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Abstract

Reduced-form models of default that attribute a large fraction of credit spreads to compensation for credit event risk typically preclude the most plausible economic justification for such risk to be priced--namely, a “contagious” response of the market portfolio during the credit event. When this channel is introduced within a general equilibrium framework for an economy comprised of a large number of firms, credit event risk premia have an upper bound of just a few basis points and are dwarfed by the contagion premium. We provide empirical evidence supporting the view that credit event risk premia are minuscule.

Key words: credit risk model, contagion

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1 Introduction

Most empirical studies of corporate bond premia find that only a small fraction of observed credit spreads can be explained in terms of expected losses and standard measures of risk (i.e., covariation with pricing kernel proxies). For example, Elton, Gruber, Agrawal, and Mann (2001) regress corporate bond returns on the Fama-French (1993) factors and report that only 40% of observed spreads on 10-year bonds can be attributed as compensation for exposure to these factors,¹ while Driessen (2005) estimates an even smaller fraction due to ‘common risk factors.’ This failure is especially severe for investment-grade bonds with short maturities. Interestingly, this empirical failure mirrors the theoretical predictions of many (diffusion-based) structural models of default (e.g., Merton (1974)).² While several recently proposed structural models have made progress,³ diffusion-based structural models still struggle to explain short-maturity spreads.

Given the failure of most structural models to generate sizeable credit spreads (especially at short maturities), researchers have also investigated the ability of reduced-form (or hazard rate) models to explain observed spreads. Reduced-form models specify a process for the risk-neutral default intensity $\lambda^Q(t)$, and then value risky claims by discounting at a default-adjusted rate under the risk-neutral measure. Under certain modeling assumptions (e.g., a Cox process), the price of a corporate bond obtains the same analytic form as that found for a risk-free bond (Lando (1998), Duffie and Singleton (1999)). Indeed, it is this tractability that explains the popularity of reduced-form models.

Most sources of risk found in structural models have an analogue in reduced-form models.⁴ For example, just as common movements in firm values lead to risk premia for corporate bonds

¹Elton, Gruber, Agrawal, and Mann (2001) argue that a large fraction of corporate spreads are due to state taxes. However, Longstaff, Mithal and Nies (2005) and Lando and Nielsen (2010), among others, find no empirical support for this proposal.

²See, for example, Jones, Mason and Rosenfeld (1984), Elton, Gruber, Agrawal, and Mann (2001), Huang and Huang (2012), and Eom, Helwege and Huang (2004).

³See, e.g., Chen, Collin-Dufresne and Goldstein (2009), Chen (2010), Bhamra, Kuehn and Strebulaev (2010), and Gomes and Schmid (2012).

⁴Indeed, Duffie and Lando (2001) demonstrate that when one adds uncertainty to the true firm value in a structural model, the model effectively becomes a reduced-form model.

in a structural framework, common movements in intensities justify these same risk premia in the reduced-form framework, since such risks are not diversifiable. However, reduced-form models have an additional channel to capture compensation for risks not found in (diffusion-based) structural models, namely, the (unpredictable) credit event itself. When this risk is priced, the risk-neutral intensity $\lambda^Q(t)$ is higher than the actual default intensity $\lambda^P(t)$. Interestingly, empirical studies of reduced-form models ascribe a large portion of the spread to this credit event risk channel. For example, Driessen (2005) estimates the jump risk premium for 10-year BBB bonds in his benchmark case to be 31 basis points (bps), and the ratio of risk-neutral intensity to actual default intensity $\left(\frac{\lambda^Q(t)}{\lambda^P(t)}\right)$ to be 2.3. Similar results are reported by Berndt, Douglas, Duffie, Ferguson and Schranz (2005), who instead focus on credit default swaps. We emphasize that these papers do not estimate the jump-risk premium directly. That is, they do not investigate how their proxy for the pricing kernel covaries with market returns during credit events. Instead, researchers typically estimate the “traditional” channels directly, and then simply *attribute the residual* to credit event risk. Thus, the accuracy of the credit event risk premium estimate depends crucially on the model being well specified.

However, we argue in this paper that this large estimate for the credit event risk premium leads to a conundrum. First, we note that most reduced-form models are specified within a doubly stochastic (or Cox process) framework, which obtains its tractability by assuming that, conditional upon the economic state of the system, the default of one firm has *no* impact on the spreads of other firms, and thus, is conditionally diversifiable.⁵ In that sense, it is internally inconsistent to use these models to estimate a credit event premium. Second, and related, if credit event risk is indeed not conditionally diversifiable, then there should be another source of a credit risk premium (which we refer to as a “contagion premium”) that most reduced-form models ignore which should compensate risky bonds for their exposure to market downturns on these event days. By not

⁵Cox processes are consistent with jump risk being priced under at least two situations: i) if firms are individually large (which precludes diversification), or ii) if the same jump event triggers many simultaneous defaults.

accounting for this additional channel, the amount of the residual attributed to credit event risk will be biased upward.

Indeed, below we demonstrate that this upward bias is very large. In particular, we investigate a production-based general equilibrium framework where jump risk is priced because the market portfolio performs poorly on these jump dates. We find that credit event premia have an upper bound of only a few basis points when the number of firms that compose the index is large. The intuition for this result is straightforward: If there are $N = 1000$ firms that compose the aggregate corporate bond market, then it is 1000-times more likely for a given corporate bond to share in the credit event of another firm than it is for that bond to suffer a credit event itself. A standard no-arbitrage argument then implies that the market portfolio's loss would have to be approximately 1000-times smaller than the loss on the defaulting bond, for the contagion premium not to dwarf the credit event premium. However, such a small impact on the market portfolio would imply that the credit event would be *almost* idiosyncratic, and therefore would not command a significant risk premium. More quantitatively, we show that the credit event premium is approximately linear, and the contagion premium quadratic, in the coefficient controlling the level of market contagion during credit events. We find that as we increase the value of this coefficient, the contagion premium 'explains' virtually all of the observed credit spread before the credit event premium can reach a size larger than a few basis points.

This implication is problematic, however, since only credit event risk, and not contagion risk, can explain large short-maturity spreads. This result suggests that short-maturity spreads are not due to credit event risk, but rather to non-credit factors, such as liquidity risk. Such conclusions have important implications for optimal portfolio decisions, risk management, and welfare concerns.

We then test this prediction by estimating credit event premia, not via residuals from a cross sectional study as in Driessen (2005), but rather via a time series 'event study' by investigating how aggregate stock and bond markets perform when there is a credit event. In particular, we identify credit events (defined either as defaults or as large jumps in spreads, and then confirmed by media

news) of investment-grade firms, and then investigate how the aggregate indices perform on event days and non-event days. We use these results to calibrate our model and find credit event risk premia are around one basis point, although contagion risk premia are significantly larger.

Our paper builds on a quickly growing literature on correlated defaults and the implications for credit event risk premium. Conditions under which credit event risk is not priced have been investigated by Jarrow, Lando and Yu (2005). They demonstrate that, under some standard APT-like assumptions, credit event risk will not be priced if the default process is assumed to follow a so-called “doubly stochastic” (or Cox) process. However, recent empirical findings question this doubly-stochastic assumption. For example, Das et al. (2006, 2007) report that the observed clustering of defaults in actual data are inconsistent with this assumption. Duffie, Eckner, Horel and Saita (2009) use a fragility-based model to identify a hidden state variable consistent with a contagion-like response. Note that the focus of these papers is on estimating the empirical default probability, whereas our focus is on pricing. Jorion and Zhang (2009) find contagious effects at the industry level. One major distinction is that they focus on the relatively large *statistical* significance of the contagion effect, whereas we focus on the relatively small *economic* significance implied by combining the parameter estimates with an equilibrium theory.

Although our theoretical model remains agnostic regarding the underlying mechanism that generates market-wide jumps when credit events occur, possibly the most natural interpretation is that there is a contagious response to the credit event, due to either counterparty risk (e.g., Jarrow and Yu (2001)) or updating of beliefs (e.g., Benzoni et al (2011)). Other models of contagion include Davis and Lo (2001), Schönbucher and Schubert (2001), Giesecke (2004), King and Wadhvani (1990) and Kodres and Pritsker (2002), who investigate contagion across international financial markets. There is also a large empirical literature that studies contagion in equity markets (e.g., Lang and Stulz (1992)) and in international finance (e.g., Bae, Karolyi and Stulz (2003)). Theocharides (2007) investigates contagion in the corporate bond market and finds empirical support for information-based transmission of crises.

The rest of the paper is organized as follows. In next section, we review the relevant literature regarding jump to default risk, and explain why it is difficult to capture contagion risk within a tractable framework. In Section 3, we investigate a simple production economy as in Ahn and Thompson (1988) and demonstrate that credit event premia have an upper bound of a few basis points if returns on the corporate bond index can serve as the proxy for the pricing kernel. In Section 4, we investigate empirically the impact of major credit events on the corporate bond index. Section 5 uses the estimates obtained in Section 4 to calibrate the model and to place an upper bound on the size of the risk premium associated with losses from a sudden default and compares that portion of the yield spread to the premium required for bearing the risk of a loss on the bond portfolio arising from such contagious events. A summary and conclusion section completes the paper.

2 Reduced Form Models: Background

Reduced-form models of default⁶ assume that default is triggered by the jump of an unpredictable point process $\mathbf{1}_{\{\tau < t\}}$, where τ is the random default time. The intensities under the historical probability measure λ^P and risk neutral measure λ^Q associated with this default event are defined via

$$\mathbf{E}_t^P \left[d\mathbf{1}_{\{\tau \leq t\}} \right] = \lambda_t^P \mathbf{1}_{\{\tau > t\}} dt \quad (1)$$

$$\mathbf{E}_t^Q \left[d\mathbf{1}_{\{\tau \leq t\}} \right] = \lambda_t^Q \mathbf{1}_{\{\tau > t\}} dt. \quad (2)$$

Intuitively, these equations imply that the probability of a jump to default (JTD) during the interval $(t, t + \Delta t)$, conditional upon no prior default, is $\lambda_t^P \Delta t$.

