Cross-Market and Cross-Firm Effects in Implied Default Probabilities and Recovery Values*

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Abstract

We examine the relation between estimates of default probabilities taken from the CDS market and the equity options market for non-financial and financial firms and investigate if it changes during the recent credit crisis. We find a strong relation between estimates of default probabilities across these two markets, and the relationship is stronger during the crisis, particularly for non-financial firms. When we use equity options' default probabilities to estimate time-varying recovery rates from CDS spreads, we find strong evidence that recovery rates vary through time, and that the recovery rates of financial firms are inversely related to measures of counterparty risk, especially during the crisis. We examine the time-series relation between changes in implied default probabilities and recovery rates and find two intriguing results. First, we find evidence that an increase in the default probability of financial firms is associated with an increase in the default probability of non-financial firms; the evidence that changes in non-financial firms' prospects influence financial firms is much weaker. Second, we find evidence that an increase in the implied default probability of financial firms leads to a decrease in the recovery rates of other financial firms; this result is consistent with fire-sale effects. Overall, there is evidence that deterioration in the prospects of financial firms has knock-on effects across the financial sector, as well as on the real economy.

1 Introduction

Derivative markets have seen enormous growth in the past four decades.[1] This growth has occurred not only in the volume of trading on individual derivative markets, but in the type of asset underlying the derivative contract. Perhaps the most substantial expansion over the past decade has been in the market for credit derivatives. This market has witnessed significant innovation, such as the introduction of credit default swaps and total return swaps trading on individual bonds, as well as collateralized debt obligations consisting of packages of many bonds (CDOs) and synthetic CDOs (which are themselves a derivative asset based on CDOs.) The growth in these markets has provided traders an unprecedented ability to take positions on fixed income securities with default risk.

The expansion of derivative markets has meant that the same asset (or assets) can underlie derivative contracts which trade in different venues. In particular, the insight of Merton (1974) suggests that the availability of separate derivative contracts based on the performance of a firm's debt and equity represent multiple derivative claims on the value of a firm's assets. If we assume that no-arbitrage links hold across these assets, so that market participants' valuation of the fundamental asset is the same across markets, an analysis of prices across multiple derivative markets may allow more precise measures of the distribution of the underlying assets' payoffs. Alternatively, differences in the implied pricing of the asset across these trading platforms may be attributable to differences related to institutional details across markets, including, for example, counterparty risk or differences in liquidity; in this case, an examination of multiple derivative markets can enable one to analyze the importance of these market features.

In this paper, we examine the relation between default probabilities for the same firm estimated from the CDS market and the equity option market. We analyze whether implied default probabilities taken from these markets are similar, whether the relation differs for financial and non-financial firms, and whether this relation changes during the recent credit crisis. Assuming that default probabilities for the underlying asset (the firm) across the two markets are the same, we test whether the recovery rates implied by CDS prices differ cross-sectionally, or change during the credit crisis. We examine whether recovery rates are related to aggregate economic indicators. We examine the time-series relation between changes in implied default probabilities and recovery rates between financial and non-financial sectors, and across individual firms within the financial sector. Such feedback effects are consistent with Diamond and Rajan (2010), and may indicate a link between funding shocks, solvency, and market illiquidity, similar to those discussed in Brunnermeier and Pedersen (2008).

Our results indicate that, for the entire sample, estimates of the levels of implied default prob-

[1] See, e.g., ISDA Market Survey 2010, or the Bank for International Settlements data.

abilities extracted from CDS and equity options are strongly, but not perfectly, correlated. If we assume constant recovery rates (as is typically done in the CDS market), simple correlations between estimates of default probabilities for the same firms extracted from these two markets average approximately 0.70. These correlations differ by subsample and by the cross-section of firms, and appear to be affected by secular trends throughout the full sample period, as well as during shorter subsamples. For example, the correlation in implied default probabilities in the two markets is higher for financial firms and increases during the crisis period, especially for non-financial firms.

