_{ij}. One way to generate an estimate of γ is based on the relationship between suppliers and their customers, exploiting information reported in Compustat's Segment database on each customer with more than ten percent of a firm's total sales (Campello and Gao, 2017). Specifically, we can set γ_{ij} as the ratio of firm i's sales to firm j over firm i's total sales. The downside of this approach is that it is based on only one explicit economic linkage between firms.[6]

3.2 Measuring Credit Risk Spillovers Using Partial Correlations of Stock Returns

Credit risk spillovers are a multifaceted phenomenon affecting firms through both explicit and implicit economic linkages.[7] In search of a proxy of γ that aggregates the assorted channels for the spillover effect, we turn to stock returns, which impound value-relevant information from various sources, including externalities arising from the financial distress of a firm's peers. It has been shown that stock prices incorporate newly arrived information within minutes (Jackson, Jiang, and Mitts, 2016). A firm's stock return also reflects its network of interconnections with others. For instance, Cohen and Frazzini (2008) and Wu and Birge (2015) document that supply chain structure affects firm returns. Saavedra et al. (2014) show that networks of interlocking directorates can explain stock returns. Hameed, Morck, Shen, and Yeung (2015) find that returns are also affected by information spillovers from

[6] In a later robustness check, we will revisit the measurement of γ using supply chain relationships.

[7] Even those that are seemingly unrelated could be affected by the updating of beliefs over some unobserved state variables. An example is the accounting scandal at Enron, which caused investors to worry about the quality of accounting information of firms that might not have any business ties with Enron.

peers that have heavy analyst coverage. We thus proxy γ by PCORR, the partial correlation between two firms' stock returns after conditioning on their exposure to common market and industry factors. A similar construct has been used to gauge firm relatedness in ex post default contagion (Jorion and Zhang, 2009) and technology spillovers and product market competition (Bloom, Schankerman, and Van Reenen, 2013; Hoberg, Phillips, and Prabhala, 2014).

Specifically, we obtain PCORR as the correlation coefficient between the residuals ε_i and ε_j, resulting from the linear regressions of r_i and r_j separately on r_M and r_I, where r_i and r_j are individual stock returns, r_M is the value-weighted market return excluding the return on industry I, and r_I is the value-weighted return of stocks in industry I excluding stocks i and j.[8] By filtering out the market and industry components, PCORR captures the firm-specific pairwise relatedness of firms i and j's valuation. Measuring γ this way aggregates potential sources of credit risk spillovers, beyond what is revealed through one specific type of interconnectedness (e.g., supply chains and interlocking boards of directors).

While the default of an industry peer could generate both credit risk contagion and product market rivalry effects for the same firm, the sign of PCORR potentially indicates the relative importance of the two. A positive (negative) PCORR suggests that the contagion (rivalry) effect plays a dominant role. Therefore, we distinguish between these two effects by defining, for each firm i in industry I:

$$\text{CRC}_{it} = \sum_{j \in I, j \neq i} 1_{\{\text{PCORR}_{ijt} > 0\}} \text{PCORR}_{ijt} \times \text{EDP}_{jt}, \tag{9}$$

$$\text{PMR}_{it} = \sum_{j \in I, j \neq i} 1_{\{\text{PCORR}_{ijt} < 0\}} |\text{PCORR}_{ijt}| \times \text{EDP}_{jt}, \tag{10}$$

where EDP denotes the expected default probability.

For the EDP, we adopt two different measures. One is based on the Altman (1968) Z-score, a widely used accounting-based estimate of financial distress. The Z-score has been found to forecast corporate failure accurately as far as two years in advance. Following Alt-

[8] For industry returns, we use the Fama-French 48 industry portfolios. These residuals are estimated using weekly stock returns over the preceding year.

man et al. (2010), we take a logistic transformation to map the Z-score into a probability of default. We also complement this accounting-based proxy with a market-based alternative, the Merton (1974) expected default frequency (EDF). Specifically, we estimate a firm's implied default probability following Bharath and Shumway (2008). Given the ongoing debate on the relative performance of alternative default risk measures (e.g., Hillegeist, Keating, Cram, and Lundstedt, 2004; Bharath and Shumway, 2008; Crouhy, Galai, and Mark, 2000; Saunders and Allen, 2002) and the well-known limitations of the Merton model, we use the Altman Z-score as the primary proxy of EDP and treat the EDF as an alternative measure.[9] Our results are fully retained using either the Z-score or the EDF in constructing the CRC and PMR measures.

3.2.1 PCORR: Anecdotal Evidence

The measures defined in equations (9) and (10) aim to capture the two distinct types of spillover effects caused by peer financial distress. For instance, Microsoft and IBM jointly developed operating systems in the 1980s and formed a partnership that bundled Microsoft's operating systems with IBM's computers. As a result, their stock valuations tended to be closely related, and one firm's financial distress would hurt the other's performance. This is evidenced by a sizable partial correlation between the two firms' stock returns in 1990 (PCORR = 0.25). More recently, however, given Microsoft's effort to enter the phone and tablet market and IBM's exit from the personal computer business, their PCORR dropped to 0.09 in 2010, suggesting a significant decrease in their spillover exposure to each other.

Another example that illustrates the rivalry effect involves Apple and Hewlett-Packard (HP). In the 1980s, the two companies competed fiercely in the market for computers and printers. A negative partial correlation (PCORR $= -0.28$) in 1990 between the two indicates

[9] The Merton (1974) model assumes that the only source of uncertainty in equity prices is the net asset value of the firm, and that the firm has constant asset volatility, debt level, and default boundary. Empirically, the Merton model produces implied credit spreads that are far smaller than actual credit spreads on corporate bonds (Eom, Helwege, and Huang, 2004). Subsequent modeling has relaxed all of these assumptions (e.g., Collin-Dufresne and Goldstein, 2001; Chen, Collin-Dufresne, and Goldstein, 2009; Zhang, Zhou, and Zhu, 2009).

that one would greatly benefit from the other's demise. However, the product lines of these two companies have diverged since then. In particular, Apple no longer brands itself as a computer company. Indeed, phones and tablets accounted for more than 75 percent of Apple's total revenue and computers for only 10 percent in 2010. As a result, the rivalry effect between Apple and HP has ebbed away, with their PCORR in 2010 dropping to only 0.03.

Because of changing economic ties, we can sometimes observe a transition between the contagion and rivalry effects for the same pair of firms. For example, SymmetriCom and IMP were both electronic equipment manufacturers that produced similar analog data communications devices and mixed-signal integrated circuits. A negative PCORR of -0.24 in 1996 suggests a strong rivalry between the two. Interestingly, PCORR flipped sign and soared to 0.33 at the end of 1997, indicating a strong contagion effect. As it turned out, the two firms formed a broad strategic alliance around July 1997. Under the alliance, SymmetriCom and IMP shared marketing knowledge and established a joint program for the licensing, design, and manufacturing of their products. This created a greater level of inter-dependency between the two firms that is reflected by their large positive PCORR.[10]

These examples underscore the ability of PCORR to capture rich patterns of dynamic interaction between firms. Therefore, CRC and PMR, calculated as PCORR-weighted sums of fellow and rival firms' default risk, respectively, offer a simple framework to measure a firm's exposure to peer financial distress. In the following two sections, we provide large sample evidence to validate the informativeness of PCORR (Section 3.2.2) as well as CRC and PMR (Section 3.2.3).

3.2.2 PCORR and Ex Post Spillovers

As shown in equations (9)-(10), PCORR is a key component in quantifying the effect of credit risk spillovers. In this subsection, we evaluate whether PCORR captures the distinct value

[10] Boone and Ivanov (2012) provide empirical evidence for the bankruptcy spillover effect on strategic alliance partners.

implications of bankruptcy filings on other industry participants. Specifically, we examine stock market reactions when industry peers encounter extreme credit events. We hypothesize that the equity price of a fellow (rival) firm, which has a positive (negative) pre-event PCORR with the failing firm, will decrease (increase) around the bankruptcy event.

[Insert Table 1 here]

Following Hertzel, Li, Officer, and Rodgers (2008), we identify the date on which the filing firm experiences the largest negative abnormal stock return as the event date. This is because the wealth effect of corporate failure often occurs well before actual filing.[11] Next, we sort the non-distressed firms into quintile portfolios based on the value of their PCORR with the distressed industry peer.[12] Table 1 reports the non-distressed firms' average cumulative abnormal returns (CAR) in event time. In Panel A, we focus on fellow firms that have a positive PCORR with the distressed peer. We find that non-distressed firms experience significantly negative return reactions on the event date (event window $[0, 0]$), and the magnitude of the average CAR decreases nearly monotonically with the value of PCORR. Similar patterns of price reactions are observed over an 11-day window ($[-5, 5]$) centered on the distress date.