Regardless of whether a model is partial equilibrium (where the pricing kernel is specified exogenously) or general equilibrium (where the pricing kernel is derived endogenously from the

⁶See, for example, Jarrow, Lando and Turnbull (1997), Madan and Unal (1998), Duffie and Singleton (1997).

agent's preferences and the technologies available), if $d\mathbf{1}_{\{\tau \leq t\}}$ is contained in the pricing kernel dynamics, then this source of risk is priced, and λ_t^Q will not equal λ_t^P .⁷ As a simple example, we specify the pricing kernel to be of the form

$$\frac{d\Lambda}{\Lambda} = -r dt + \Gamma \left(d\mathbf{1}_{\{\tau \leq t\}} - \lambda_t^P \mathbf{1}_{\{\tau > t\}} dt \right), \quad (3)$$

where r is the risk free rate and Γ is the size of the jump in the pricing kernel in the event of default (i.e., $d\mathbf{1}_{\{\tau \leq t\}} = 1$). Consider a risky bond with (ex-dividend) price $P(t)$ that, upon default, becomes worthless upon paying out a terminal dividend equal to the fraction $(1-L)$ of its pre-default market value. Its historical and risk-neutral dynamics are expressed as (on $t < \tau$):

$$\frac{dP + (1-L)P d\mathbf{1}_{\{\tau \leq t\}}}{P} = \mu dt - L \left(d\mathbf{1}_{\{\tau \leq t\}} - \lambda_t^P \mathbf{1}_{\{\tau > t\}} dt \right) \quad (4)$$

$$= r dt - L \left(d\mathbf{1}_{\{\tau \leq t\}} - \lambda_t^Q \mathbf{1}_{\{\tau > t\}} dt \right). \quad (5)$$

Combined, these equations imply:

$$(\mu - r) = L (\lambda^Q - \lambda^P) \mathbf{1}_{\{\tau > t\}}. \quad (6)$$

Using the definition of a pricing kernel, we find the relation

$$\begin{aligned} 0 &= \frac{1}{dt} \mathbb{E}^P \left[\frac{dP}{P} + \frac{d\Lambda}{\Lambda} + \frac{dP}{P} \frac{d\Lambda}{\Lambda} \right] \\ &= \mu - r - L\Gamma \lambda^P \mathbf{1}_{\{\tau > t\}}. \end{aligned} \quad (7)$$

Combining this with equation (6), we find

$$\frac{\lambda^Q}{\lambda^P} = (1 + \Gamma). \quad (8)$$

⁷This is the well-known result of the change of measure, i.e., Girsanov's theorem for point processes. If the Radon-Nykodim derivative has a common jump with the point process then its intensity may be modified under the new measure. Examples of this are provided in equations (8) and (23) below.

This simple example demonstrates two important implications of credit event risk. First, the credit event risk of firm i is priced if and only if the pricing kernel jumps at the time of firm i 's default ($\Gamma \neq 0$). In that case, the ratio $\left(\frac{\lambda^Q}{\lambda^P}\right)$ will differ from unity, and the compensation (i.e., expected excess return) for credit event risk is

$$(\mu - r) = L(\lambda^Q - \lambda^P) \mathbf{1}_{\{\tau > t\}} = L\Gamma\lambda^P \mathbf{1}_{\{\tau > t\}}. \quad (9)$$

Note that the premium is a product of three factors: the probability of the credit event occurring (λ^P), the jump in the pricing kernel (Γ), and the loss given default (L). This additional channel of risk premia (which is not present in diffusion-based structural models) can *potentially* explain high risk premia on corporate bonds.

Second, credit event risk can generate sizeable credit spreads even at short maturities. Indeed, in the current example the instantaneous credit spread is $\lambda^Q L$, as can be seen from solving equation (5):

$$P(t, T) = e^{-(r + \lambda^Q L)(T-t)} \mathbf{1}_{\{\tau > t\}}. \quad (10)$$

Note that this spread exceeds the instantaneous expected loss $\lambda^P L$ if the credit event is priced (that is, if $\Gamma > 0$). Indeed, the credit spread equals $\lambda^Q L = \lambda^P L(1 + \Gamma)$, and therefore the spread exceeds expected losses by $\lambda^P L\Gamma$, which equals the risk premium in equation (9).

In this example, because intensities are specified to be constant, the term structure of credit spreads is flat, and the only source of credit risk premium is the jump-to-default risk. In contrast, had we modeled intensities as stochastic, then long-maturity credit spreads would be affected by other sources of risk, which would provide additional channels for risk premium. We emphasize, however, that these additional channels would not impact the short maturity risk premium. Indeed, at the very short end, only jump-to-default risk premia can affect credit spreads, even when intensities are stochastic, since credit spreads converge to the instantaneous risk-neutral expected

loss at infinitesimal maturities. Consequently, absent other frictions (such as liquidity or taxes), instantaneous credit spreads can exceed the instantaneous expected loss only if there is a significant jump-to-default risk premium which drives a wedge between the instantaneous risk-neutral and actual expected loss.

2.1 Conditions for Credit Event Risk to be Priced

In equation (3), we have simply assumed that credit event risk is priced in a partial equilibrium setting. One major focus of this paper is to investigate the conditions under which credit event risk is priced within a general equilibrium framework.⁸ Recently, there has been considerable research on this topic. For example, by extending the arguments implicit in the APT framework, Jarrow, Lando and Yu (2005) discuss the conditions needed for the existence of systematic credit event risk. Essentially, their results show that if the following two conditions are satisfied:

- (i) Conditional on the state variables driving intensities, default events are independent.
- (ii) A large number of bonds are available for trading,

then jump risk is conditionally diversifiable, and therefore should not command a risk premium.

There are at least two scenarios where condition (i) would not hold, and thus jump risk would be priced. First, there may exist be *systemic risk* in the sense that several firms can default at the same time (i.e., $\left[d\mathbf{1}_{\{\tau_i \leq t\}} d\mathbf{1}_{\{\tau_j \leq t\}} \right] \neq 0 \forall i, j \in [1, N]$). Intuitively, if the number of firms N is large enough that a non-negligible part of the economy defaults at the same date, then such a risk would command a risk premium. However, there is little empirical support for such a notion. (Of course, there is always the concern of a ‘peso problem.’)

Second, there can be *contagion risk* in the sense that the default of one firm can trigger an increase in the default risk (i.e., an increase in the intensity) of other firms. Mathematically, we

⁸We emphasize that this paper focuses on the credit event premium for the typical or average bond. There is little doubt that credit events associated with the largest firms in the economy would command significantly larger credit event premia.

can write this as $\left[d\mathbf{1}_{\{\tau_i \leq t\}} d\lambda_j(t) \right] \neq 0 \quad \forall i, j \in [1, N]$. In this paper, we show how introducing contagion risk allows credit event risk to be priced, and then demonstrate the quantitative restrictions contagion risk imposes on the size of the credit event premium.

Unfortunately, accounting for contagion risk often destroys the tractability of the previously proposed models in the literature. Indeed, the empirical literature has typically focused on those models where the zero-recovery, zero-coupon risky bond price

$$P^T(0) = \mathbb{E}_0^Q \left[e^{-\int_0^T ds r(s)} \mathbf{1}_{\{\tau > T\}} \right] \quad (11)$$

can be re-expressed as

$$P^T(0) \stackrel{?}{=} \mathbb{E}_0^Q \left[e^{-\int_0^T dt (\tau(t) + \lambda^Q(t))} \right] \mathbf{1}_{\{\tau > 0\}}. \quad (12)$$

However, as noted by Duffie, Schroeder and Skiadas (1996), Duffie and Singleton (1999) and Lando (1998), when there is contagion risk, then equation (11) is typically not equal to equation (12).

An example where the equality between (11) and (12) does not hold is the ($N = 2$) counterparty risk model of Jarrow and Yu (2001):⁹

$$\lambda_1^Q(t) = a_{11} + a_{12} \mathbf{1}_{\{\tau_2 \leq t\}} \quad (13)$$

$$\lambda_2^Q(t) = a_{21} \mathbf{1}_{\{\tau_1 \leq t\}} + a_{22}. \quad (14)$$

Intuitively, this model captures the notion that the default of one firm affects the intensity/probability of future default of another firm. There are at least two mechanisms that might trigger such ‘contagion.’ First, there may be direct counterparty default risk due to direct economic links between the firms (as advocated in Jarrow and Yu (2001)). Second, there may be information in one firm’s credit event that leads to market-wide updating about some common unobserved risk factors (as

⁹The exact solution to this model is given in Collin-Dufresne, Goldstein and Hugonnier (2005).

modeled in Benzoni, Collin-Dufresne, Goldstein and Helwege (2012)). The crucial point is that these models do *not* generate bond price solutions of the form in equation (12). Moreover, the bond price formulas that these models satisfy imply the existence of not only a credit event premium, but also a “contagion premium,” which compensates holders of corporate bonds for exposure to market downturns on credit event days. It is this contagion channel which, we argue, provides the most plausible economic justification for credit events to be priced, because only then will this source of risk be non-diversifiable.

3 Identifying Credit Event Risk Premia and Contagion Premia in a Production Economy

In this section, we investigate within a general equilibrium production economy the relative sizes of jump risk premium and contagion premium when there is a large number of firms. Recall that Jarrow, Lando and Yu (2005) use APT-like arguments to show that if the jump risk is conditionally diversifiable, and N becomes large, then the jump risk premium goes to zero. Instead, we propose a framework where jump risk is not conditionally diversifiable because of ‘contagion risk.’

We consider a production economy with linear technologies as in Cox, Ingersoll and Ross (1985) and Ahn and Thompson (1988). For reasons of tractability, we consider N identical production technologies with return dynamics:¹⁰

$$\frac{dS_i}{S_i} = \mu dt + \sigma_0 dz + \sigma_1 dz_i - \Gamma_J (dq_i - \lambda^P dt) - \Gamma_C \sum_{j \neq i}^N (dq_j - \lambda^P dt), \quad (15)$$

where dz is a Brownian motion common to all firms, the $\{dz_i\}$ are idiosyncratic Brownian motions orthogonal to each other and orthogonal to dz , and the $\{dq_i\}$ are Poisson random variables with intensity λ^P . The term $\Gamma_J dq_i$ is meant to capture a “credit event” associated with firm i , whereas

¹⁰We emphasize that choosing identical firm dynamics does not generate our results, but only makes the argument more transparent. As the APT literature has shown previously, similar arguments hold for the ‘typical firm’ so long as each firm is ‘small’.

the term $\Gamma_C dq_{j \neq i}$ is meant to capture firm i 's contagious response to a credit event associated with firm j .¹¹ As such, we anticipate $\Gamma_J \gg \Gamma_C$. That is, we expect a credit event associated with firm i to affect the return on firm i significantly more than the return on the overall index. As we will see in Table 1 below, this result occurs naturally in our framework.