We analyze the relation between changes in default probabilities implied by the two sets of securities using an error-correction model. We find several noteworthy results. First, there is significant evidence of a contemporaneous relation between changes in the two markets' estimates of default probabilities, for all types of firms and during all subperiods. This result indicates that the two markets' estimates of default are linked. Second, we find evidence of lagged error correction in both CDS and option-implied default probabilities. This result suggests that, at least at the weekly level, information concerning default risk flows in both directions across the CDS and the equity options market. Third, for financial firms, the relation between both contemporaneous and lagged option-implied default probabilities and CDS-implied default probabilities strengthens during the crisis period for both financial and non-financial firms. Finally, the links between the estimates of default probabilities taken from the two markets are largely unaffected by controlling for aggregate determinants of credit risk, as in Collin-Dufresne, Goldstein, and Martin (2001).

Our results also suggest that the conventional assumption that recovery rates are constant (at 40.0%) seems to be quite poor for our sample; consistent with Pan and Singleton (2008), who examine sovereign CDS, we find evidence that implied recovery rates vary across firms. We use the joint information in option-implied default probabilities and CDS-implied default probabilities to retrieve a measure of recovery rates that varies both across time and across firms. We show that this measure does indeed exhibit significant time series and cross-sectional variation ranging, across firms and across time, from 0.0% to 99.0%, with an average of approximately 75%. We investigate the determinants of these recovery rates using variables similar to those employed in Collin-Dufresne, Goldstein, and Martin (2001) and Longstaff, Pan, Pedersen, and Singleton (2010). We find that the TED (Treasury minus Eurodollar) spread, a proxy for counterparty risk, is negatively related to recovery rates, particularly for financial firms in the crisis period. In addition, recovery rates are positively related to returns in the equity market in the crisis period for both financial and non-financial firms.

We also find strong evidence that worsening conditions in financials are propagated across the economy. Specifically, increases in the default probabilities, and decreases in the recovery rates, of financial firms are related to increases in the default probabilities and decreases in the recovery rates of non-financial firms, while the reverse effects (from the non-financial to financial sector) are much weaker. When we subdivide the financial industry into subsectors, we find the majority of the financial firms effects come from the banking sector.

Finally, we examine the effects of changes in the default probabilities and recovery rates of individual firms in the financial sector on one another. We find marked differences in individual firms effects, with changes in the recovery rates of firms such as Citigroup, Lehmann and Wells Fargo having the largest impact on other financial firms. We also find evidence of contagion in default probabilities across financial firms, consistent with the results of Jorion and Zhang (2007). In addition, we find that increases in the default probabilities of financial firms are associated with subsequent declines in the recovery rates at other financial firms, consistent with the fire-sale intuition in Diamond and Rajan (2010).

The remainder of the paper is organized as follows. In Section 2, we discuss the methodology we employ for extracting risk neutral default probabilities from options and from CDS spreads and their implications for recovery rates. We describe the data that we employ in this paper in section 3. Section 4 presents results for the relation among risk neutral default probabilities across different markets. We analyze recovery rates, cross-sector and cross-market effects in Section 5. Cross-firm effects are discussed in Section 6, and Section 7 provides concluding remarks.

2 Method

The comparison of option-implied default probabilities, and default probabilities implied in the CDS market, is similar in spirit to the analysis of Carr and Wu (2008). Our method of constructing implied default probabilities from CDS data follows their method closely, and is described in Section 2.1. However, our method of estimating default probabilities from equity options data differs substantially, and is described in Section 2.2.