In Panel B, we focus on rival firms that have a negative value of PCORR with the distressed peer. The evidence is broadly consistent with the rivalry effect, namely, the CARs are all positive. Again, the return reaction is the strongest among the quintile portfolio with the most negative PCORR (Q5).[13] These findings demonstrate that PCORR is capable of diagnosing differential credit risk spillover effects before actual credit events occur.

[11] We identify 421 Chapter 11 distress dates from 1981 to 2012 using the UCLA-LoPucki Bankruptcy Research Database (BRD). We thank Lynn M. LoPucki, the founder of the BRD, for granting access to the database, available at http://lopucki.law.ucla.edu/index.htm.

[12] The value of PCORR is estimated over the year prior to the distress event date.

[13] These average CARs are also economically significant in terms of the mean dollar loss (gain), which is the product of the average market value of the firms in each portfolio prior to the distress date and the average CAR over the event period. Over the $[-5, 5]$ event window, using the average market value of the non-distressed firms in Q5 of Panel A, the -0.333 percent CAR translates into a \$3.87 million loss. Similarly, the 0.759 percent $[-5, 5]$ CAR for Q5 in Panel B translates into a \$14.71 million gain.

3.2.3 Credit Risk Spillovers and the Likelihood of Financial Distress

If CRC captures the negative effect of intra-industry credit risk spillovers, we would expect firms with a higher CRC to be more susceptible to peer financial collapses, and ceteris paribus, have a greater likelihood of financial distress themselves. Table 2 evaluates the predictive power of CRC for the likelihood of financial distress during the next year. In Column (1), the dependent variable is equal to one if the firm experiences annual return lower than -30 percent, and zero otherwise. In Column (2), the dependent variable takes a value of one if the firm's interest coverage ratio is less than one in the past two years, and zero otherwise (Andrade and Kaplan, 1998).

Following the literature on financial distress (e.g., Gilson, John, and Lang, 1990; Opler and Titman, 1994; Shumway 2001; Acharya, Bharath, and Srinivasan, 2007), we include a set of firm-level controls as well as industry-year fixed effects.[14] Moreover, we control for market and industry betas (Acharya, Almeida, and Campello, 2013; James and Kizilaslan, 2014). All independent variables are lagged by one year.

[Insert Table 2 here]

Using different distress dummies, Columns (1) and (2) of Table 2 show that firms with greater CRC are more likely to enter financial distress after controlling for an extensive set of firm-level attributes relevant to credit risk. The evidence, albeit weaker, also suggests that greater PMR tends to reduce distress risk.

Although the CDS market mostly covers large firms and has disproportionate representation in the financial and insurance sectors, the CDS premium arguably provides a more direct measure of corporate credit risk than the two aforementioned distress dummies. Therefore, we supplement our previous analysis using the CDS premium as an alternative measure of a firm's credit quality.[15] We regress the natural logarithm of a firm's annual CDS premium

[14] The industry-year fixed effects remove the influence of industry-wide shocks from the relation between the dependent variable and the credit risk spillover measures. We include them in most of our subsequent analysis as well.

[15] Our CDS data are obtained from IHS Markit.

on our credit risk spillover measures and other firm-level controls employed previously. The results are reported in Column (3) of Table 2. Given the limited availability of CDS data, our sample size is much smaller than before. Nonetheless, the coefficient of CRC remains positive and significant. According to the estimates, a one-standard-deviation increase in CRC would raise the level of the CDS premium by around 12 percent, which is an economically significant effect.[16] In summary, the results presented in Sections 3.2.2 and 3.2.3 suggest that CRC and PMR indeed capture the differential aspects of spillovers from corporate defaults.

4 Empirical Results

In this section, we present our empirical estimation of the effects of CRC and PMR on corporate cash holdings, corporate payout, and bank loan contracting.

4.1 Data

The data used in the following analysis come from three sources: the CRSP (Center for Research in Security Prices) database, the CRSP-Compustat merged database, and the DealScan database. To calculate the two spillover proxies, we collect returns for all common stocks listed on NYSE, AMEX, and NASDAQ from CRSP.[17] To estimate the relation between cash holdings and credit risk spillovers, we draw firm-level data for publicly traded non-financial and non-utility U.S. firms from the CRSP/Compustat merged database. The sample contains 10,743 unique firms representing 113,832 firm-year observations. Missing values of the explanatory variables reduce the panel used in our baseline model to 90,019 firm-year observations covering 10,649 unique firms. The sample period is from 1980 to 2013. When examining how contagion affects bank loan contracting, we merge the CRSP/Compustat

[16] Using the sample standard deviation of CRC of 0.209 from Table 3, this is computed as $0.569 \times 0.209 \approx 0.12$. Since the dependent variable is the logarithm of the CDS premium, this is interpreted as a 12 percent increase in the level of the CDS premium.

[17] The universe of stocks is restricted to ordinary common stocks with share code 10 or 11. As a result, ADRs, shares of beneficial interest, companies incorporated outside the U.S., Americus Trust components, closed-end funds, preferred stocks, and REITs have been excluded.

database with Loan Pricing Corporation (LPC)'s DealScan database.[18] After removing observations with incomplete DealScan or Compustat information, we obtain a final sample of 23,432 loan facilities for 4,349 unique borrowing firms over the period of 1987 to 2013.

[Insert Table 3 here]

Table 3 presents the descriptive statistics of the sample. The detailed constructions of the variables are documented in the appendix. All continuous variables are winsorized at the first and 99th percentiles. The mean and median of cash holdings are 14 percent and 8.5 percent of total assets, respectively. CRC and PMR calculated according to equations (9) and (10) average 0.131 and 0.054, respectively. This suggests that the credit risk contagion effect dominates the product market rivalry effect, and the average firm faces a net negative externality from its peers' financial distress. The summary statistics of other variables are similar to those reported in previous studies of cash holdings (e.g., Bates, Kahle, and Stulz, 2009). Turning to loan facilities, the average loan spread and loan size are 198 basis points and $321 million, respectively. The average loan maturity is 46 months. Around 31 percent of the loans have collateral requirements, and the average number of lenders in these loans is 7.5. These loan characteristics are in line with those reported in Graham, Li, and Qiu (2008) and Li, Qiu, and Wan (2011).

4.2 Cash Holdings

Our baseline econometric model follows Bates, Kahle, and Stulz (2009) and is specified as:

$$\text{Cash}_{ikt} = \delta \text{CRC}_{ik,t-1} + \eta \text{PMR}_{ik,t-1} + \beta' X_{ik,t-1} + \theta_{kt} + \varepsilon_{ikt}, \tag{11}$$

where i, k, and t denote firm, industry, and year, respectively, and ε is an independently and identically distributed residual term. The dependent variable is cash plus marketable

[18] The bank loan borrowers are matched to CRSP and Compustat using the DealScan-Compustat link file from Chava and Roberts (2008). We then hand-match the remaining firms to CRSP and Compustat based on their names and ticker symbols. We are grateful to Sudheer Chava and Michael Roberts for providing the DealScan-Compustat link file.

securities deflated by total assets. Our primary interest is in the marginal effects of CRC and PMR on cash holdings (denoted by δ and η, respectively). The vector X represents a comprehensive set of firm-level controls, including a constant term and the firm's exposure to industry and market risks (proxied by industry and market asset beta, respectively), the firm's own default probability (calculated based on Altman's Z-score), market to book, the logarithm of book assets, cash flow, the volatility of the firm's profit, net working capital, capital expenditures, total book leverage, and R&D expenditures. To address the possibility that industry-wide shocks are simultaneously affecting the credit risk spillover measures and cash holdings, we include industry-year fixed effects θ.[19] Lastly, the standard errors are adjusted for heteroscedasticity and clustered at the firm level, taking into account the serial correlation of residuals within each firm.

[Insert Table 4 here]

Table 4 presents the results of our estimation. In the first two columns, we include either CRC or PMR with other firm-level control variables. In the last column, we include both CRC and PMR with the controls. The sign and significance of the CRC and PMR coefficients are robust to these variations in the regression specification. In Column (3), the coefficient of CRC is positive and highly statistically significant, with a t-statistic of 8.73, which suggests a strong positive relation between a firm's cash holdings and its exposure to the credit risk contagion from the fellow firms. This effect is also highly economically significant. Using the sample standard deviation of 0.209 for CRC from Table 3, a one-standard-deviation increase in CRC raises the cash-to-assets ratio by nearly two percentage points (0.091×0.209), a sizable effect relative to the sample average cash ratio of 14.0 percent.