Assume that the representative agent in the economy maximizes her expected utility:

$$J(W_t) = \max E \left[\int_t^\infty e^{-\delta(u-t)} \frac{C(u)^{1-\gamma}}{1-\gamma} du \right], \quad (16)$$

subject to her budget constraint

$$\begin{aligned} dW_t = & \left\{ rW_t - C_t + W_t \left(\sum_{i=1}^N \pi_i \right) \left[(\mu - r) + \lambda^P (\Gamma_J + (N-1)\Gamma_C) \right] \right\} dt + W_t \sigma_0 \left(\sum_{i=1}^N \pi_i \right) dz \\ & + W_t \sigma_1 \left(\sum_{i=1}^N \pi_i dz_i \right) - W_t (\Gamma_J - \Gamma_C) \left(\sum_{i=1}^N \pi_i dq_i \right) - W_t \Gamma_C \left(\sum_{i=1}^N \pi_i \right) \sum_{j=1}^N dq_j. \end{aligned} \quad (17)$$

Here, we have defined π_i to be the proportion of wealth placed into investment technology i . Note that the budget constraint implicitly assumes the existence of a risk-free security. However, in equilibrium, the risk-free rate r_t will be chosen so that the representative agent holds this security in zero net supply (Cox, Ingersoll, and Ross (1985)).

Applying Ito's lemma, the value function $J(W, t)$ satisfies the HJB equation:

$$\begin{aligned} 0 = & \max_{C, \pi} \left\{ \frac{C^{1-\gamma}}{1-\gamma} - \delta J + J_W \left[rW_t - C_t + W_t \left(\sum_{i=1}^N \pi_i \right) \left[(\mu - r) + \lambda^P (\Gamma_J + (N-1)\Gamma_C) \right] \right] \right. \\ & + \frac{1}{2} W^2 J_{WW} \left[\sigma_0^2 \left(\sum_{i=1}^N \pi_i \right)^2 + \sigma_1^2 \left(\sum_{i=1}^N \pi_i^2 \right) \right] \\ & \left. + \lambda^P \sum_{i=1}^N \left[J \left(W - W(\Gamma_J - \Gamma_C)\pi_i - W\Gamma_C \left(\sum_{i'=1}^N \pi_{i'} \right) \right) - J(W) \right] \right\}. \end{aligned} \quad (18)$$

¹¹We note that, while we have been calling this risk "contagion risk", in the context of this economy, it might be more appropriate to refer to it as "covariation risk" in that it need not be the case that the credit event of firm j causes all the other firms i to be negatively impacted.

The first order conditions are:

$$\frac{\partial}{\partial C} : \quad 0 = C_t^{-\gamma} - J_W \quad (19)$$

$$\begin{aligned} \frac{\partial}{\partial \pi_k} : \quad 0 = & W_t J_W [(\mu - r) + \lambda^P (\Gamma_J + (N - 1)\Gamma_C)] + W^2 J_{WW} \left[\sigma_0^2 \left(\sum_{i=1}^N \pi_i \right) + \sigma_1^2 \pi_k \right] \quad (20) \\ & - \lambda^P W \sum_{i=1}^N \left\{ J' \left(W - W(\Gamma_J - \Gamma_C)\pi_i - W\Gamma_C \left(\sum_{j=1}^N \pi_j \right) \right) \left[(\Gamma_J - \Gamma_C) \mathbf{1}_{(i=k)} + \Gamma_C \right] \right\}. \end{aligned}$$

Due to the symmetric nature of all returns, and due to the fact that in equilibrium the risk-free rate r will adjust so that the bond is held in zero net supply, it follows that the agent will place a constant fraction of her wealth in each investment technology: $\pi_i = \frac{1}{N} \forall i$. Hence, the wealth dynamics simplify to

$$\frac{dW_t}{W_t} = \left(\mu - \frac{C_t}{W_t} \right) dt + \sigma_0 dz + \frac{\sigma_1}{N} \left(\sum_{i=1}^N dz_i \right) - \left[\left(\frac{1}{N} \right) \Gamma_J + \left(\frac{N-1}{N} \right) \Gamma_C \right] \sum_{i=1}^N [dq_i - \lambda^P dt]. \quad (21)$$

As we discuss below, the main findings of this section are due to the functional form of the coefficient multiplying the jump processes, $\left[\left(\frac{1}{N} \right) \Gamma_J + \left(\frac{N-1}{N} \right) \Gamma_C \right]$.

Ahn and Thompson (1989) show that the solution to the indirect utility function takes the form

$$J(W) = A^{-\gamma} \frac{W^{1-\gamma}}{1-\gamma} \quad (22)$$

for some constant A . Therefore, we can express the marginal utility dynamics (which take on the role of the pricing kernel in this model) as

$$\frac{dJ_W}{J_W} = -r dt - \gamma \sigma_0 dz - \gamma \frac{\sigma_1}{N} \sum_{i=1}^N dz_i + \left\{ \left[1 - \frac{1}{N} (\Gamma_J + (N-1)\Gamma_C) \right]^{-\gamma} - 1 \right\} \sum_{i=1}^N [dq_i - \lambda^P dt].$$

One implication of this result is that the “credit events” $\{dq_i\}$ are priced, since they show up in the pricing kernel. Moreover, as can be seen by analogy with equations (3) and (8), the ratio of the risk-neutral intensity to the actual intensity $\left(\frac{\lambda^Q}{\lambda^P}\right)$ can be expressed as

$$\left(\frac{\lambda^Q}{\lambda^P}\right) = \left[1 - \frac{1}{N}(\Gamma_J + (N-1)\Gamma_C)\right]^{-\gamma}. \quad (23)$$

Plugging equation (22) into the consumption first order condition, we see that the price-consumption ratio is a constant:

$$C = AW. \quad (24)$$

More relevant for the issue at hand, plugging equation (22) into the portfolio weight first order condition, we find that the equilibrium excess return for each investment technology follows

$$(\mu - r) = \gamma \left(\sigma_0^2 + \frac{\sigma_1^2}{N} \right) + \lambda^P [\Gamma_J + (N-1)\Gamma_C] \left\{ \left[1 - \frac{1}{N}(\Gamma_J + (N-1)\Gamma_C) \right]^{-\gamma} - 1 \right\}. \quad (25)$$

Equation (25) has a straightforward interpretation: The first term on the right hand side is the contribution to the excess return due to the diffusion sources of risk ($dz, \{dz_i\}$):

$$(\mu - r)_{diffusion} = \gamma \left(\sigma_0^2 + \frac{\sigma_1^2}{N} \right). \quad (26)$$

As in the standard diffusive model, the diffusion premium is a combination of relative risk-aversion γ and market variance. Consistent with standard APT arguments, we see that the idiosyncratic diffusive component $\left(\gamma \frac{\sigma_1^2}{N}\right)$ becomes negligible as the number of firms N increases.

The second term on the right hand side is the contribution of the excess return due to the jump sources of risk ($\{dq_i\}$). It is useful to decompose this second term into a jump-risk component and a contagion-risk component:

$$(\mu - r)_{jump} = \lambda^P \Gamma_J \left\{ \left[1 - \frac{1}{N} (\Gamma_J + (N-1)\Gamma_C) \right]^{-\gamma} - 1 \right\} \quad (27)$$

$$(\mu - r)_{contagion} = \lambda^P (N-1)\Gamma_C \left\{ \left[1 - \frac{1}{N} (\Gamma_J + (N-1)\Gamma_C) \right]^{-\gamma} - 1 \right\}. \quad (28)$$

It is worth noting that when the contagion-risk parameter Γ_C is greater than zero, then a jump event leads to a market-wide response in returns, and both components contribute to investment returns. However, if $\Gamma_C = 0$, then not only is the contagion risk zero (by definition), but the jump component of the excess return also vanishes as N becomes large:

$$\begin{aligned} (\mu - r)|_{jump, \Gamma_C=0} &= \lambda^P \Gamma_J \left\{ \left[1 - \frac{\Gamma_J}{N} \right]^{-\gamma} - 1 \right\} \\ &\stackrel{N \rightarrow \infty}{\approx} \left(\frac{1}{N} \right) \lambda^P \gamma \Gamma_J^2. \end{aligned} \quad (29)$$

That is, without contagion risk, credit events become idiosyncratic, and their associated risk premia fall as $\sim \left(\frac{1}{N}\right)$, just as the idiosyncratic volatility term does in equation (26). Hence, credit event premia can be sizeable only if contagion risk is sufficiently large.

Now, let us calibrate this model using equations (27) and (28). We need estimates for $\{N, \gamma, \lambda^P, (\mu - r), \Gamma_J, \Gamma_C\}$. In order to estimate an upper bound for jump risk premia, we take the following approach:

- We set $N = 1000$, since there were approximately 10^3 firms with investment-grade status over the time period that we investigate empirically.
- In choosing reasonable estimates for the relative risk-aversion coefficient γ , we emphasize that the “risk premium puzzle” considered in this paper is not related to the one studied by Mehra

and Prescott (1985), who demonstrate that the relative risk-aversion coefficient implied from consumption data must be set to implausibly large values to capture the historical equity premium. Indeed, equations (26)-(28) show that we are investigating premia on assets with respect to their own levels of uncertainty. For example, note that if we apply equation (26) to the stock market index with $(\mu - r) = 0.06$ and $\sigma = 0.16$, we obtain a very sensible risk-aversion coefficient of about 3. Because of this, we limit our calibration to values of γ no higher than 10. We report results for five different values: $\gamma = (2, 4, 6, 8, 10)$.