2.1 Measuring Default Probabilities from CDS Spreads

To measure the probability of default from the spread on a credit default swap (CDS), we make several simplifying assumptions about the contract. We assume that the contract struck at time t has a maturity of $\tau = 5$ years, and that swap payments are made at the end of each quarter year $t + j$ that the underlying entity does not default, with $j = \{1, 2, 3, ..., 20\}$. The swap spread, s, represents the annualized premium paid to insure \$1 of the underlying payout over the life of the contract. The risk neutral probability at time t that the contract will default over the horizon $t + j, t + j + 1$, q_t, is projected to be constant over the life of the contract, with continuation probability $(1 - q_t)$. Payments are discounted using a zero coupon term structure. The discount rate from period t to period $t+j$ is designated as $d_t(j)$. Following convention, it is assumed that if a default occurs, the swap payer (that is, the counterparty paying the premium) owes accrued swap payments from the previous quarter's end through the default event date.

Under these assumptions, the swap is struck at time t with a premium such that the cost of the premium leg is equal to the value of the contingent payment leg. That is, the swap is struck at a premium that satisfies

$$\frac{s_t}{4}\sum_{j=1}^{20} d_t(j)(1-q_t)^j + \frac{s_t}{8}\sum_{j=1}^{20} d_t(j)q_t(1-q_t)^j = (1-R)\sum_{j=1}^{20} d_t(j)q_t(1-q_t)^j \tag{1}$$

The first term on the left-hand-side of this expression is the present value of the swap rates if the underlying does not default; the expression $(1-q_t)^j$ represents the cumulative probability that the underlying does not default through period j. The second term on the left-hand-side is the expected accrued swap payments in quarter j if the underlying does default in that quarter. The term on the right-hand-side represents the expected payout on the protection leg of the contract, with R the recovery rate on the value of the underlying asset in the event of default. Rearranging this expression to solve for the probability of default in a single quarter, we obtain

$$q_t^C(\tau) = \frac{s_t/4}{\left(1-R+\frac{s_t}{8}\right)}, \tag{2}$$

where the superscript C indicates that the default probability has been recovered from CDS.

2.2 Measuring Default Probabilities from Option Prices

We measure risk neutral default probabilities in the equity markets by inferring risk neutral probability density functions from the prices of options. Our approach utilizes the Normal Inverse Gaussian (henceforth, NIG) density, suggested by Eriksson, Forsberg, and Ghysels (2004), to approximate the unknown risk neutral density function. As discussed by Eriksson, Forsberg, and Ghysels (2004) and Eriksson, Ghysels, and Wang (2009), the NIG class possesses many advantages relative to alternative methods for inferring risk neutral density functions, such as Gram-Charlier expansions. Importantly for our analysis, Eriksson, Forsberg, and Ghysels (2004) show that this method performs better in the tails of the distribution, particularly when the underlying distribution exhibits skewness and fat tails. In addition, this density can be characterized by its first four moments. Specific details about the likelihood function are provided in the appendix.

The risk neutral moments that represent the arguments for the NIG density can be calculated from option prices. We follow Bakshi, Kapadia, and Madan (2003), who show that the price of quadratic, cubic, and quartic payoff on a security can be represented by

$$
\begin{aligned}
V_{i,t}(\tau) &= \int_{S_{i,t}}^{\infty} \frac{2(1-ln(K_i/S_{i,t}))}{K_i^2} C_{i,t}(\tau;K_i)dK_i \\
&+ \int_{0}^{S_{i,t}} \frac{2(1+ln(K_i/S_{i,t}))}{K_i^2} P_{i,t}(\tau;K_i)dK_i
\end{aligned} \tag{3}
$$

$$
\begin{aligned}
W_{i,t}(\tau) &= \int_{S_{i,t}}^{\infty} \frac{6ln(K_i/S_{i,t}) - 3(ln(K_i/S_{i,t}))^2)}{K_i^2} C_{i,t}(\tau;K_i)dK_i \\
&- \int_{0}^{S_{i,t}} \frac{6ln(K_i/S_{i,t}) + 3(ln(K_i/S_{i,t}))^2}{K_i^2} P_{i,t}(\tau;K_i)dK_i
\end{aligned} \tag{4}
$$