In contrast, the product market rivalry component of credit risk spillovers, PMR, bears a negative and significant coefficient, which indicates that the demand for corporate liquidity

[19] For example, a negative industry-wide shock can increase the credit risk of a given firm, thus raising its cash holdings through the precautionary savings motive. At the same time, it can also increase the credit risk of the firm's industry peers, leading to an increase of the firm's credit risk contagion (CRC) exposure. Under this scenario, we cannot conclude that it is credit risk contagion that increases the firm's cash holdings.

eases as the rival firms become more distressed. Therefore, the firm's incentive to accumulate cash and invest to take advantage of weakened rivals is apparently not as powerful as the relaxation of its precautionary savings motive. Even though the magnitude of the PMR coefficient is similar to that of CRC, its economic significance is smaller given a smaller sample standard deviation of PMR. Specifically, a one-standard-deviation increase in PMR results in only a 0.7 percentage point (0.089×0.075) reduction of the cash-to-assets ratio. This suggests that CRC dominates PMR in shaping a firm's cash policy.

Turning to the control variables, the majority are drawn from Bates, Kahle, and Stulz (2009) and their coefficients are also consistent with those estimated therein. Among the additional variables, the firm's own default probability has a strongly positive coefficient, which is consistent with the precautionary savings motive of holding cash. It is noteworthy that we find significant credit risk spillover effects even when controlling for the firm's own default probability. This suggests that conventional default risk proxies such as Altman's Z-score cannot capture the impact of credit risk spillovers on a firm's probability of default.[20]

In these baseline regressions, we also include lagged industry and market asset betas to absorb other important sources of risk that could affect a firm's cash holdings. Acharya, Almeida, and Campello (2013) suggest that firms with large aggregate risk exposure choose to hoard cash because market downturns can tighten banks' liquidity constraints. James and Kizilaslan (2014) point out that industry downturns are associated with lower expected loan recovery rates, which limit external financing and stimulate cash accumulation for firms with high industry risk. Our estimated coefficients of market and industry asset betas are consistent with the findings of these authors. Still, the intra-industry credit risk spillover measures have incremental explanatory power in determining corporate cash reserves in the presence of these control variables.

[20] We repeat our baseline regressions using CRC and PMR based on Merton's expected default frequency (EDF) instead of Altman's Z-score. Our results remain qualitatively unchanged.

4.3 Value of Cash

Having demonstrated the effect of credit risk spillovers on corporate cash holdings, we turn to examining the marginal value of cash. We adopt the methodology of Faulkender and Wang (2006) and augment their regression specification to include CRC and PMR:

$$\begin{aligned} r_{it} - R_{it}^{B} &= \alpha + \delta_1 \frac{\Delta \text{Cash}_{it}}{\text{MV}_{i,t-1}} + \delta_2 \text{CRC}_{i,t-1} \times \frac{\Delta \text{Cash}_{it}}{\text{MV}_{i,t-1}} + \delta_3 \text{CRC}_{i,t-1} \\ &\quad + \delta_4 \text{PMR}_{i,t-1} \times \frac{\Delta \text{Cash}_{it}}{\text{MV}_{i,t-1}} + \delta_5 \text{PMR}_{i,t-1} + \beta' X_{it} + \varepsilon_{it}. \end{aligned} \tag{12}$$

Here, the dependent variable is the annual stock return of firm i minus its benchmark portfolio return,[21] MV the lagged market value of equity of firm i, X the same set of control variables as included in Faulkender and Wang (2006), and ε an independently and identically distributed residual term. This specification allows us to interpret the magnitude of a coefficient estimate as the dollar change in value for a one-dollar increase in the corresponding independent variable.[22] For instance, δ_1 is the marginal value of cash for a firm with no exposure to credit risk spillovers. The coefficients of key interest are δ_2 and δ_4, which gauge the impact of CRC and PMR, respectively, on the market value of an extra dollar of cash.

[Insert Table 5 here]

In Table 5, Column (1), we replicate the benchmark regression in Faulkender and Wang (2006). The coefficient on the change in cash holdings shows that the marginal value of an extra dollar of cash to shareholders equals \$1.04 for a firm with zero cash reserve and no leverage. When considering the average firm, the marginal value of cash is \$0.83.[23]

In Column (2), the positive and significant coefficient on the interaction between CRC and the change in cash holdings indicates that firms value cash more when they face greater

[21] The benchmark return proxies for firm i's expected stock return. The benchmark portfolios are the Fama and French 5×5 size and book-to-market portfolios. The return of the portfolio matching firm i's size and market-to-book ratio at the beginning of year t is chosen as R_{it}^{B}.

[22] As highlighted by Faulkender and Wang (2006), this methodology can be viewed as a long-run event study. The event is an unexpected change in cash holdings, and the event window is a fiscal year.

[23] This is calculated as $1.042 - 0.093 \times 0.166 - 0.911 \times 0.217 = 0.83$, with the mean value of market leverage being 0.217 and the mean value of lagged cash holdings as a percentage of market value of equity being 0.166. In comparison, Falkender and Wang estimate a marginal value of cash of \$0.94 for the average firm in their sample.

credit risk contagion. A one-standard-deviation increase in CRC raises the marginal value of an extra dollar of cash by around five cents (0.263×0.209). On the other hand, the negative and marginally significant coefficient on the interaction between PMR and the change in cash holdings suggests that a firm's marginal value of cash is lowered when its rivals' credit risk intensifies. A one-standard-deviation increase in PMR lowers the marginal value of an extra dollar of cash by around five cents (0.605×0.075) as well. Incidentally, as indicated by the estimates of δ_3 (δ_5), a higher level of CRC (PMR) at the beginning of the year corresponds to a lower (higher) excess stock return for that year, which is consistent with the distress risk puzzle (Campbell, Hilscher, and Szilagyi, 2008).

Our findings thus far paint a rather coherent picture of corporate liquidity management—firms save more cash and value cash more highly when they anticipate an increase in credit risk contagion, while the weakening of product market rivals has the opposite effect.

4.4 Payout Policy

In this subsection, we study the effect of credit risk spillovers on corporate payout policy. We first examine how the two components of credit risk spillovers, CRC and PMR, affect a firm's dividend yield, constructed as cash dividends on common stocks scaled by the market value of common equity. Second, we examine how CRC and PMR influence a firm's total payout ratio, calculated as total distributions, including dividends for preferred stocks, dividends for common stocks, and net share repurchases, divided by total assets.[24] Following Brown, Liang, and Weisbenner (2007), Becker, Jacob, and Jacob (2013), and Li, Liu, Ni, and Ye (2017), we control for the natural logarithm of market value, total book leverage, market-to-book ratio, return on equity, free cash flow, cash-to-assets ratio, monthly stock volatility over the previous two years, and stock return over the previous year. We also include the market and industry asset betas as in the earlier regressions of cash holdings, as well as industry-year fixed effects. All independent variables are measured at the beginning of the

[24] Though firms have historically favored dividends over share repurchases, the latter has experienced an extraordinary growth among U.S. corporations over the past two decades (Grullon and Michaely, 2002).

year.

[Insert Table 6 here]

Column (1) of Table 6 presents a negative (positive) coefficient on CRC (PMR). The highly significant CRC coefficient of -0.006 implies a 15.7 percent decrease of the dividend yield for a one-standard-deviation increase in CRC.[25] On the other hand, the marginally significant PMR coefficient of 0.003 implies a much smaller 2.8 percent increase of the dividend yield for a one-standard-deviation increase in PMR.

Moving on to Column (2) of Table 6, we find similar results when including net share repurchases and other forms of payout—the total payout ratio is lowered by CRC and raised (though to a smaller degree) by PMR. Thus, credit risk spillovers have a substantial influence on corporate payout policies. These findings further support our earlier results that high CRC firms tend to build up cash savings and adopt more conservative financial policies, while high PMR firms seem to take a more relaxed approach.

4.5 Instrumental Variables Regression

One concern with our spillover measures is that, in the calculation of CRC and PMR, the expected default probabilities of industry peer firms can reflect some common unobservable factors (e.g., local demand shocks), which may also influence the focal firm's cash holdings. To alleviate this concern, we draw from the literature on banking industry deregulations and isolate a plausibly exogenous variation in peer firms' credit risk. Related studies document that deregulation increases bank competition (Strahan, 2003; Kerr and Nanda 2009), and as a result, banks are more likely to extend credit at lower interest rates (Klein, 1971; Rice and Strahan, 2010).[26] We thus expect a firm's credit risk to be negatively associated with the removal of intrastate and interstate banking restrictions.

[25] The sample mean dividend yield is 0.008. Therefore, the percentage change in the dividend yield relative to its mean, given a one-standard-deviation increase in CRC, is $-0.006 \times 0.209/0.008 = -0.157$.

[26] U.S. states relaxed the restrictions on the entry and geographic expansion of banks across and within states between the 1970s and the 1990s. Intrastate deregulations facilitate expansion through mergers and acquisitions and de novo branch opening, and interstate deregulations allow banks to acquire out-of-state branches.