- Historically, the non-callable BBB-Treasury spread on four-year debt has been estimated to be about 150 bps (See, for example, Huang and Huang (2012) and Chen, Collin-Dufresne and Goldstein (2009)). Approximately 25 bps of that spread covers historical losses,¹² and at least 25 bps can be captured in terms of systematic risk (Elton, Gruber, Agrawal and Mann (2001) and Driessen (2005)). Thus, in an attempt to estimate an upper bound for the credit event risk premium, we set the unexplained premium to 100 bps.¹³
- We consider two different calibrations of the credit event jump size (Γ_J) and the intensity (λ^P). For the first calibration, we note that historical recovery rates on corporate bonds have been approximately 40%.¹⁴ Hence, when investigating credit events, we set $\Gamma_J = 0.6$. Furthermore, we use the historical one-year default rate for BBB-rated bonds of 0.2% obtained from Moody's as an upper bound for the *instantaneous* default intensity, $\lambda^P = 0.002$.¹⁵

For our second calibration, which is more closely related to our empirical section, we investigate credit events where a firm's bond price fell on average by 10%, so when studying that case, we set $\Gamma_J = 0.10$, with an intensity of $\lambda^P = 0.02$.

¹²See Moody's Report (2005) and Elton, Gruber, Agrawal, and Mann (2001).

¹³If we use CDS spreads rather than corporate bond spreads, or if we measure corporate spreads off of the swap curve rather than the Treasury curve, the unexplained component would reduce to less than 70 bps. We focus on the larger number above to provide an upper bound.

¹⁴See Moody's Report (2005).

¹⁵We emphasize that this intensity significantly overestimates the historical intensity associated with default over a one month horizon. Indeed, we are aware of only a handful of firms that have defaulted with investment-grade status. Furthermore, the majority of these did not possess investment-grade spreads – that is, the market realized that these bonds were not truly investment-grade, and that the rating agencies were slow to downgrade.

Using equations (27) and (28), we identify the implied value for the contagion risk parameter Γ_C , and in turn, the contagion premium and the credit event premium for different values of the risk-aversion coefficient γ under the first set of calibration coefficients $\{\Gamma_J = 0.6, \lambda^P = 0.002\}$. As reported in Scenario A of Table 1, we find that for risk-aversion coefficients ranging from $\gamma = 2$ to $\gamma = 10$, we can attribute only 1.2 bps to 2.8 bps of the risk premium to credit event risk – the remaining 97 bps or more being attributed to contagion risk.

[Table 1 about here.]

As we discuss more fully in our empirical section, this calibration is based on parameter values that are likely to understate significantly the true size of Γ_C . Indeed, we simply do not observe losses of $\Gamma_J = 60\%$ over a short horizon (e.g., one month) with an intensity as large as $\lambda^P = 0.002$. As such, we also investigate much more modest jumps in spreads (e.g., 10% loss in the bond (i.e., $\Gamma_J = 0.10$)), with an intensity equal to our empirical estimate of 0.2%. We report in Scenario B of Table 1 that the premium for jump risk varies from 0.6 bp to 1.4 bps as we go from $\gamma = 2$ to $\gamma = 10$. Hence, in our model, we are unable to find a calibration where credit event risk is large when the number of firms N is large. Instead, we find that contagion risk must make up almost the entire unexplained risk premium.

The intuition for these results are as follows: As noted previously in equation (9), the no-arbitrage relation

$$(\mu - r) = -E \left[\frac{d\Lambda}{\Lambda} \frac{dP}{P} \right] \quad (30)$$

implies that jump risk premia are a product of three numbers: i) the probability of a jump event, ii) the jump in the pricing kernel conditional on the event, and iii) the fractional loss conditional on the event. Equations (27)-(28) emphasize that jump premia and contagion premia, by definition, share the same pricing kernel jump $\frac{d\Lambda}{\Lambda} \Big|_{jump} = \left\{ \left[1 - \frac{1}{N} (\Gamma_J + (N-1)\Gamma_C) \right]^{-\gamma} - 1 \right\}$. Thus, the relative

size of the jump component to the contagion component is the ratio $\frac{\lambda^P \Gamma_J}{(N-1)\lambda^P \Gamma_C} = \frac{\Gamma_J}{(N-1)\Gamma_C}$. Even though we estimate Γ_J to be much larger than Γ_C , (i.e., the firm suffering the credit event performs much worse than does the index which shares in the contagion), the typical bond is $(N-1) \approx 1000$ -times more likely to suffer a contagion event than a credit event. Combining these two factors, the contagion risk premium turns out to be much larger than the jump-to-default premium for all calibrations.

The reason these magnitudes necessarily occur in this framework is because the functional form of the pricing kernel implies that the credit event risk premia can be sizeable only if Γ_C is sizeable. Indeed, taking a Taylor series approximation of the pricing kernel jump

$$\begin{aligned} \left[1 - \frac{1}{N} (\Gamma_J + (N-1)\Gamma_C)\right]^{-\gamma} - 1 &\approx \gamma \left(\frac{1}{N}\Gamma_J + \frac{(N-1)}{N}\Gamma_C\right) \\ &\approx \gamma\Gamma_C \end{aligned} \quad (31)$$

implies that equations (27)-(28) simplify to

$$(\mu - r)_{jump} \approx \gamma\lambda^P \Gamma_C \Gamma_J \quad (32)$$

$$(\mu - r)_{contagion} \approx \gamma\lambda^P (N-1)\Gamma_C^2. \quad (33)$$

Note that the jump premium is approximately linear, and the contagion premium quadratic, in Γ_C . These equations make transparent why the credit event premium $(\mu - r)_{jump}$ cannot be large: If Γ_C is small, then both components are small. Because of the quadratic dependence, as one begins to increase Γ_C , the contagion component quickly becomes the size of the entire unexplained premium before the jump component can reach even 2 bps.

It is worth noting that, under this approximation, the pricing kernel is approximately proportional to the return on the aggregate index:

$$\left. \frac{dJ_W}{J_W} \right|_{stoch} \approx -\gamma \left. \frac{dW}{W} \right|_{stoch}. \quad (34)$$

The implication is that if we can use returns on corporate bond indices to identify risk premia, then the argument above implies that credit event premia have an upper bound of a few basis points.¹⁶

However, these conclusions lead to a problem. Recall in equation (10) we showed that credit event risk can generate sizeable credit spreads at short maturities. However, contagion risk cannot. Since investment-grade credit spreads are rather large at short maturities, this suggests that that a sizeable fraction of spreads is due to non-credit factors, such as liquidity.

4 Empirical Analysis of Credit Events

In this section we investigate how aggregate stock and bond markets perform when an individual investment-grade firm suffers a credit event. We then use these empirical findings to calibrate the model proposed in the previous section, in turn providing an estimate for the the jump-to-default premium and the contagion-risk premium. The tacit assumption being made here is that the return on the market portfolio can be used as a proxy for the pricing kernel. Because risk premia are compensation for covariation with the pricing kernel, and are independent of the underlying mechanism that generates this covariation, we remain agnostic about this mechanism.¹⁷

We note that the majority of corporate bonds that default do so while holding a speculative-grade rating (see Moody’s (2012)), and moreover carried such a rating for a considerable amount

¹⁶ Admittedly, one can write down a model where, for example, the credit event of one firm dramatically impacts the labor income of the representative agent without impacting the market portfolio, but we find such models implausible.

¹⁷ Models which propose that causality runs from the individual credit event to the market portfolio include “counterparty risk” model of Jarrow and Yu (2001), and “updating of beliefs” model of Benzoni et al (2011).

of time before default occurred.¹⁸ That is, most corporate bond defaults are not huge surprises, but rather are the result of a long, slow decline of firm value, consistent with the ‘structural model’ approach (e.g., Merton (1974)) to bond pricing. Consistent with the defaults of these junk bonds not being a surprise to market participants, we find no response of aggregate indices on the default days of junk bonds. We therefore focus on credit events associated with investment-grade firms. However, in the post-War history of the U.S., only five firms have defaulted on a corporate bond while holding an investment-grade rating: Lehman in 2008, Southern California Edison in 2001, Pacific Gas and Electric in 2001, Johns Manville in 1984 (bankruptcy filing to avoid the costs of lawsuits), and Penn Central in 1970 (a failing railroad that maintained an investment-grade rating up to the day that the U.S. government declined to extend it an emergency loan). A sample of five is too small to draw reliable inferences on, so we instead investigate how market indices perform during credit events where credit spreads of individual investment-grade firms jump significantly over a small time horizon.

To identify instances of large changes in creditworthiness and thus large bond price declines, we use two screens. First, we use daily CDS data from 2001 to 2010. We examine the single-name CDS premia that rise by more than 100 bps over a three-day window. Increases in CDS premia of this magnitude for investment-grade firms are extremely unusual. By definition this means that the number of events in any given period is fairly small, and since the time period examined is only about a decade, our sample is fairly small. Thus, we also examine a second sample of credit events defined by changes in month-end corporate bond spreads during the period 1973-1998. While these data allow us to create a dataset with a larger number of observations, the fact that the spreads are only observed monthly restricts our ability to estimate the market reaction to a credit event. To make the results comparable across the CDS and the corporate bond samples, we also investigate changes in CDS premia over a window as wide as one month. As a robustness check, we also consider the impact of bankruptcies on the CDS index.

¹⁸Note that our discussion here refers to defaults, and not to bankruptcies. Helwege (1999) shows that half of the 129 bond defaults by large issuers of high-yield bonds are not bankruptcy filings but exchange offers or missed coupons. Of these, half eventually file for bankruptcy but some do not enter bankruptcy until years after default.

4.1 Credit Default Swap Data

We start with all single-name credit default swap trades recorded in the Markit database between January 1, 2001 and December 31, 2010. Then we match each firm by name to its stock counterpart in the Center for Research in Security Prices (CRSP) data and eliminate all CDS that are not written on the debt of publicly listed firms. Only U.S. firms are included in the analysis. Next, we retrieve rating histories for these bonds from Standard & Poor’s as well as Moody’s and take the average as the final rating.

CDS protection is intended to cover a credit event, but over the years some CDS contracts have paid out when there is no loss on bonds, while others have not paid out when most market participants would agree that a credit event has occurred. Consequently, the typical definition of a credit event changes over time as buyers of protection attempt to obtain coverage for the appropriate premium (see Packer and Zhu (2005)).¹⁹ To maintain comparability of the expected payout across contracts, we restrict our analysis to CDS contracts with the same definition of a default. During our sample the most commonly used contract defines a credit event using the “modified restructuring” convention (MR), and thus we restrict our sample to CDS contracts with MR.