$$
\begin{aligned}
X_{i,t}(\tau) &= \int_{S_{i,t}}^{\infty} \frac{12(ln(K_i/S_{i,t}))^2 - 4(ln(K_i/S_{i,t}))^3)}{K_i^2} C_{i,t}(\tau;K_i)dK_i \\
&+ \int_{0}^{S_{i,t}} \frac{12(ln(K_i/S_{i,t}))^2 + 4(ln(K_i/S_{i,t}))^3}{K_i^2} P_{i,t}(\tau;K_i)dK_i
\end{aligned} \tag{5}
$$

where $V_{i,t}(\tau)$, $W_{i,t}(\tau)$, and $X_{i,t}(\tau)$ are the time t prices of τ-maturity quadratic, cubic, and quartic contracts, respectively. $C_{i,t}(\tau;K)$ and $P_{i,t}(\tau;K)$ are the time t prices of European calls and puts written on the underlying stock with strike price K and expiration τ periods from time t. As equations (3), (4) and (5) show, the procedure involves using a weighted sum of (out-of-the-money) options across varying strike prices to construct the prices of payoffs related to the second, third and fourth moments of returns. We follow Dennis and Mayhew (2002), and use a trapezoidal approximation to estimate the integrals in expressions (3)-(5) above using discrete data.[2]

Using the prices of these contracts, standard unscaled central moment definitions suggest that the risk-neutral moments can be calculated as

$$
\begin{aligned}
\mathcal{V}_{i,t}(\tau) &= e^{r\tau}V_{i,t}(\tau) - \mu_{i,t}(\tau)^2 && (6)\\
\mathcal{S}_{i,t}(\tau) &= e^{r\tau}W_{i,t}(\tau) - 3\mu_{i,t}(\tau)e^{r\tau}V_{i,t}(\tau) + 2\mu_{i,t}(\tau)^3 && (7)\\
\mathcal{K}_{i,t}(\tau) &= e^{r\tau}X_{i,t}(\tau) - 4\mu_{i,t}(\tau)W_{i,t}(\tau) + 6e^{r\tau}\mu_{i,t}(\tau)^2V_{i,t}(\tau) - \mu_{i,t}(\tau)^4 && (8)
\end{aligned}
$$

where

$$\mu_{i,t}(\tau) = e^{r\tau} - 1 - e^{r\tau}V_{i,t}(\tau)/2 - e^{r\tau}W_{i,t}(\tau)/6 - e^{r\tau}X_{i,t}(\tau)/24 \tag{9}$$

and r represents the risk-free rate.

Given these moments, and the risk free rate to compute expectations, we use the NIG density function to compute probabilities. The benchmark Merton (1974) model suggests that default

[2]We are grateful to Patrick Dennis for providing us with his code to perform the estimation.

occurs when the market value of assets decreases below the market value of debt; equivalently, upon default the market value of equity is zero. We utilize the NIG density to compute the cumulative density

$$q_{it}^{O}(\tau) = \int_{-\infty}^{0} f_{NIG}\left(x, 1 + R_{f,t}(\tau), \mathcal{V}_{it}(\tau), \mathcal{S}_{it}(\tau), \mathcal{K}_{it}(\tau)\right) dx \tag{10}$$

where f_{NIG} is the NIG density function evaluated at x with parameters given by the risk free rate, $R_{f,t}(\tau)$, risk neutral volatility, $\mathcal{V}_{i,t}(\tau)$, risk neutral skewness, $\mathcal{S}_{it}(\tau)$, and risk neutral kurtosis, $\mathcal{K}_{it}(\tau)$. The superscript O in equation 10 indicates that the risk neutral probability has been recovered from options data.

As mentioned above, Carr and Wu (2008) also use options data to construct an implied default probability. They show that the prices of two American put options on an underlying equity share, with the same maturity and different strike prices, and the strike prices lying within a default corridor, can be used to create a standardized credit insurance contract and hence to infer a risk-neutral default probability. In contrast, we use information in all out-of-the-money options to generate the entire risk-neutral distribution, and use that to infer the default probability.