The instruments are constructed in two steps. First, firm-level EDP is instrumented with U.S. intrastate and interstate banking deregulation dummies. The intrastate deregulation dummy equals one in the years after a state implements either de novo or M&A deregulation (Jayaratne and Strahan, 1996; Kroszner and Strahan, 1999). The interstate deregulation dummy takes the value of one in the years after entry by out-of-state bank holding companies is permitted (Kroszner and Strahan, 1999; Kerr and Nanda, 2009). Specifically, we project firms' EDP onto the two deregulation dummies while controlling for year and firm fixed effects, and calculate the predicted value of EDP (denoted as $\widehat{EDP}$).[27]

In the second step, for each firm i headquartered in state S_{it} in year t, we calculate the instrumental variables of CRC and PMR by aggregating PCORR-weighted $\widehat{EDP}$ of firm i's peers, whose headquarters are located in other states (i.e, $S_{jt} \neq S_{it}$). Specifically, the two instruments, denoted as CRC^{IV} and PMR^{IV}, are defined as follows:

$$\text{CRC}_{it}^{IV} = \sum_{j \in I, j \neq i, \mathbf{S}_{jt} \neq \mathbf{S}_{it}} 1_{\{\text{PCORR}_{ijt} > 0\}} \text{PCORR}_{ijt} \times \widehat{EDP}_{jt}, \tag{13}$$

$$\text{PMR}_{it}^{IV} = \sum_{j \in I, j \neq i, \mathbf{S}_{jt} \neq \mathbf{S}_{it}} 1_{\{\text{PCORR}_{ijt} < 0\}} \left|\text{PCORR}_{ijt}\right| \times \widehat{EDP}_{jt}. \tag{14}$$

CRC^{IV} and PMR^{IV} capture exogenous shocks to industry peers' default risk due to banking regulatory changes, and are therefore correlated with CRC and PMR. Meanwhile, as only out-of-state firms are retained in the summation, the instruments should not directly affect the focal firm's cash holdings and should be uncorrelated with the regression error term, especially after we control for industry and year fixed effects and their interactions.

[Insert Table 7 here]

Table 7 reports the second-stage coefficients on CRC and PMR using out-of-state peers' predicted EDP (CRC^{IV} and PMR^{IV}) as instruments. After controlling for potential endogeneity, in both cash (Column 1) and payout (Columns 2 and 3) regressions, CRC and PMR

[27] The untabulated results indicate that the deregulation dummies are negatively related to EDP and are highly significant with a joint F-statistic of 40.73.

are correctly signed and remain statistically significant with magnitudes that are comparable with the baseline estimates.[28]

4.6 Bank Loan Contracting

It is possible that firms manage their liquidity conservatively in the presence of credit risk spillovers because contagion risk forces them to confront an unfavorable external capital market. Given the importance of bank loans as the primary external corporate funding source, we examine how credit risk spillovers affect the pricing and non-price terms of a firm's bank loans in this subsection. The research question, in essence, is whether lenders pay attention to credit risk spillovers.

[Insert Table 8 here]

In Table 8, Column (1), we examine the impact of a borrower's exposure to CRC and PMR on its cost of bank loans. Our regression specification is akin to Chava, Livdan, and Purnanandam (2009), Graham, Li, and Qiu (2008), and Li, Qiu, and Wan (2011). Specifically, the dependent variable is the natural logarithm of the all-in-drawn spread, which is the amount that the borrower pays in basis points over LIBOR for each dollar drawn down. We include a comprehensive set of firm and loan characteristics, and add fixed effects for industry-year, loan type, and loan purpose.

Turning now to the coefficient estimates, we find that CRC is positively related to the loan cost. Economically, a one-standard-deviation increase in CRC leads to a six percent (0.285×0.209) increase in the average loan cost, showing that ex ante credit risk contagion has a significant impact on the firm's cost of debt financing. This is consistent with our previous finding that CRC increases cash holdings, and suggests that the effect is at least partially driven by the heightened external financing cost.

[28] The identification test shows that the two instruments are highly correlated with CRC and PMR with the F-statistic significant at the one percent level and the Cragg-Donald F-statistic greater than the corresponding Stock-Yogo critical value. As the system is exactly identified, no instrument exogeneity test is performed.

Next, we analyze the spillover effects on the non-price loan terms. Stricter non-price terms, such as shorter maturity or collateral requirement, impose significant indirect costs on a borrowing firm (Graham, Li, and Qiu, 2008; Smith and Warner, 1979). Column (2) confirms that banks shorten loan maturity for high CRC borrowers. For the collateral requirement in Column (3), we estimate a multivariate logit regression model where the dependent variable is equal to one if the loan is secured, and zero otherwise. Economically, the estimate suggests that a one-standard-deviation increase in CRC from its mean increases the probability of collateral requirement by 13.6 percent, ceteris paribus.

Turning to loan syndication, when credit risk is high due to potential contagion, we expect creditors to prefer diffused ownership in order to deter strategic default (Gertner and Scharfstein, 1991; Diamond, 1991; Bolton and Scharfstein, 1996; Esty and Megginson, 2003) or diversify borrower risk (Esty and Megginson, 2003; Graham, Li, and Qiu, 2008). Consistent with these motives, the result reported in Column (4) shows that loan ownership is indeed more diluted among participating banks for high CRC borrowers. Overall, these findings suggest that banks may be specialized in lending in certain industries and cannot completely diversify away their exposure to firm-level credit risk contagion. As a result, they use a host of stricter price and non-price terms to mitigate potential losses when borrowers succumb to contagion risk. Therefore, firms with greater exposure to credit risk contagion would rely more on internal cash reserves partly due to the higher financing frictions they face in the bank loan market.

4.7 Robustness Checks

In this subsection, we first examine the spillover effect through a well-defined economic linkage between firms—the customer-supplier relationship. Then, we re-assess the impact of credit risk spillovers on cash holdings by switching either more broadly to the entire economy comprising all sample firms or more narrowly to finer industry classifications (i.e., three- and four-digit SIC industries).

4.7.1 Credit Risk Spillovers through Supply Chain Networks

In Equation (6) and related discussion of Section 3.1, we show that the credit risk spillover effect can be conceptualized as $\sum_{j \neq i} \gamma_{ij} N_{jt}$, where γ_{ij} represents the increase in firm i's default intensity when firm j is defaulting.

For the first robustness check, we use another empirical estimate of γ derived from a well-defined firm linkage–the customer-supplier relationship. Specifically, drawn on Cohen and Frazzini (2008), we set γ_{ij} as the proportion of firm i's total sales bought by firm j. In this way, γ_{ij} proxies the impact of firm j's default on i's future cash flows and thus its default risk. Then, CRC for a supplier is defined as the sum of each of its principal customer's expected default probability weighted by the share of its total sales attributed to that customer. In other words, CRC is calculated as follows.

$$\text{CRC}_{it} = \sum_{j \neq i} 1_{\left\{\text{Sales\_Share}_{ijt} > 0.1\right\}} \text{Sales\_Share}_{ijt} \times \text{EDP}_{jt}, \tag{15}$$

where Sales_Share_{ijt} = (Sales from i to j in year t) / (Total Sales of i in year t).

This credit risk contagion measure allows for both intra-industry and inter-industry credit contagion originating from major customers in a supply chain. It is also quite intuitive as the spillover proxy is based on a concrete economic channel through which credit risk contagion can propagate. However, for the same reason, the sales-based construction of γ and thus CRC defined in Equation (15) cannot provide an assessment of a firm's overall exposure to credit risk contagion. As it is beholden to one particular mechanism of credit risk spillover, the sales-based γ cannot properly reflect firm interaction in other dimensions and cannot capture the product market rivalry effect due to peers' potential exit.

Following Campello and Gao (2017), we manually match reported major customer names in the Compustat Segment Customer database to their unique Compustat identifiers. We only keep suppliers that are incorporated in the United States and report an identifiable principal customer that accounts for at least ten percent of the supplier's annual revenue.

Financial and utility firms are excluded.

[Insert Table 9 here]

Table 9 replicates our analyses of cash holdings from Table 4 and corporate payout from Table 6 when using the supply chain based measure of credit risk spillovers. CRC has expected effects on cash holdings and corporate payout and the impact remains highly significant.

4.7.2 Alternative Industry Classifications

In the original construction, CRC and PMR are computed as the PCORR-weighted sum of industry peers' expected default probabilities. So far, our analyses have mainly focused on credit risk spillovers within the Fama-French 48 industries. In the second robustness check, we broaden the scope of this calculation to include all firms, since credit risk spillovers can conceivably go beyond industry boundaries. This also requires us to modify the original definition of PCORR. Previously, we use a two-factor model with market and industry factors to estimate the return residuals for two firms in the same Fama-French 48 industry, and then compute PCORR as the correlation of those residuals. Now, we use a similar market model to estimate the return residuals for any pair of firms regardless of whether they are in the same industry or not. Accordingly, the augmented market model further controls for the industry factor(s) of the pair.