[Table 2 about here.]

Panel A in Table 2 summarizes the number of firms per year and by each rating category, which starts low as 229 firms in 2001 and gradually grows to the peak of 488 firms in 2007, then slightly drops to 404 firms in 2010. All firms have an investment-grade rating, using an average rating by Standard & Poor’s and Moody’s definitions. The majority of firms come from the BBB category.

¹⁹The International Swap and Derivative Association (ISDA) listed six items as credit events in 2003: (1) bankruptcy, (2) failure to pay principal or coupons, (3) repudiation or moratorium, (4) obligation acceleration, (5) obligation default, and (6) restructuring. For more details, see “2003 ISDA Credit Derivatives Definitions,” February 11, 2003.

Panels B and C in Table 2 report the distribution of the CDS spread changes at daily and monthly frequencies, respectively. The average daily CDS spread change is 0.06 bp for AAA/AA firms, 0.02 bp for single-A firms, and 0.03 for BBB firms. The higher average CDS spread change in the AAA/AA category is mainly driven by the large average change in 2008.

4.2 Corporate Bond Data

While the CDS data have the advantage of allowing us to investigate spread changes over a short window, the CDS market was in its infancy in 2001 when our sample starts. Thus, the analysis is limited to a fairly short time period. This is problematic for our analysis, given that we expect such extreme events to occur infrequently. Consequently, we also consider credit events using a much longer time series dataset, the Fixed Income Database, which contains month-end trader quotes from January 1973 to March 1998. These data have the advantage of reasonably good quality price data (see Warga (1991) and Warga and Welch (1993)) over a long time series.

We calculate corporate bond spreads as the difference between the bond's yield to maturity and corresponding Treasury bond yield with a similar maturity. The Treasury bond yields are the Federal Reserve's Constant Maturity Treasury daily series, using only yields from this series in time periods when the bond is actually auctioned. When corporate bonds have different maturity from Treasury bonds, we use interpolated Treasury bond yields using the Nelson-Siegel method.

The Fixed Income dataset has both trader quotes and matrix prices. The latter are far less reliable and we delete them from the analysis, as suggested by Warga (1991). We consider spreads on all U.S. corporate bonds rated investment-grade in the dataset as long as they are not private placements, medium term notes, or Euro-bonds. We delete offerings by government-sponsored enterprises and supranational organizations, as well as mortgage-backed and other asset-backed securities. We also exclude bonds that are convertible into preferred stock and bonds with floating rate.

[Table 3 about here.]

With these qualifications, we obtain 52,828 instances where corporate bond spreads widen. Table 3 shows the distribution of spread increases on corporate bonds over the sample period. The vast majority of the credit spread increases are quite small. Indeed, less than 3% are more than 50 bps.

4.3 Identification of Credit Events

We examine two types of credit events that might affect bond spreads and CDS premia: (1) large increases in CDS premia or bond spreads of individual firms, and (2) bankruptcies. Because the bankruptcies are not typically surprises and the data over the period 1973-1998 is less easily obtained, we only consider bankruptcies that occurred during the same time period covered by the CDS data.

Given the distribution of the CDS spread change in Table 2, we consider a jump event if the CDS spread goes up by 100 bps or more in a three-day window. Because the corporate bond spread increases are based on month-end data, and thus the changes occur over the space of 20 trading days, we consider a jump event if the bond or CDS spread increases by at least 200 bps when the event window is expanded to one month.

We further require that the firm starts the pre-event period with CDS spread of no higher than 400 bps, which indicates the market considered it to be a relatively safe investment. This criterion is required because, even though all of the bonds are investment grade prior to the event, ratings usually lag the market, and this is especially true in the recent financial crisis. We conclude that if a firm has high CDS spread, even though it still has an investment-grade rating, most investors would not be very surprised to learn that it is close to default. Similarly, for jumps defined in the corporate bond dataset, we require that the firm starts the pre-event period with bond price of no lower than \$80.

Some of the corporate bonds in our sample lost substantial value in one month, and then went on to lose additional value in ensuing months. A similar situation could have occurred with the bonds underlying our CDS premia. Because it is conceivable that such bonds were no longer considered ‘investment-grade’ in the minds of the market investors after the first event, we use only the first credit shock in a series of episodes. By a series of episodes, we mean more than one credit shock for a bond over the course of one year.

To get a sense of the types of credit events that our filter picks up, we investigate each of these large spread changes in the financial press (Bloomberg, Factiva, Lexis-Nexis and Standard and Poor’s Creditweek) to ascertain that a credit event actually occurred. As reported in Appendix A, the type of events include news of a bond rating downgrade, dividend cuts, major losses or other negative information in an earnings announcement, depressed stock prices, a major lawsuit or accident, a subsequent default or bankruptcy, or a leverage-increasing merger. Most of the events that cause the credit spread widen sharply involve economic hardship.

Bankruptcy cases that might affect credit event risk premia are collected from Capital IQ. There are 11716 events that US firms file for Chapter 11 bankruptcy from 2001 to 2010, of which 782 were listed in CRSP at the time of the bankruptcy. Only 64 firms have both CDS quotes and stock returns at the bankruptcy date. The majority of the bankruptcies occurred during the recent financial crisis.

4.4 Market Responses to Credit Events

We apply the event study methodology to test the market reactions to credit events. In particular, we report the changes around the event days of the corporate bond index, the CDS index, the stock market index, the Treasury bond yield, and the interest rate swap rate. The event studies examine the changes in various market portfolios when a single bond experiences severe losses. We consider the results related to the 128 CDS-jump events that occur during 2001-2010 as the most reliable

because the CDS spreads are likely to be more precise than bond prices (especially for events that occurred in the 1970s) and because the daily data allow us to limit the event window to three days. In contrast, the relationships between the various markets and the credit events that occur between 1973 and 1997 are based on month-end bond prices and may be imprecise because the event window is quite long. In order to compare the effects of the longer window on the estimates, we also re-examine the CDS data with one month changes.

[Table 4 about here.]

Table 4 presents the results of the event study using daily CDS data. We find a significant relationship between the negative events (as measured by the CDS premia) and the average spread on a corporate bond index. This suggests that credit events are priced as if they are not completely diversifiable. We also find that the Treasury bond yield falls significantly during these episodes, which is consistent with a flight-to-quality effect. In addition, the corporate bond index, as measured by the Merrill Lynch Investment-Grade index, falls significantly on the event day.²⁰

Moreover, the stock market also observes a negative shock in response to credit event measured by sharp jump in the CDS spread. In theory, credit events could be positive or negative for stocks, depending on the nature of the event. If the event involves a redistribution of wealth from bondholders to shareholders, the equity returns of the affected stockholders will be positive. In situations like RJR Nabisco in 1989, such positive effects for shareholders are enjoyed across a broad spectrum of companies because investors are now aware that they might be the beneficiary of a takeover attempt. Other events are uniformly negative for all security holders because they involve a drop in firm value. During the subprime crisis, the events are frequently related to real estate or the effects of the financial sector's problems on the real economy. Thus, for the time period of 2001-2010, the typical stock market return is negative when these events occur. The

²⁰Note that since Treasury bonds experience a 'flight-to-quality' decrease in yield, and since corporate bonds are priced off of a risk-free benchmark, the effect of the event day on corporate bond index is somewhat smaller than what is expected based on the increase in credit spreads.

event day return is estimated at -0.77% and statistically significant. We note that both the event day and the days prior to the event have consistent signs and are almost all statistically significant in Table 4.

As a robustness check, we also analyze the relationship between credit events and market returns using monthly corporate bond data. Because the data are only available at the end of month, we expect that it will be more difficult to find a statistically significant relationship between events and the market responses. Thus, we further refine our event study to include only large company credit events, on the expectation that credit events of large firms will have a greater impact on the market than those of small firms. We measure firm size by the amount of corporate bonds outstanding and by total assets.²¹

[Table 5 about here.]

Table 5 reports the results of the event study using corporate bond data from 1973–1997. In this exercise, we compare the 25 credit event months with other months by examining how returns of aggregate portfolios differ when a credit event occurs. We investigate the relationship between these events and the corporate bond index, the stock market index and the Treasury index. Note in Table 5 that the Treasury data are prices, not yields, so a flight-to-quality episode means that the index rises. The events that occur during 1973-1997 are associated with significant negative returns on the corporate bond index of 33 basis points. This compares to a positive return of six basis points in normal months. As expected, the difference in excess returns is mainly driven by the largest firms. Measured by bonds outstanding, the larger firms' events occur in months when the corporate bond index drops by more than one percent. Measured by book level of assets, the larger firms have an impact on the market of negative 53 basis points. These negative returns on corporate bonds occur despite the fact that some of the months' events are ones in which Treasury

²¹Corporate bonds outstanding is the sum of bonds in the Fixed-Income dataset for the issuer's six-digit cusip, which can be inaccurate if cusips vary across a firm's bond issues. Total assets is for the year in which the credit event occurs and comes from Compustat, except for one firm whose assets are from Moody's Transportation Manual.

instruments experience a flight to quality. However, a lower fraction of the events during the 1973–1997 period are related to declines in firm value than in the more recent sample of CDS spreads and events in the financial crisis. Thus, it is not so surprising that the corporate bond index moves in a way that is consistent with the CDS spreads. We check the robustness by re-examine the CDS data with one-month change and show the results in Table 6.

[Table 6 about here.]

Our initial analysis compares credit event months with other months using t -tests. In unreported results we control for other factors in a regression setting, including controls for macroeconomic factors identified by Fleming and Remolona (1999) and others, unrelated episodes of flight to quality (see Longstaff (2004)).

A major concern is whether the bonds in our sample whose prices fall precipitously as a result of the events constitute such a large fraction of the corporate bond index that their own price movements drive the returns on the index. This is unlikely as our events usually involve only a single firm in any given month. The month with the largest number of affected bonds is September 1990, during which 11 firms and 27 bonds are classified as experiencing a credit event. These do not drive the index, as 3811 corporate bonds are in the index that month. Furthermore, we find similar results (unreported) if we include only those months where a single firm suffered a credit shock.