2.3 Implementation

A first issue in implementation is the fact that, while the CDS data are constant maturity at five years with quarterly payments, the options data have varying maturity primarily of less than one year. We deal with this issue as follows. For each firm day, we choose the options that are closest to, but less than, three months to maturity and twelve months to maturity. We treat these options as if they are constant maturity three month and twelve month options. In the case of the CDS data, as mentioned above, we assume that the contract pays a quarterly premium over a constant maturity of five years, and that conditional default rates are constant. Thus, the retrieved default probability represents the conditional default probability over the quarter. In the case of three month options, we compare the recovered (quarterly) CDS probability directly to the default probability from options. When we use the default probability estimated from twelve month options, we use the compounded (CDS) probability of default over the next four quarters, measured as $1 - (1 - q_t^C)^4$.

The second issue in implementation is the recovery rate assumed for retrieving probabilities from CDS spreads. As, for example, Duffie (1998) points out, the entanglement between default probabilities and recovery rates in equation (1) implies that they cannot both be estimated from single-maturity CDS spread data. The standard procedure in estimating default probabilities is to assume some constant recovery, such as $R = 0.4$. This approach ignores any potential cross-sectional or time-series variation in perceived recovery rates. We begin with this standard assumption, but go on to relax it in a subsequent test.

Specifically, we let recovery rates vary not only cross-sectionally, but also over time. This consideration is particularly important during the sample period that we examine, 2006-2009, as perceptions about recovery from CDS contracts may have changed substantially during the financial crisis of late 2008, due to concerns about underlying asset values, 'fire sales' undertaken by other firms, and/or concerns about market liquidity. To accommodate this possibility, we also solve at each time t for the recovery rate $\hat{R}_t$ that sets the option-implied and CDS-implied probabilities equal:

$$q_t^O(\tau) = 1 - \left(1 - \frac{0.25 s_t}{1 - \hat{R}_t + s_t/8}\right)^{4\tau}. \tag{11}$$

This procedure implicitly treats the recovery rate as the residual that satisfies equality between the option-implied and CDS-implied probabilities. As such, it may include alternative sources of divergence in these markets, including liquidity, counterparty risk and mispricing.

The assumption in the recovery rate relation is that equity is a zero-recovery asset, a condition that should hold given absolute priority. This assumption is also made in modeling recovery rates in Das and Hanouna (2006) and Le (2006). A principal difference in our approach is that it is largely nonparametric. Rather than assuming a specific structural model, our framework applies a general distributional framework and market prices to estimating implied recovery rates.

These approaches to determining recovery rates lead to one final problem. In satisfying equation (11), the resulting recovery rate and default probabilities can take on values that are not possible either theoretically or practically. That is, we should have default probabilities that satisfy $0 \leq q_t^C \leq 1$ and recovery rates that satisfy $0 \leq \hat{R} \leq 1$. The non-negativity constraint for the recovery rate is sometimes violated. Consequently, if the implied recovery rate is less than zero, we set the recovery rate equal to zero.

3 Data

3.1 Data Description

Data on CDS spreads are obtained from CMA.[3] Prices are the average of bid and ask quotes, based on the last set of quotes available at the end of each day. For each firm in our sample, we use the CDS prices for senior debt with five years to maturity. Our sample covers the period July 1, 2006 through December 30, 2010, and is restricted to firms in the S&P 500 as of July 1, 2006. We restrict

[3]An earlier version of this paper used data from Bloomberg. CMA data over the sample period we examine appear to be slightly less noisy, however, the results we obtain using either data set are very similar.

our attention to these firms as they are most likely to have CDS and options data, yet represent a fairly broad cross-section of types of firms. The number of firms with available CDS data varies, with a maximum of 328 firms.