In the third robustness check, we move to the opposite extreme of industry classification and examine credit risk spillovers in more granular three- and four-digit SIC industries. The purpose of this exercise is to alleviate the concern that our results are driven by omitted state variables that simultaneously affect the credit risk and cash holdings of subsets of firms within each Fama-French 48 industry. For instance, if a group of firms are hit by a negative and common demand shock, their default probabilities will all increase, which will raise our CRC measure. At the same time, the negative shock may induce more precautionary savings by the affected firms, leading to a positive association between CRC and cash reserves. With a more refined industry classification, a firm would be more similar to its industry peers in the product market space. Therefore, purging the (now more granular) industry factor in our PCORR construction is a first step toward addressing the concern with heterogeneities within the same Fama-French 48 industry. In our sample, there are 242 and 388 three-digit and four-digit SIC industries, respectively. Correspondingly, we control for a much greater number of industry-year fixed effects in our regression analyses, which is a second step toward absorbing the impact of within-FF48 industry heterogeneities that could confound our results.

[Insert Tables 10 and 11]

Table 10 performs the same replication exercise using the market-wide measures of credit risk spillovers. While the magnitude of the coefficients has changed due to the redefinition of CRC and PMR, the significance and direction of the estimated effects remain unchanged. We then re-examine our key results using spillover proxies constructed based on three- and four-digit SIC industry classifications. Table 11 shows that the new results are corroborative—the impact of CRC on cash holdings remains positive and that on payout policy negative. As expected, since we focus on more "localized" credit risk spillovers within more narrowly defined industries, the effect is diminished but still remains highly significant both statistically and economically. For instance, the marginal effect of CRC on cash holdings is lowered from 13.6 percent in FF48 industries (Table 4, Column 3) to 10.4 percent in four-digit SIC industries (Table 11, Panel B, Column 1).[29]

Overall, the main findings of our paper are not sensitive to these rather significant changes to how the credit risk spillover measures are defined.

[29]Note that these marginal effects use the standard deviation of CRC, which depends on the choice of the industry classification. The standard deviation of CRC is much lower when we switch from FF48 industries to three-digit or four-digit SIC industries.

5 Conclusion

In spite of recent studies that have closely examined the ex post impact of extreme credit events (e.g., bankruptcies) on peer firms' equity returns and credit spreads, little is known about how firms shape their cash and related financial policies in response to their exposure to credit risk spillovers. This paper seeks to bridge this gap. We develop novel measures of a firm's ex ante exposure to credit risk contagion (CRC) and product market rivalry (PMR)—two components of credit risk spillovers, which have distinct implications for corporate cash policy. We find strong evidence that the proposed measures differentiate patterns of interdependence of firms' financial health through the spillovers of negative externalities (CRC) and potential benefits (PMR), both originating from peer firms' financial distress. In particular, we show that the proposed credit risk spillover measures predict the likelihood of future financial distress, and they also explain CDS premiums in the expected direction.

Taking the proposed credit risk spillover measures to the data, we analyze how a firm's CRC and PMR exposures affect its short term liquidity management. We find that firms with greater contagion risk hold more cash, have a higher marginal value of cash, and cut back on their payout. Consistent with our findings that greater CRC is associated with more conservative corporate financial policies, subsequent analysis indicates that bank loans to firms with greater CRC have higher spreads, more restrictive non-price terms such as shorter maturity and a greater likelihood of collateral demand, and more dispersed syndication ownership. Our results also show that a greater PMR reduces precautionary cash holdings and lowers the cost of bank loans. However, CRC generally dominates PMR in shaping related corporate policies and in determining bank loan contracting.

The contagion of extreme credit events has been vividly demonstrated during the 2007-09 financial crisis. We show that firms, in fact, take measures to cope with their ex ante exposure to contagion risk. Depending on the relatedness of firm valuation (i.e., fellows with PCORR>0 or rivals with PCORR<0), the spillovers of peer firms' credit risk can have different implications for corporate financial policies and bank lending.

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Appendix A. Variable Definitions
This table provides the definition of variables used in the study.

	Definitions with corresponding Compustat item names
Measures of credit risk spillovers	
CRC	Credit Risk Contagion$_{it} = \sum_{j \in I, j \neq i} 1_{\{PCORR_{ijt} > 0\}} PCORR_{ijt} \times EDP_{jt}$, where $1_{\{\cdot\}}$ is an indicator function that takes the value of one if the statement is true and zero otherwise; $PCORR_{ijt}$ is the pairwise partial stock return correlation between firm i and firm j; and EDP_{jt} denotes the expected default probability of firm j (computed from Altman's (1968) *Z*-score through 1/(1+exp(*Z*-score)) based on Altman et al. (2010)). Altman's (1968) *Z*-score = (3.3*Earnings Before Interest and Taxes (EBIT) + 1.0*Net Sales (SALE) + 1.4*Retained Earnings (RE) + 1.2*Working Capital (WCAP))/Total Assets (AT) + 0.6*Market Value of Equity (PRCC_F*CSHO)/Total Liabilities (DLTT+DLC). To prevent spurious inferences, we only keep those $PCORRs$ that are statistically significant at the 10% level. The variable is divided by 10.
PMR	Product Market Rivalry$_{it} = \sum_{j \in I, j \neq i} 1_{\{PCORR_{ijt} < 0\}} \left\| PCORR_{ijt} \right\| \times EDP_{jt}$, where $1_{\{\cdot\}}$ is an indicator function that takes the value of one if the statement is true and zero otherwise; $PCORR_{ijt}$ is the pairwise partial stock return correlation between firm i and firm j; and EDP_{jt} denotes the expected default probability of firm j (computed from Altman's (1968) *Z*-score through 1/(1+exp(*Z*-score)) based on Altman et al. (2010)). To prevent spurious inferences, we only keep those $PCORRs$ that are statistically significant at the 10% level. The variable is divided by 10.
Other firm-level variables	
Cash/Assets	Cash plus marketable securities (CHE) divided by book value of total assets (AT).
Market asset beta	Market asset (unlevered) beta is calculated from the market equity (levered) beta. The market equity (levered) beta is obtained from a two-factor model in which firm return is regressed on market return and industry return: $r_{i,t} = a_i + \beta^{MKT}_{Equity} b_i r_{M,-K,t} + \beta^{IND}_{Equity} r_{K,-i,t} + \varepsilon_{i,t}$, where $r_{i,t}$ is the stock return in week *t* for firm *i*. $r_{M,-K,t}$ is the weekly value-weighted CRSP market index return, excluding the return on industry *K*, and $r_{K,-i,t}$ is a value-weighted return of all industry *K* stocks, where firm *i* is excluded from the industry portfolio. Industries are defined according to Fama-French's (1997) 48-industry classification. Since high leverage firms tend to have larger betas, we unlever equity betas as follows: $\beta_{Asset} = \beta_{Equity}\frac{E}{V}$, where *E* is the market value of a firm's equity and *V* is the underlying value of the firm, or market value of asset.
Industry asset beta	Industry asset (unlevered) beta is calculated from the industry equity (levered) beta. The industry equity (levered) beta is obtained from the same two-factor model used in the calculation of market equity (levered) beta. We then unlever industry equity beta using $\beta_{Asset} = \beta_{Equity}\frac{E}{V}$, where *E* is the market value of a firm's equity and *V* is the underlying value of the firm, or market value of asset.
Own default probability	A logistic transformation is used to map a modified Altman's (1968) *Z*-score to an implied probability of default through 1/(1+exp(*Z*-score)) based on Altman et al. (2010). We use a modified *Z*-score, which does not include the ratio of market

	value of equity to book value of total debt, because a similar term, market-to-book, enters the regressions as a separate variable.
Market-to-Book	The market value of common equity (fiscal year end price (PRCC_F) times shares outstanding (CSHO), plus total assets (AT) minus book value of common equity (CEQ)) divided by book value of total assets (AT).
Ln (real book assets)	Natural logarithm of book value of total assets (AT) in millions of 2006 U.S. dollars.
Cash flow	Operating income before depreciation (OIBDP), less interest and related expense (XINT), income taxes (TXT), and dividends (DVC), divided by book value of total assets (AT).
Firm profit volatility	The firm-level standard deviation of annual changes in the level of operating income before depreciation (OIBDP), calculated using five lags, and scaled by average lagged total assets (AT).
Net working capital	Working capital (WCAP) minus cash (CHE) divided by total assets (AT).
Capital expenditures	The ratio of capital expenditures (CAPX) to the book value of total assets (AT). The capital expenditure from the statement of cash flows is often missing. Following Dittmar and Mahrt-Smith (2007), we impute any missing CAPX from the change in net fixed assets plus depreciation and amortization over the year.
Total book leverage	The ratio of long-term debt (DLTT) plus debt in current liabilities (DLC) to total assets (AT).
R&D expenditures	The ratio of R&D expenditure (XRD) to sales (SALE). If R&D expenditure is missing, we follow the tradition to set the missing value to zero.
Return on equity	Net income (NI) during the previous fiscal year divided by book value of equity (CEQ) at the previous fiscal year-end.
Monthly stock volatility	The standard deviation of monthly returns during the past 24 months.
Stock return	The stock return during the previous fiscal year.
Asset tangibility	Net property, plant, and equipment (PPENT) divided by total assets (AT).
Stock return volatility	Standard deviation of the quarterly stock return over the 20 quarters before the quarter containing the loan origination date.
Cash flow volatility	Standard deviation of operating income before depreciation (OIBDPQ) divided by total assets (ATQ) over the 20 quarters before the quarter containing the loan origination date.
Borrower modified Altman's (1968) *Z*-score	(3.3*Earnings Before Interest and Taxes (EBIT) + 1.0*Net Sales (SALE) + 1.4*Retained Earnings (RE) + 1.2*Working Capital (WCAP))/Total Assets (AT), as used in MacKie-Mason (1990).
Dividend yield	Cash dividends on common stock (DVC) scaled by the market value of common equity (PRCC_F*CSHO).
Total payout ratio	The ratio of total distributions including dividends for preferred stocks (DVP), dividends for common stocks (DVC), and net share repurchases (PRSTKC-PSTKRV), divided by total assets (AT).