[Table 7 about here.]

Finally, we present the results of an event study of bankruptcy (as opposed to a large drop in price) effects on the same portfolios in Table 7. Only the stock market has a statistically significant relationship to the bankruptcy events and the effect is only on the day before the event, not $T = 0$. By the time the bankruptcy occurs, it is likely that most investors are aware of the imminent failure and have already ‘priced in’ the bad news. This result shows that one cannot take the reduced-form

model interpretation literally in defining the credit event as bankruptcy. Indeed, the bankruptcy date is associated neither with a jump in price nor with a common jump with the index. A better interpretation of the reduced-form model, it seems, is to view the credit event as the instance when imminent bankruptcy becomes public information, and the price drops to its ultimate recovery value. This is the interpretation we focus on henceforth.²²

The theoretical model in Section 3 demonstrates that even if we wish to attribute 100 bps of corporate bond excess returns to two channels – credit event premia and contagion premia – less than 3 bps can be attributed to the credit event premia channel. In this section we have investigated empirically the magnitude of large credit event and contagion premia by investigating market reactions on credit event days and during credit event months. Looking at equations (32) and (33), in order to estimate the relative magnitude of the jump-to-default premia vs. the contagion risk premium component, we need the estimates for: i) the fractional loss in the bond that suffers the credit event Γ_J , ii) the fractional loss on the market portfolio during such an event Γ_C , iii) the probability/intensity of credit events λ^P , iv) the number of firms N in the market portfolio, and v) an estimate of the risk-aversion coefficient γ .

5 Calibration of the Model Using Estimates from the Empirical Analysis

Our model was derived under the assumption that all securities are identical for simplicity. However, to obtain a more realistic calibration we assume that there are two types of securities (stocks and bonds) with different (diffusion and jump) risks. This implies that the jump in the pricing kernel is now not necessarily identical (even in the limit of the large economy) to the contagious jump in the

²²We emphasize however, that a literal interpretation of reduced-form models, as models that represent the actual bankruptcy event as an unpredictable stopping time, seems to be inconsistent with the data. Furthermore, Table 7 shows that the literal interpretation is consistent with the default time being conditionally diversifiable, and therefore seems inconsistent with allowing a positive jump-to-default risk premium $\lambda^Q - \lambda^P$, as proved by Jarrow, Lando, and Yu (2005).

bond price. Instead, it is a weighted average in the contagious jumps of all securities comprising the market portfolio. Specifically, equations (32)–(33) become as follows:

$$(\mu - r)_{jump} \approx \lambda^P (\gamma \Gamma_{C,M}) \Gamma_J \quad (35)$$

$$(\mu - r)_{contagion} \approx (\lambda^P (N - 1)) (\gamma \Gamma_{C,M}) \Gamma_{C,B}. \quad (36)$$

Now risk premia are a product of three numbers: i) the probability of an event occurring (which equals (λ^P) for a credit event and $(\lambda^P(N - 1))$ for a contagious event), ii) the jump in the pricing kernel if a credit event occurs ($\gamma \Gamma_{C,M}$), and iii) the fractional loss of security value when an event occurs (which equals Γ_J for a credit event and $\Gamma_{C,B}$ for a contagious event). We calibrate the jump in market value to be a weighted average of stock and corporate bond returns over the three-day credit event identified in Table 4:

$$\begin{aligned} \Gamma_{C,M} &= 0.6 * 0.029 + 0.4 * 0.0031 \\ &= 0.0186 \end{aligned} \quad (37)$$

Similarly, we calibrate the jump in corporate bond index as

$$\Gamma_{C,B} = 0.0031. \quad (38)$$

Lastly, we find that the average jump in the CDS amongst the firms experiencing the event was 129 bps over a three-day window up to the event day. This translates (using the five year spread duration estimated from the average CDS levels on each day) to a three-day downward jump in the security price of

$$\Gamma_J = 0.053. \quad (39)$$

The empirical estimate of intensity is estimated by dividing the 128 credit events by the number of firm-years over 2001 - 2010 reported in Table 2 (the sum of firm-year numbers is 4006 by adding the

last column of Panel A). Hence, we set $\lambda^P = 128/4006 = 0.032$. Therefore, choosing a ‘reasonable’ risk-aversion coefficient $\gamma = 4$,²³ we find

$$\begin{aligned} (\mu - r)_{jump} &\approx (0.032)(4 * 0.0186) * (0.053) \\ &= 1bp. \end{aligned} \tag{40}$$

$$\begin{aligned} (\mu - r)_{contagion} &\approx (0.032 * 1000) (4 * 0.0186) (0.0031) \\ &= 74bps. \end{aligned} \tag{41}$$

Note that these results mirror our theoretical implications: Indeed, we find credit event risk premia to be approximately one basis point, but contagion premia to be substantial (74 bps). This is important, since as shown in equation (10) and the ensuing discussion, only jump-to-default risk premia can generate sizeable spreads at short maturities. Without a jump-to-default risk premium the short maturity spreads are equal to the instantaneous expected loss, which in our example is equal to $\lambda^P * \Gamma_J = 0.032 * 0.056 = 17bps$. Instead, with jump-to-default risk-premium, short term spreads would be equal to $\lambda^Q * \Gamma_J > \lambda^P * \Gamma_J$. However, as our calibration illustrates, the magnitude of jump-to-default premia is too small to generate sizeable short term spreads. Indeed, for our particular calibration, instantaneous spreads would be only 1 bp higher: $\lambda^Q * \Gamma_J = 18bps$. In contrast, Driessen (2005) estimates the short-term jump-to-default risk premium at approximately 30 bps. Our calibration illustrates that contagion risk premia can explain a sizeable portion – 74 bps with our parameter values – of longer maturity credit spreads.

6 Conclusion

In principle, reduced-form models can generate large short-term credit spreads by ascribing the difference between the short-term spread and the instantaneous expected loss to a credit event

²³Note that if we want the stock-bond allocation to be close to 60/40 for an agent with CRRA preferences and a risk-aversion coefficient γ in an i.i.d. world, we need $\frac{\mu_S - r}{\gamma \sigma_S^2} = 0.6$, which assuming a historical Sharpe ratio of 0.4 and a stock market volatility of 0.16, translates into a risk-aversion coefficient $\gamma = \frac{0.4}{0.6 * 0.16} = 4.2$.

risk premium. Empirical estimates of that premium, which are based on the analysis of a residual unexplained component of credit spreads, are usually fairly high. For example, Driessen (2005) and Berndt et al. (2005) estimate a ratio $\lambda^Q/\lambda^P \approx 2$ which implies that a sizeable component of the credit risk-premium is due to jump-to-default risk.²⁴

In this paper, we argue that such estimates are likely too high. Economically, jump-to-default risk premia can only arise if credit events are not diversifiable (Jarrow, Lando and Yu (2005)). We thus investigate a simple equilibrium model where credit event risk is not diversifiable because there is ‘contagion’ risk, defined as a concurrent jump in the prices of other securities upon the arrival of a credit event of one firm. In such an economy, jump-to-default risk is indeed priced. More interestingly, we find that, in equilibrium, credit risk premia will reflect not only a jump-to-default premium, but also a so-called ‘contagion’ risk premium. Furthermore, we find that the latter dominates the former for any reasonable calibration that we consider. Specifically, with only a few basis points due to jump-to-default risk, the model generates a contagion risk component that explains the entire ‘residual’ credit spread considered in the empirical literature. We conclude that if contagion and hence jump-to-default risk are present then the latter can only explain a very small fraction of the credit risk premium.

Empirically, we find some evidence for ‘contagion risk’ by investigating common jumps in individual firms’ credit spreads and corporate bond, Treasury bond, and equity indices using an event study methodology. We use the result of this empirical analysis to calibrate the model. The calibration analysis suggests that only about one basis point can be ascribed to jump-to-default risk premia, but that as much as 74 bps could be due to contagion risk premium.

Taken at face value, our analysis suggests that short-term spreads in excess of the instantaneous loss cannot be due to jump-to-default risk, nor indeed to contagion risk, which only affects longer maturity spreads. Instead, our analysis suggests that contagion premia can explain a large fraction

²⁴For a firm with loss-given default $L = 0.6$ and historical default intensity of 0.011, the component due to jump-to-default risk-premium would be $L * (\lambda^Q - \lambda^P) = 66bps$.

of long-maturity credit spreads. This has important implications for asset allocation, pricing, and risk management, as it forces us to reconsider current approaches to modeling short-term bond spreads.

References

- [1] C. M. Ahn and H. E. Thompson. Jump-diffusion processes and the term structure of interest rates. *Journal of Finance*, 1:155–175, 1988.
- [2] K.-H. Bae, A. Karolyi, and R. Stulz. A new approach to measuring financial contagion. *Review of Financial Studies*, 16:717–763, 2003.
- [3] L. Benzoni, P. Collin-Dufresne, R. Goldstein, and J. Helwege. Modeling credit contagion via the updating of fragile beliefs. working paper, Federal Reserve Bank of Chicago, 2012.
- [4] A. Berndt, R. Douglas, D. Duffie, M. Ferguson, and D. Schranz. Measuring default risk premia from default swap rates and EDFs. Working Paper Stanford University, 2005.
- [5] H. Bhamra, L.-A. Kuehn, and I. A. Strebulaev. The aggregate dynamics of capital structure and macroeconomic risk. 23(12):4187–4241, 2010. *Review of Financial Studies*.
- [6] H. Chen. Macroeconomic conditions and the puzzles of credit spreads and capital structure. *Journal of Finance*, 65:2171–2212, 2010.
- [7] L. Chen, P. Collin-Dufresne, and R. Goldstein. On the relation between the credit spread puzzle and the equity premium puzzle. *Review of Financial Studies*, 22:3367–3409, 2009.
- [8] P. Collin-Dufresne, R. Goldstein, and J. Hugonnier. A general formula for the valuation of defaultable securities. *Econometrica*, 72:1377–1407, 2004.
- [9] J. C. Cox, J. E. Ingersoll Jr., and S. A. Ross. An intertemporal general equilibrium model of asset prices. *Econometrica*, 53:363–384, 1985.
- [10] L. E. Crabbe. Event risk: An analysis of losses to bondholders and "Super Poison Put" bond covenants. *Journal of Finance*, 46:689–706, 1991.
- [11] S. Das, D. Duffie, N. Kapadia, and L. Saita. Common failings: How corporate defaults are correlated. *Journal of Finance*, 62:93–117, 2007.