Our options data come from IVolatility. The data are the NBBO (National Best Bid and Offer) daily closing prices for all available expirations and strikes. Similar to the CDS data, we sample the options over the period July 1, 2006 through December 30, 2010. We remove from the data options with prices less than \$0.25, as these options appear to frequently violate standard no-arbitrage restrictions. Further, we confine attention in this paper to options that are closest to, but less than, 92 and 365 days to maturity (three- and twelve-month options, respectively). As with the CDS data, we also confine our attention to constituents of the S&P 500 as of July 1, 2006. The average maturity of the options in the twelve month grouping is 0.627 years, and that of the three month grouping is 0.167 years. The number of firms for which we have data and can calculate valid option moments varies from 286 to 430.

Finally, we obtain data on risk free rates from the Federal Reserve and sector definitions from Compustat. Specifically, the risk free rates are three month secondary yields obtained from the H.15 report at the Federal Reserve Board of Governors. We define sectors using the Standard and Poors GICS (Global Industry Classification Standard) from Compustat. Each firm is assigned to either the 'Non-financial' or the 'Financial' sector using these codes. The 'Non-financial' firms are in sectors represented as Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Healthcare, Information Technology, Telecommunications, and Utilities. The 'Financial' sector includes the following sub-sectors: Banks, Diversified Financials, Insurance and Real Estate.

To reduce estimation error in the option-implied estimates, we follow Bakshi, Kapadia and Madan (2003) and average moment estimates from a calendar week. For consistency, we also use CDS prices sampled weekly. In order to be included in our final sample, a firm must have at least 52 weekly observations available. An observation consists of a week for which we have both options and CDS data available for at least 3 days within the week; we also require that there be a minimum of 10 firms with valid data on each sample day. Our final data sample consists of 37 financial firms and 223 non-financial firms over 1,185 trading days or 237 weeks.

3.2 Aggregate Implied Default Probabilities and Recovery Rates

For each week in our sample, we calculate the probability of default implied by the firm's option prices ($q_t^O(\tau)$), the probability of default implied by the firm's CDS spread assuming a recovery rate of 0.4 ($q_t^{C,0.4}(\tau)$), a probability of default implied by the firm's CDS spread assuming a recovery rate that minimizes the distance between the options default probability and the CDS probability ($q_t^{C,\overline{R}}(\tau)$), and the recovery rate implied by equating the options and the CDS default probabilities

($q_t^{C,R_t}(\tau)$). We then average these data across firms within non-financial and financial sector groupings discussed above, in order to simplify data description. For brevity, in the tables we report results using only 12-month options data.

Time series plots of the implied default probabilities, separated by financial and non-financial sector, are presented in Figure 1. Specifically, Figure 1 plots the average default rates constructed from the CDS and options markets, with non-financial firms in Panel A and financial firms in Panel B. We discuss the implied risk neutral probabilities and recovery rates in greater detail in the next sections. Here, we simply make a few observations. First, as expected, implied default probabilities from both markets are relatively low on average in the earlier part of the sample, and rise throughout the financial crisis, peaking before June 2009. The average implied default probabilities have declined in the late 2009 and early 2010, and remains significantly below the levels reached during the crisis. There is greater variation in the default probabilities for financial firms than non-financial firms. Additionally, the peak for financial firms is substantially higher than for non-financial firms (approximately 11% vs. 4.5%, based on CDS implied default probabilities). Finally, in aggregate, the time series of default probabilities taken from CDS and equity options data are highly correlated. For example, the default probabilities implied by CDS data for non-financial firms with 40 percent recovery rate have a correlation coefficient of 0.91 with those implied by options data. For financial firms, this correlation is similar at 0.92.

Figure 2 depicts the average implied recovery rates for financial and non-financial firms. Again, the time series patterns seem plausible. Prior to the crisis, the implied recovery rates for both financial and non-financial firms are quite high, averaging in the neighborhood of 90% and 80%, respectively. At the inception of the crisis, recovery rates begin to steadily deteriorate; in mid 2009, recovery rates for non-financial firms drop below 60%. The recovery rates for financial firms drop close to 50% in several occasions. These rates for both sets of firms stabilize within a narrower band of 65% and 75% in the second half of 2010. Recovery rates are also fairly highly correlated across sectors, with a correlation of 0.85 in the full sample period.