Loan variables

Ln (loan spreads)	Natural logarithm of the loan all-in-drawn spread above LIBOR, including any annual fee paid to the bank group. The "All-in-Drawn" variable in the DealScan database describes the amount the borrower pays in basis points over LIBOR for each dollar drawn down. It also adds the spread of the loan with any annual (or facility) fee paid to the bank or bank group.
Ln (loan amount)	Natural logarithm of the loan facility amount. Loan amount is measured in millions of U.S. dollars.
Ln (loan maturity)	Natural logarithm of the loan maturity measured in months.

Collateral	An indicator variable equals to one if the loan facility is secured, and zero otherwise.
Number of lenders	Total number of lenders in a single loan.
Loan type	Indicator variables for loan types, including 364-day facility, revolver less than 1 year, revolver/term loan, term loan, acquisition facility, bridge loan, demand loan, limited line, and others.
Loan purpose	Indicator variables for loan purposes, including corporate purposes, debt repayment, working capital, takeover, CP backup, acquisition line, LBO/MBO, debtor-in-possession, recapitalization, and others.

Table 1. Credit risk spillovers around peers' pre-chapter 11 bankruptcy distress dates

The table reports the mean (cumulative) abnormal stock returns of non-bankrupt firms surrounding peers' pre-bankruptcy distress date. The sample contains 421 Chapter 11 distress dates from 1981 to 2012 and 56,702 firm-year observations from non-filing firms. The distress dates are identified using the approach of Hertzel, Li, Officer, and Rogers (2008). Specifically, it is the day with the largest decrease in abnormal returns within the year prior to the bankruptcy announcement. Following Brown and Warner (1985), the abnormal return on stock *i* over day t is calculated as $AR_{i,t} = r_{i,t} - r_{m,t}$, where $r_{i,t}$ and $r_{m,t}$ are the returns for stock i and the market portfolio m (CRSP's value-weighted index) on day t, respectively. Quintile portfolios are formed based on positive and negative partial return correlation between a filing firm and its non-bankrupt peers within the same Fama-French's (1997) 48-industry. Distress period CAR is the cumulative abnormal returns centered on the distress date (day 0) for an 11-day (-5, +5) window. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Fellow firms (with $PCORR > 0$) sorted by $PCORR$

Event window	Quintile Portfolio	Average PCORR (%)	Average CAR (%)	t-statistic	N	Diff. (%) (Q5 – Q1)
	Q5 (High)	7.5	-0.205***	-4.37	6,797	
	Q4	3.8	-0.165***	-3.55	6,657	
[0, 0]	Q3	2.3	-0.090**	-2.00	6,651	-0.161**
	Q2	1.3	-0.117**	-2.54	6,654	
	Q1 (Low)	0.5	-0.044	-0.97	6,523	
	Q5 (High)	7.5	-0.333***	-2.39	6,824	
	Q4	3.8	-0.287**	-2.10	6,709	
[-5, +5]	Q3	2.3	-0.144	-1.08	6,692	-0.520***
	Q2	1.3	-0.238*	-1.78	6,691	
	Q1 (Low)	0.5	-0.187	1.40	6,571	

Panel B: Rival firms (with $PCORR < 0$) sorted by $|PCORR|$

Event window	Quintile Portfolio	Average PCORR (%)	Average CAR (%)	t-statistic	N	Diff. (%) (Q5 – Q1)
	Q5 (High)	-5.3	0.269***	2.74	4,711	
	Q4	-2.5	0.194**	2.36	4,618	
[0, 0]	Q3	-1.4	0.153*	1.76	4,615	0.238**
	Q2	-0.7	0.199**	2.40	4,622	
	Q1 (Low)	-0.2	0.031	0.38	4,470	
	Q5 (High)	-5.3	0.759***	3.23	4,749	
	Q4	-2.5	0.045	0.22	4,649	
[-5, +5]	Q3	-1.4	0.155	0.72	4,659	
	Q2	-0.7	0.025	0.12	4,648	0.331*
	Q1 (Low)	-0.2	0.428*	1.95	4,509	

Table 2. Credit risk spillovers and the likelihood of financial distress

This table presents the results of multivariate logit and OLS regressions that examine whether the proposed measures of credit risk spillovers are related to the probability of being financially distressed in the next year. In Column (1), the dependent variable equals one if the stock price loses more than -30% in a given year, and zero otherwise. In Column (2), following Andrade and Kaplan (1998), the dependent variable equals one if the interest coverage ratio of the firm is less than one for two consecutive years, and zero otherwise. In Column (3), the dependent variable is the natural log of CDS spreads. The CDS data come from Markit for the period from 2001 to 2013. As a company's default risk rises, its CDS spread increases. All independent variables are measured at the beginning of the year. Data on firm characteristics are collected from the merged Compustat-CRSP database for the period 1980–2013. Details on the construction of all variables are provided in the Appendix. Heteroskedasticity-robust and firm-level clustered *z*-statistics for logit regressions are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Distress dummy based on stock returns	Distress dummy based on interest coverage	Ln(CDS spreads)
	(1) Logit	(2) Logit	(3) OLS
CRC	0.530***	0.871***	0.569***
	(5.11)	(4.95)	(2.71)
PMR	-0.540**	-0.549	-0.595**
	(-2.34)	(-1.44)	(-2.22)
Industry asset beta	0.328***	0.395***	0.148**
	(17.66)	(12.41)	(2.40)
Market asset beta	0.255***	0.297***	0.105**
	(17.81)	(12.43)	(2.19)
EBITDA/book assets	-0.219***	-11.548***	-3.263***
	(-4.12)	(-44.55)	(-7.72)
Net worth/book assets	-0.206***	-0.068	-1.709***
	(-5.40)	(-0.86)	(-13.10)
Market to book	-0.078***	-0.015	-0.346***
	(-12.59)	(-1.33)	(-9.81)
Ln(real book assets)	-0.094***	-0.374***	-0.287***
	(-16.63)	(-30.93)	(-12.41)
Industry × year fixed effects	Yes	Yes	Yes
No. of observations	94,311	82,486	4,600
Adj. (Pseudo) R^2	0.13	0.46	0.57

Table 3. Summary statistics

This table provides mean, standard deviations, three quartiles, and the number of observations of key variables employed in the analysis. Data on firm characteristics are collected from the merged Compustat-CRSP database for the period 1980–2013. Loan data come from the Loan Pricing Corporation's (LPC) Dealscan database for the period 1987–2013. Variables are winsorized at the 1% and 99% levels. Details on the construction of all variables are provided in the Appendix.