- [12] S. Das, L. Freed, G. Geng, and N. Kapadia. Correlated default risk. *Journal of Fixed Income*, 16:1–26, 2006.
- [13] M. Davis and V. Lo. Infectious defaults. *Quantitative Finance*, 1:382–387, 2001.
- [14] J. Driessen. Is default event risk priced in corporate bonds? *Review of Financial Studies*, 18:165–195, 2005.
- [15] G. R. Duffee. Estimating the price of default risk. *Review of Financial Studies*, 12:187–226, 1999.
- [16] D. Duffie, A. Eckner, G. Horel, and L. Saita. Frailty correlated default. *Journal of Finance*, 64:2089–2123, 2009.
- [17] D. Duffie and R. Kan. A yield-factor model of interest rates. *Mathematical Finance*, 6:379–406, 1996.
- [18] D. Duffie and D. Lando. Term structure of credit spreads with incomplete accounting standards. *Econometrica*, 69:633–664, 2001.
- [19] D. Duffie, M. Schroder, and C. Skiadas. Recursive valuation of defaultable securities and the timing of resolution of uncertainty. *Annals of Applied Probabilities*, 6(4):1075–1090, 1996.
- [20] D. Duffie and K. Singleton. An econometric model of the term structure of interest rate swap yields. *Journal of Finance*, 52(4):1287–1322, 1997.
- [21] D. Duffie and K. Singleton. Modeling term structure of defaultable bonds. *Review of Financial Studies*, 12(3):687–720, 1999.
- [22] E. J. Elton, M. J. Gruber, D. Agrawal, and C. Mann. Explaining the rate spread on corporate bonds. *Journal of Finance*, 56:247–277, 2001.
- [23] Y. H. Eom, J. Helwege, and J. Huang. Structural models of corporate bond pricing: An empirical analysis. *Review of Financial Studies*, 17:499–544, 2004.

- [24] A. Estrella and G. Hardouvelis. The term structure as a predictor of real economic activity. *Journal of Finance*, 46:555–576, 1991.
- [25] E. F. Fama and K. R. French. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56, 1993.
- [26] M. J. Fleming and E. M. Remolona. Price formation and liquidity in the US treasury market: The response to public information. *Journal of Finance*, 54-55:1901–1915, 1999.
- [27] K. Giesecke. Correlated default with incomplete information. *Journal of Banking and Finance*, 28:1521–1545, 2004.
- [28] J. F. Gomes and L. Schmid. Equilibrium credit spreads and the macroeconomy. Working Paper, Duke University, 2012.
- [29] J. Helwege. How long do junk bonds spend in default? *Journal of Finance*, 54:341–357, 1999.
- [30] J. Huang and M. Huang. How much of the corporate-treasury yield spread is due to credit risk? a new calibration approach. Forthcoming, Review of Asset Pricing Studies, 2012.
- [31] R. Jarrow, D. Lando, and S. Turnbull. A Markov model for the term structure of credit spreads. *Review of Financial Studies*, 10:481–523, 1997.
- [32] R. Jarrow, D. Lando, and F. Yu. Default risk and diversification: Theory and application. *Mathematical Finance*, 15:1–26, 2005.
- [33] R. Jarrow and F. Yu. Counterparty risk and the pricing of defaultable securities. *Journal of Finance*, 56:1765–99, 2001.
- [34] E. P. Jones, S. P. Mason, and E. Rosenfeld. Contingent claim analysis of corporate capital structures: An empirical investigation. *Journal of Finance*, 39(3):611–625, 1984.
- [35] P. Jorion and G. Zhang. Credit contagion from counterparty risk. *Journal of Finance*, 64:20532087, 2009.

- [36] M. A. King and S. Wadhvani. Transmission of volatility between stock markets. *Review of Financial Studies*, 3:5–33, 1990.
- [37] L. E. Kodres and M. Pritsker. A rational expectations model of financial contagion. *Journal of Finance*, 57:769–799, 2002.
- [38] D. Lando. On cox processes and credit risky securities. *Review of Derivatives Research*, 2:99–120, 1998.
- [39] D. Lando and M. S. Nielsen. Correlation in corporate defaults: Contagion or conditional independence? *Journal of Fixed Income*, 19:355–372, 2010.
- [40] L. Lang and R. Stulz. Contagion and competitive intra-industry effects of bankruptcy announcements. *Journal of Financial Economics*, 32:45–60, 1992.
- [41] F. Longstaff. The flight to liquidity premium in U.S. treasury bond prices. *Journal of Business*, 77:511–526, 2004.
- [42] F. A. Longstaff, S. Mithal, and E. Neis. Corporate yield spreads: Default risk or liquidity? New evidence from the credit-default swap market. *Journal of Finance*, 60(5):2213–2253, 2005.
- [43] D. Madan and H. Unal. Pricing the risks of default. *Review of Derivatives Research*, 2:121–160, 1998.
- [44] R. Mehra and E. C. Prescott. The equity premium: A puzzle. *Journal of Monetary Economics*, 15(2):145–161, 1985.
- [45] R. C. Merton. On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance*, 29:449–470, 1974.
- [46] C. Nelson and A. Siegel. Parsimonious modeling of yield curves. *Journal of Business*, 60:473–489, 1987.

- [47] F. Packer and H. Zhu. Contractual terms and cds pricing. *BIS Quarterly Review*, pages 89–100, 2005.
- [48] P. J. Schönbucher and D. Schubert. Copula-dependent default risk in intensity models. Working Paper, Bonn University, 2001.
- [49] J. Taylor. Discretion versus policy rules in practice. *Carnegie-Rochester Conference Series on Public Policy*, 39:195–214, 1993.
- [50] G. Theocharides. Contagion: Evidence from the bond market. working paper, Cyprus International Institute of Management, 2007.
- [51] A. Warga. Corporate bond price discrepancies in the dealer and exchange markets. *Journal of Fixed Income*, 1:7–16, 1991.
- [52] A. Warga and I. Welch. Bondholder losses in leveraged buyouts. *Review of Financial Studies*, 6:959–982, 1993.

Appendix

A. Media Check for Credit Events

We show the list of identified jumps, after media check in Bloomberg and Factiva, including company name, jump event month, and jump reason. The jump is

Time	Company	Note
Dec2001	Halliburton Co	Litigation about industrial damage, jury ruled against the firm, shares tumble 42.5%
Feb2002	Sprint Corp	2001Q4 earnings release on February 21, a loss of \$127 million due to rising costs.
Jun2002	Omnicom Gp Inc	Moody's reviewing for possible downgrade, concerns over accounting fraud lawsuit
Jul2002	Amern Elec Pwr	2002Q2 earnings release on July 25, earnings tumble 91%
Mar2005	J C Penney Co Inc	LBO rumor circulates
Jul2007	D R Horton Inc	Reported in early July that its net
Jul2007	Pulte Homes Inc	2007Q2 earnings release on July 25, net loss of \$507.8 million
Oct2007	MBIA Inc.	2007Q3 earnings release on October 25, loss of \$36.6 million
Oct2007	MGIC Invt Corp	2007Q3 earnings release on October 27, loss of \$372.5 million
Jan2008	CAMDEN Ppty Tr	Reported high exposure to housing markets
Feb2008	Natl City Corp	Various lawsuits
Feb2008	NY Times Co	Revenue fell 5.5% in January as advertising sales declined
Oct2008	Lexmark Intl Inc	Third quarter revenue dropped 5% falling short of analyst's expectations
Oct2008	Staples Inc	UBS cut their stock performance rating
Nov2008	Avnet, Inc.	AVNET acquired Nippon Denso Industry
Nov2008	Southwest Air	Downgrade by Fitch from A to BBB+, with airline industry uncertainty
Fed2010	Edison Intl	Announced that its fourth quarter profit fell
Apr2010	Allied Cap Corp	Acquired by ARCC Oddssey Corp

Table 1: **Calibration: Composition of Credit Event Risk and Contagion Risk**

We decompose 100 bps of excess return into that due to credit event risk, $(\mu - r)_J$ and that due to contagion risk, $(\mu - r)_C$ for selected values of the constant relative risk-aversion coefficient γ . We denote Γ_J as the credit event jump size, Γ_C as the contagion size. λ^P is the historical probability measure and λ^Q is the risk-neutral probability measure. We set the number of firms in the economy as $N = 1000$ for both scenarios.

Scenario A: $\Gamma_J = 0.6$, $\lambda^P = 0.002$

γ	$\Gamma_C^{implied}$	$(\mu - r)_C$	$(\mu - r)_J$	$\left(\frac{\lambda^Q}{\lambda^P}\right)$
2	0.048	98.8	1.2	1.10
4	0.033	98.2	1.8	1.15
6	0.027	97.8	2.2	1.18
8	0.023	97.5	2.5	1.21
10	0.020	97.2	2.8	1.24

Scenario B: $\Gamma_J = 0.1$, $\lambda^P = 0.02$

γ	$\Gamma_C^{implied}$	$(\mu - r)_C$	$(\mu - r)_J$	$\left(\frac{\lambda^Q}{\lambda^P}\right)$
2	0.016	99.4	0.6	1.03
4	0.011	99.1	0.9	1.05
6	0.009	98.9	1.1	1.06
8	0.008	98.7	1.3	1.06
10	0.007	98.6	1.4	1.07

Table 2: **Distribution of Firms and CDS Spreads**

This table reports the summary statistics of the CDS dataset from January 1, 2001 to December 31, 2010. Panel A describes the distribution of investment-grade firms by year and by Standard & Poor's credit rating. In Panels B and C, we report the summary statistics of 5-year CDS spread changes for daily and monthly frequencies, respectively.

Panel A: Firm Distribution by Rating

Year	AAA/AA	A	BBB	Total
2001	21	89	119	229
2002	25	108	171	304
2003	28	126	218	372
2004	28	144	248	420
2005	32	142	258	432
2006	36	146	266	448
2007	39	162	287	488
2008	39	160	281	480
2009	27	141	261	429
2010	22	126	256	404

Panel B Daily changes of 5-year CDS Spreads (in bps)

Year	AAA/AA		A		BBB	
	Mean	Std	Mean	Std	Mean	Std
2001	-0.03	2.21	-0.02	4.72	0.09	20.77
2002	-0.03	6.78	-0.01	5.52	0.12	25.99
2003	-0.08	2.23	-0.15	5.11	-0.41	15.78
2004	-0.01	0.80	-0.01	3.18	-0.07	5.16
2005	0.00	0.83	0.01	1.39	0.02	3.06
2006	-0.02	0.37	-0.03	1.05	-0.04	2.17
2007	0.24	4.75	0.15	4.75	0.19	4.15
2008	0.75	21.90	0.59	30.63	1.21	35.93
2009	-0.22	18.22	-0.34	17.26	-0.84	34.96
2010	0.01	4.20	0.01	5.51	0.04	6.04
Average	0.06	6.23	0.02	7.91	0.03	15.40

Panel C Monthly changes of 5-year CDS Spreads (in bps)

Year	AAA/AA		A		BBB	
	Mean	Std	Mean	Std	Mean	Std
2001	-0.07	9.24	-0.08	16.62	1.00	48.26
2002	-0.78	31.53	-0.19	18.42	2.19	70.91
2003	-1.78	6.40	-3.13	15.34	-9.13	44.37
2004	-0.11	2.39	-0.44	4.32	-1.40	11.80
2005	-0.11	3.52	0.32	6.07	0.51	12.35
2006	-0.38	1.53	-0.54	4.40	-0.79	9.17
2007	4.95	24.72	3.09	17.73	4.20	21.41
2008	11.23	46.75	13.77	132.23	26.21	142.11
2009	-4.67	41.44	-7.73	101.66	-18.33	100.14
2010	0.15	17.90	0.24	18.98	0.98	26.32
Average	0.84	18.54	0.53	33.58	0.54	48.68

Table 3: Distribution of Corporate Bond Spread Change

This table reports the summary statistics of the bond dataset from January, 1973 to December, 1997. The data show the distribution of corporate-bond spread changes for investment-grade firms. The corporate bond spread change is defined as the corporate bond yield to maturity minus the Treasury bond yield with corresponding maturity.

Δ Credit Spread	Number of observations	Percentage	Average Return	Excess Return
[10.00%, ∞)	7	0.01%	-31.33%	-31.37%
[5.00%, 10.00%)	6	0.01%	-17.43%	-16.79%
[3.00%, 5.00%)	32	0.06%	-12.40%	-12.91%
[2.00%, 3.00%)	113	0.21%	-7.74%	-8.93%
[1.50%, 2.00%)	146	0.28%	-5.42%	-6.69%
[1.25%, 1.50%)	131	0.25%	-4.08%	-5.50%
[1.00%, 1.25%)	273	0.52%	-2.85%	-4.08%
[0.75%, 1.00%)	572	1.08%	-2.00%	-3.63%
[0.50%, 0.75%)	1919	3.63%	-1.08%	-2.84%
[0.25%, 0.75%)	5776	10.93%	-0.54%	-1.18%
[0, 0.25%)	43853	83.01%	0.08%	-0.23%

Table 4: **The Impact of Three-day Cumulative CDS Jumps upon the Market (Events N=128)**

This table presents the impact of jumps in CDS spreads on the corporate bond market, the CDS market, the stock market, and the Treasury bond market. $T = 0$ refers to the event day when a jump is identified. In the pool of investment-grade firms with a CDS spread equal to or smaller than 400 bps, we identify a jump event when (i) the firm's three-day cumulative CDS spread change is larger than 100 bps, and (ii) the jump is the first one in any consecutive twelve months. The market impact is measured by the log return of the Merrill Lynch Investment-Grade Corporate Bond Index, the equal-weighted CDS spread change across investment-grade firms, the log return of the S&P 500 index, the five-year Treasury bond rate, and the five-year swap rate, all at a daily frequency. We also report the impact two days before the event day, and the joint impact over the three-day window. t -statistics are reported in the second row. Entries with 1% statistical significance are in bold script.

The three-day cumulative jump size is 129 bps on average.					
T	Bond (%)	CDS (bps)	Equity (%)	Swap (%)	Trsy (%)
-2	-0.03	1.96	-0.94	-0.03	-0.75
	-0.75	3.60	-3.78	-2.69	-2.60
-1	-0.12	3.34	-1.20	-0.03	-0.03
	-2.21	5.36	-4.69	-2.56	-3.33
0	-0.16	4.27	-0.77	-0.02	-0.03
	-2.89	7.67	-2.51	-1.89	-2.97
$T \neq 0$	0.03	-0.12	0.02	0.00	0.00
	4.26	-2.84	0.80	-0.53	-0.09
[-2, 0]	-0.31	9.58	-2.90	-0.07	-0.09
	-2.56	7.54	-7.25	-3.99	-5.43
t -test for $H_0 : \mu(T = 0) = \mu(T \neq 0)$					
Difference	0.18	-4.39	0.79	0.02	0.03
t -statistic	3.39	-7.87	2.57	1.81	2.93
p -value	0.00	0.00	0.01	0.07	0.00

Table 5: **The Impact of Monthly Corporate Bond Credit Events on the Market (Events N=25)**

This table presents the impact of jumps in corporate bond spreads on the corporate bond market, the stock market, and the Treasury bond market. $T = 0$ refers to the event month when a jump is identified. In the pool of investment-grade firms with a bond spread equal to or smaller than 400 bps, we identify a jump event when (i) the firm's monthly bond spread change is larger than 200 bps, (ii) the jump is the first one in any consecutive twelve months, and (iii) the monthly change is not due to cumulation over the whole month but a sharp shift. We confirm the (iii) criterion by a media check in Lexis-Nexis and Standard and Poor's Creditweek. The market impact is measured by the log return of the Lehman Investment-Grade Corporate Bond Index, the CRSP market return, and the Lehman Treasury bond index, all at a monthly frequency.

	Size measured by bond outstanding			Size measured by total assets	
	All Events	Events	Events	Events	Events
		Involving Large Issuers	Involving Small Issuers	Involving Large Issuers	Involving Small Issuers
Number of events	25	11	14	13	12
Corporate Bond Returns (%)					
$T = 0$	-0.33	-1.05	0.24	-0.53	-0.11
$T \neq 0$	0.06	0.07	0.02	0.06	0.04
Difference	0.39	1.12	-0.22	0.58	0.15
t -statistic	1.74	3.42	-1.50	1.91	0.47
p -value	0.08	0.00	0.15	0.06	0.64
Stock Market Returns (%)					
$T = 0$	0.80	0.05	1.38	0.24	1.40
$T \neq 0$	1.13	1.14	1.09	1.14	1.09
Difference	0.33	-1.09	-0.30	0.90	-0.31
t -statistic	0.36	0.57	-0.25	0.72	-0.24
p -value	0.72	0.58	0.81	0.47	0.81
Treasury Bond Returns (%)					
$T = 0$	1.28	1.22	1.33	1.55	0.30
$T \neq 0$	0.70	0.73	0.72	0.71	0.76
Difference	-0.59	-0.49	-0.62	-0.84	0.46
t -statistic	-1.70	-0.96	-1.37	-3.05	0.72
p -value	0.09	0.34	0.17	0.01	0.47

Table 6: **The Impact of Monthly CDS Jumps on the Market (Events N=18)**

This table presents the impact of jumps in CDS spreads on the corporate bond market, the CDS market, the stock market, and the Treasury bond market. $T = 0$ refers to the event month when a jump is identified. In the pool of investment-grade firms with a CDS spread equal to or smaller than 400 bps, we identify a jump event when (i) the firm's monthly CDS spread change is larger than 200 bps, (ii) the jump is the first one in any consecutive twelve months, and (iii) the monthly change is not due to cumulation over the whole month but a sharp shift. We confirm the (iii) criterion by a media check in Bloomberg and Factiva. The market impact is measured by the log return of the Merrill Lynch Investment-Grade Corporate Bond Index, the equal-weighted CDS spread change across investment-graded firms, the log return of the S&P 500 index, the five-year Treasury bond rate, and the five-year swap rate, all at a monthly frequency. We also report the impact one month before and after the event month. t -statistics are reported in the second row. Entries with 1% statistical significance are in bold script.

T	Bond (%)	CDS (bps)	Equity (%)	Swap (%)	Trsy (%)
-1	-1.41	12.49	-3.62	-0.07	-0.07
	-1.71	2.85	-2.10	-0.97	-0.89
0	-0.13	22.46	-4.69	-0.26	-0.28
	-0.19	4.24	-3.22	-3.03	-3.76
1	1.33	12.24	-1.60	-0.35	-0.31
	2.49	2.23	-1.65	-3.39	-3.12
$T \neq 0$	0.58	-2.23	0.45	-0.01	0.00
	3.52	-2.00	1.03	-0.24	0.11
t -test for $H_0 : \mu(T = 0) = \mu(T \neq 0)$					
Difference	0.71	-24.69	5.14	0.25	0.28
t -statistic	0.97	-4.56	3.38	2.77	3.53
p -value	0.35	0.00	0.00	0.00	0.00

Table 7: **The Impact of Bankruptcy upon the Market (Events N=64)**

This table presents the impact of bankruptcy on the corporate bond market, the CDS market, and the stock market. $T=0$ refers to the event day when a firm files Chapter 11 bankruptcy and the firm is traded in both the stock market and the CDS market. The impact is measured by the log return of the Merrill Lynch Investment-Grade Corporate Bond Index, the equal-weighted CDS spread change across investment-grade firms, the log return of the S&P 500 index, the five-year swap rate and the five-year Treasury bond rate, all at a daily frequency. We also report the impact one day before and after the event days. t -statistics are reported in the second row. Entries with 1% statistical significance are in bold script.

T	Bond (%)	CDS (bps)	Stock (%)	Swap (%)	Trsy (%)
-1	0.04	-0.74	0.58	0.00	0.00
	0.89	-1.90	3.41	-0.15	0.43
0	0.03	-0.46	-0.34	0.00	0.00
	0.38	-0.62	-1.35	-0.22	-0.19
1	0.02	0.01	0.00	0.00	0.00
	0.31	0.03	0.01	0.13	0.12