Variable	Mean	Median	Std. Dev.	25th percentile	75th percentile	*N*
Credit risk spillovers						
CRC	0.131	0.051	0.209	0.020	0.138	90,019
PMR	0.054	0.026	0.075	0.009	0.064	90,019
Other firm characteristics						
Cash/Assets	0.140	0.085	0.198	0.024	0.236	90,019
Industry asset beta	0.338	0.287	0.684	-0.053	0.715	90,019
Market asset beta	0.454	0.365	0.858	-0.033	0.887	90,019
Own default probability	0.275	0.123	0.325	0.024	0.428	90,019
Market to book	1.970	1.399	1.916	1.054	2.119	90,019
Book assets ($ million)	1342	187	3659	52	765	90,019
Cash flow	0.024	0.068	0.213	0.019	0.108	90,019
Firm profit volatility	0.106	0.060	0.135	0.031	0.121	90,019
Net working capital	0.121	0.113	0.202	-0.007	0.252	90,019
Capital expenditures	0.067	0.046	0.069	0.023	0.085	90,019
Total book leverage	0.221	0.188	0.204	0.035	0.341	90,019
R&D expenditures	0.211	0.000	1.158	0.000	0.054	90,019
Dividend yield	0.008	0.000	0.016	0.000	0.013	90,644
Total payout ratio	0.014	0.001	0.068	0.000	0.024	90,644
Loan characteristics						
Spreads (basis points)	198	175	140	88	275	23,432
Loan size ($ million)	321	100	788	27	300	23,432
Loan maturity (month)	46	48	25	24	60	23,432
Collateral	0.308	0	0.462	0	1	23,432
Number of lenders	7.534	5	8.649	1	10	23,432

Table 4. Baseline results: credit risk spillovers and cash holdings

This table presents baseline regressions that examine the relationship between a firm's exposure to peers' risk of financial distress and its cash holdings. The dependent variable is the ratio of cash plus marketable securities to total assets. All independent variables are measured at the beginning of the year. Details on the construction of all variables are provided in the Appendix. Values of *t*-statistics that are based on robust standard errors and firm-level clustering are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Cash/Assets	(1)	(2)	(3)
CRC	0.105***		0.091***
	(10.80)		(8.73)
PMR		-0.157***	-0.089***
		(-8.31)	(-4.60)
Industry asset beta	0.030***	0.032***	0.030***
	(17.91)	(18.82)	(17.92)
Market asset beta	0.019***	0.020***	0.019***
	(14.72)	(15.56)	(14.87)
Own default probability	0.066***	0.070***	0.070***
	(7.39)	(7.72)	(7.67)
Market to book	0.009***	0.009***	0.009***
	(11.76)	(11.53)	(11.33)
Ln (real book assets)	-0.014***	-0.013***	-0.013***
	(-18.08)	(-17.86)	(-17.62)
Cash flow	0.031***	0.032***	0.035***
	(4.08)	(4.12)	(4.52)
Firm profit volatility	0.036***	0.036***	0.035***
	(4.10)	(4.09)	(3.88)
Net working capital	-0.222***	-0.222***	-0.226***
	(-24.12)	(-23.95)	(-23.77)
Capital expenditures	-0.387***	-0.386***	-0.390***
	(-24.88)	(-24.77)	(-24.53)
Total book leverage	-0.285***	-0.285***	-0.287***
	(-43.79)	(-43.50)	(-43.06)
R&D expenditures	0.024***	0.024***	0.024***
	(18.22)	(18.32)	(18.24)
Industry × year fixed effects	Yes	Yes	Yes
No. of observations	90,019	90,019	90,019
Adj. R^2	0.49	0.49	0.49

Table 5. Credit risk spillovers and the market valuation of cash holdings

This table presents regressions that examine whether equity investors assign higher market value of cash held by firms with a greater exposure to peers' risk of financial distress. We use the methodology developed in Faulkender and Wang (2006) to estimate the role of credit risk spillovers in the value of an additional dollar of cash to equity holders. Specifically, we regress the excess stock return $r_{i,t} - R_{r,t}^{B}$ (the firm's annual stock return minus the firm's matched Fama and French 5×5 size and book-to-market portfolio return) on changes in firm characteristics over the fiscal year. Column (1) of this table reports a regression similar to Model II in Table II of Faulkender and Wang (2006). In Column (2), we augmented Faulkender and Wang's framework to include the impact of CRC and PMR. Values of t-statistics that are based on robust standard errors and firm-level clustering are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Excess stock return	(1)	(2)
Δ Cash holdings	1.042***	0.959***
	(31.25)	(25.20)
CRC × Δ Cash holdings		0.263**
		(1.98)
CRC		-0.083***
		(-5.93)
PMR × Δ Cash holdings		-0.605*
		(-1.69)
PMR		0.267***
		(7.86)
Δ Earnings	0.468***	0.469***
	(36.83)	(36.87)
Δ Net assets	0.199***	0.195***
	(26.56)	(26.10)
Δ R&D expenditures	0.675***	0.668***
	(6.20)	(6.13)
Δ Interest expenses	-1.710***	-1.677***
	(-16.51)	(-16.26)
Δ Dividends	2.129***	2.117***
	(10.12)	(10.11)
Cash holdings$_{t-1}$	0.232***	0.246***
	(19.68)	(20.12)
Market leverage	-0.354***	-0.386***
	(-44.60)	(-46.12)
Net financing	-0.034**	-0.026*
	(-2.56)	(-1.95)
Cash holdings$_{t-1}$ × Δ Cash holdings	-0.093***	-0.104***
	(-2.59)	(-2.90)
Market leverage × Δ Cash holdings	-0.911***	-0.818***
	(-15.13)	(-13.14)
No. of observations	78,382	78,382
Adj. R^2	0.16	0.16

Table 6. Credit risk spillovers and corporate payout

This table presents regressions that examine the effects of a firm's exposure to credit risk spillovers on its payout policy. Dividend yield is constructed as cash dividends on common stock scaled by the market value of common equity. Total payout ratio is total distributions including dividends for preferred stocks, dividends for common stocks, and net share repurchases, divided by total assets. Following Brown, Liang, and Weisbenner (2007), Becker, Jacob, and Jacob (2013), Li, Liu, Ni, and Ye (2017), we control for natural log of market value, total book leverage, market-to-book ratio, return on equity, free cash flow-to-assets, cash-to-assets, monthly stock volatility over the past two years, and past year stock return. All independent variables are measured at the beginning of the year. Details on the construction of all variables are provided in the Appendix. Values of *t*-statistics that are based on robust standard errors and firm-level clustering are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Dividend yield	Total payout ratio
	(1)	(2)
CRC	-0.006***	-0.013***
	(-5.65)	(-5.68)
PMR	0.003*	0.016***
	(1.81)	(3.24)
Industry asset beta	-0.004***	-0.008***
	(-20.09)	(-20.09)
Market asset beta	-0.003***	-0.007***
	(-19.00)	(-21.50)
Own default probability	-0.002***	-0.006***
	(-3.50)	(-3.47)
Ln (market value)	0.003***	0.006***
	(25.00)	(30.37)
Total book leverage	-0.015***	-0.026***
	(-18.93)	(-17.67)
Market to book	0.000***	0.001***
	(6.30)	(9.43)
Return on equity	0.001***	0.003***
	(3.87)	(7.26)
Free cash flow	0.014***	0.040***
	(13.49)	(16.31)
Cash	0.003***	0.027***
	(3.06)	(13.65)
Monthly stock volatility	-0.000***	-0.000***
	(-7.47)	(-4.60)
Stock return	-0.002***	-0.005***
	(-14.65)	(-12.96)
Industry × year fixed effects	Yes	Yes
No. of observations	90,644	90,644
Adj. R^2	0.25	0.19

Table 7. Credit risk spillovers and financial flexibility: instrumental variable regressions

This table presents the second-stage instrumental variable (IV) estimates of firm-level panel regressions used to identify the effect of credit risk spillovers on cash holdings and corporate payout policies. We explore the identification provided by the removal of intrastate and interstate banking restrictions. We implement an IV approach in two steps. First, EDP is regressed on U.S. intrastate and interstate banking deregulation dummies. The intrastate deregulation dummy variable equals one after a state implements either de novo or M&A deregulation (Jayaratne and Strahan, 1996; Kroszner and Strahan, 1999). The interstate deregulation dummy variable equals one after entry by out-of-state bank holding companies is permitted (Kroszner and Strahan, 1999; Kerr and Nanda, 2009). Industry and year fixed effects and their interactions are also controlled for. The predicted value of EDP is denoted as $\widehat{EDP}$.

In the second step, for each firm i, we respectively calculate the instrumental variables for CRC and PMR by aggregating $PCORR$-weighted $\widehat{EDP}$ over peer firms, whose headquarters are located in different states from that of the focal firm in year t (i.e., $S_{jt} \neq S_{it}$). More specifically, the two instruments, denoted as CRC^{IV} and PMR^{IV} respectively, are calculated as follws: $\sum_{j\in I, j\neq i, \boldsymbol{S_{jt}}\neq \boldsymbol{S_{it}}} 1_{\{PCORR_{ijt}>0\}} \times PCORR_{ijt} \times \widehat{EDP}_{jt}$, and $\sum_{j\in I, j\neq i, \boldsymbol{S_{jt}}\neq \boldsymbol{S_{it}}} 1_{\{PCORR_{ijt}<0\}} \times \left|PCORR_{ijt}\right| \times \widehat{EDP}_{jt}$. This practice aims to remove common effects of banking deregulation on in-state peers' EDP and the focal firm's cash holdings. In Column (1), the dependent variable is the ratio of cash plus marketable securities to total assets. In Column (2), the dependent variable is the dividend yield, constructed as cash dividends on common stock scaled by the market value of common equity. In Column (3), the dependent variable is the total payout ratio, calculated as total distributions including dividends for preferred stocks, dividends for common stocks, and net share repurchases, divided by total assets. All independent variables are measured at the beginning of the year. Details on variable construction are provided in the appendix. Values of t-statistics reported in parentheses are based on robust standard errors and firm-level clustering. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Cash holdings	Dividend yield	Total payout ratio
	(1)	(2)	(3)
CRC	0.097***	-0.009***	-0.016*
	(4.85)	(-6.71)	(-1.79)
PMR	-0.158***	0.004**	0.024***
	(-5.67)	(2.05)	(2.92)
Other controls	Same as in Table 4	Same as in Table 6	Same as in Table 6
Industry × year fixed effects	Yes	Yes	Yes
No. of observations	87,365	88,357	88,357
Adj. R^2	0.53	0.28	0.20

Table 8. Credit risk spillovers and bank loan contracting

This table presents regressions that examine the role of a borrowing firm's exposure to peers' risk of financial distress in bank loan contracting. The sample period is from 1987 to 2013. All independent variables are measured at the beginning of the year. Details on the construction of all variables are provided in the Appendix. Heteroskedasticity-robust and clustered *t*-statistics for OLS regression and heteroskedasticity-robust and clustered *z*-statistics for logit and Poisson regressions are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Ln(spreads)	Ln(maturity)	Collateral	No. of lenders
	(1) OLS	(2) OLS	(3) Logit	(4) Poisson
CRC	0.285***	-0.060**	0.996***	0.127**
	(5.37)	(-2.02)	(3.58)	(2.00)
PMR	-0.187*	0.058	-0.883***	-0.301**
	(-1.74)	(1.09)	(-4.87)	(-2.27)
Firm characteristics				
Industry asset beta	0.032***	-0.014*	0.168***	0.075***
	(3.27)	(-1.68)	(2.94)	(4.60)
Market asset beta	0.031***	-0.001	0.202***	0.079***
	(4.00)	(-0.20)	(4.43)	(6.43)
Ln (real book assets)	-0.132***	-0.012***	-0.401***	0.110***
	(-31.08)	(-3.48)	(-17.92)	(15.87)
Market to book	-0.040***	0.000	-0.103***	-0.004
	(-6.58)	(0.04)	(-3.51)	(-0.67)
Total book leverage	0.585***	0.106***	1.862***	0.209***
	(27.56)	(6.20)	(15.11)	(6.13)
Profitability	-0.598***	0.134***	-1.336***	0.352***
	(-8.22)	(3.63)	(-4.29)	(3.77)
Tangibility	-0.288***	0.062***	0.155	-0.140***
	(-11.85)	(3.26)	(1.17)	(-3.76)
Stock return volatility	0.006*	-0.001	0.024	-0.010**
	(1.94)	(-0.39)	(0.89)	(-2.04)
Cash flow volatility	0.085**	-0.054*	2.783**	-0.348
	(2.23)	(-1.87)	(2.12)	(-1.01)
Borrower modified *Z*-score	-0.040***	0.000	-0.024	0.001
	(-8.70)	(0.12)	(-1.03)	(0.17)
Loan characteristics				
Ln (loan amount)	-0.074***	0.094***	0.027	0.368***
	(-16.86)	(25.82)	(1.18)	(46.43)
Ln (loan maturity)	-0.082***		0.376***	0.189***
	(-8.68)		(7.35)	(10.86)
Collateral	0.347***	0.059***		0.132***
	(41.28)	(7.96)		(8.45)
Loan type fixed effects	Yes	Yes	Yes	Yes
Loan purpose fixed effects	Yes	Yes	Yes	Yes
Industry × year fixed effects	Yes	Yes	Yes	Yes
No. of observations	23,432	23,432	23,432	23,432
Adj. (Pseudo) R^2	0.60	0.63	0.36	0.42

Table 9. Robustness checks: credit risk spillovers through supply chains

This table presents baseline regressions that examine the relationship between a firm's exposure to the risk of principal customers' financial distress and its cash holdings and payouts. Credit risk contagion is the aggregate of principal customers' expected probability of default multiplied by their shares of each supplier's total sales. In Column (1), the dependent variable is the ratio of cash plus marketable securities to total assets. In Column (2), the dependent variable is dividend yield, constructed as cash dividends on common stock scaled by the market value of common equity. In Column (3), the dependent variable is total payout ratio, calculated as total distributions including dividends for preferred stocks, dividends for common stocks, and net share repurchases, divided by total assets. All independent variables are measured at the beginning of the year. The sample includes 2,710 unique U.S. suppliers ranging from 1980 to 2013. In Column (1), a set of control variables the same as in Table 4 are included (but not reported). In Columns (2) and (3), a set of control variables the same as in Table 6 are included (but not reported). Details on the construction of all variables are provided in the Appendix. Values of *t*-statistics that are based on robust standard errors and firm-level clustering are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Cash holdings	Dividend yield	Total payout ratio
	(1)	(2)	(3)
CRC	0.133**	-0.014***	-0.026**
	(2.47)	(-2.91)	(-2.02)
Other controls	Same as in Table 4	Same as in Table 6	Same as in Table 6
Industry × year fixed effects	Yes	Yes	Yes
No. of observations	11,501	11,063	11,063
Adj. R^2	0.54	0.35	0.18

Table 10. Robustness checks: market-wide credit risk spillovers and financial flexibility

This table presents baseline regressions that examine the relationship between a firm's exposure to peers' risk of financial distress and its cash holdings and payouts, allowing for both intra-industry and inter-industry credit risk spillovers. Credit risk contagion (product market rivalry) is the aggregate of peers' probability of financial distress multiplied by the corresponding partial correlations of those with positive (negative) pairwise partial correlations with the firm. Both CRC and PMR are divided by 100. In Column (1), the dependent variable is the ratio of cash plus marketable securities to total assets. In Column (2), the dependent variable is dividend yield, constructed as cash dividends on common stock scaled by the market value of common equity. In Column (3), the dependent variable is total payout ratio, calculated as total distributions including dividends for preferred stocks, dividends for common stocks, and net share repurchases, divided by total assets. All independent variables are measured at the beginning of the year. In Column (1), a set of control variables the same as in Table 4 are included (but not reported). In Columns (2) and (3), a set of control variables the same as in Table 6 are included (but not reported). Details on the construction of all variables are provided in the Appendix. Values of *t*-statistics that are based on robust standard errors and firm-level clustering are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Cash holdings	Dividend yield	Total payout ratio
	(1)	(2)	(3)
CRC	0.024**	-0.005***	-0.015***
	(2.53)	(-5.27)	(-6.35)
PMR	-0.060***	0.006***	0.021***
	(-3.99)	(3.42)	(4.99)
Other controls	Same as in Table 4	Same as in Table 6	Same as in Table 6
Industry × year fixed effects	Yes	Yes	Yes
No. of observations	90,019	90,644	90,644
Adj. R^2	0.51	0.26	0.20

Table 11. Robustness checks: credit risk spillovers in three- and four-digit SIC industries

This table examines the relationship between credit risk spillovers and corporate cash and payout policy in three- and four-digit SIC industries. The results are shown in Panels A and B, respectively. Credit contagion risk (product market rivalry) is the aggregate of peers' probability of financial distress multiplied by the corresponding pairwise partial correlations. Both CRC and PMR are divided by 10. In Column (1), the dependent variable is the ratio of cash plus marketable securities to total assets. In Column (2), the dependent variable is dividend yield, calculated as cash dividends on common stock scaled by the market value of common equity. The dependent variable in Column (3) is total payout ratio, defined as total distributions including dividends for preferred stocks, dividends for common stocks, and net share repurchases, divided by total assets. All independent variables are measured at the beginning of the year. Detailed variable definitions are provided in the Appendix. The construction of industry fixed effects is consistent with the calculation of CRC and PMR. Values of *t*-statistics that are based on robust standard errors and firm-level clustering are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Spillover in three-digit SIC industries

Dependent variable	Cash holdings	Dividend yield	Total payout ratio
	(1)	(2)	(3)
CRC	0.133***	-0.010***	-0.019***
	(8.82)	(-6.97)	(-5.98)
PMR	0.041	0.002	0.018**
	(1.46)	(0.72)	(2.47)
Other controls	Same as in Table 4	Same as in Table 6	Same as in Table 6
Industry × year fixed effects	Yes	Yes	Yes
No. of observations	90,019	90,644	90,644
Adj. R^2	0.51	0.28	0.19

Panel B. Spillover in four-digit SIC industries

Dependent variable	Cash holdings	Dividend yield	Total payout ratio
	(1)	(2)	(3)
CRC	0.179***	-0.009***	-0.017***
	(7.06)	(-6.00)	(-5.19)
PMR	0.074	0.003	0.019**
	(1.58)	(0.93)	(2.56)
Other controls	Same as in Table 4	Same as in Table 6	Same as in Table 6
Industry × year fixed effects	Yes	Yes	Yes
No. of observations	90,019	90,644	90,644
Adj. R^2	0.52	0.29	0.19