4 Risk Neutral Default Probabilities

In the previous section, we discussed the data used in our study and examined broad time series patterns and relations in the aggregate (cross-sectionally averaged) data. In this section, we examine the link between these variables on a more disaggregated basis, and consider the impact of other proposed determinants of credit spreads on the relation between default probabilities implied by CDS and options.

4.1 Descriptive Statistics

In Table 1, Panel A, we report descriptive statistics for CDS spreads, risk-neutral default probabilities estimated from these spreads (with a 40% recovery rate assumption), as well as default probabilities estimated from 12-month equity options, for the overall sample, and for both Financial and Non-financial firms separately, for the entire sample period. We also report recovery rates for the entire sample and for each sector, assuming that recovery rates differ across firms and across time (using equation (11)).

There is substantial variation in CDS spreads in the sample, with a minimum spread of 2.3 basis points, and a maximum of more than 3500 basis points (the maximum observation was for Ford, in April of 2009). Related, we also observe very substantial variation in the default probability estimated from CDS spreads: the average default probability in the full sample (assuming a constant recovery rate of 40% across firms and across time) is approximately 2.14%, with a minimum default probability of 0.038% and a maximum observation of 49.91% (again, Ford in April of 2009). The average default probability estimated from equity options is higher, at 4.32%. When we use the default probability from the equity option market to identify time-series variation in recovery rates, the average recovery rate is 75%, and we also see very significant variation in this rate across firms, ranging from 0% to 99%. These results suggest that, similar to the results of Pan and Singleton (2008) in the sovereign debt market, the assumption of a constant recovery rate across firms is not well-specified. In addition, however, our results suggest that the assumption of a constant recovery rate across time is not well-specified.

In Table 1, Panel B, we report average default probabilities and recovery rates across the sector of financial and non-financial firms. The default probabilities implied by CDS and options markets are on average higher for financial firms. The full-sample implied recovery rates averages to about 75% for both groups.

In Panels C-E, we report these statistics for all firms and across sectors for two different subperiods: specifically, we break the sample period into a 'non-crisis' and 'crisis' period, where we use August 9, 2007 and June 30, 2009 as the start date and end date of the crisis period, respectively. [4]We define the remaining sample period as 'non-crisis', consisting of the pre-crisis period from July 1, 2006 to August 9, 2007 and the interval from July 1, 2009 to December 30, 2010. In Panel C, it is clear that default probabilities measured using both markets increase sharply from the pre-crisis period to the crisis period. The CDS-implied default probabilities display a sharper increase than the option implied probabilities during the crisis period (from 1.5% to 3.0%), although the magni-

[4]This date was used as the start of the crisis based on the increase in the inter-bank lending rates which resulted from BNP Paribas suspending redemptions from three of its funds, due to difficulty in calculating their NAVs. This event has been dated as occurring in close proximity to the start of the crisis by, among others, Brunnermeier (2009). The end date of the crisis matches the recession's end, as defined by the National Bureau of Economic Research.

tude of default probabilities estimated from the CDS market continues to be lower. The average recovery rates also decline from 78% to 71% during the crisis.

While the credit crisis corresponds to increases in default probabilities estimated using either method, in comparing Panel D to Panel E, we see that these changes are particularly acute for the financial sector. During the pre-crisis interval, it appears that financial firms' remarkably low CDS spreads are due to both a low estimated probability of default compared to non-financial firms, and a high estimated recovery rate compared to non-financial firms. As the credit crisis deepened, average CDS spreads for financial firms increase from 25 basis points in the pre-crisis period to over 200 basis points in the crisis period ending June 2009. By comparison, CDS spreads for non-financial firms also increase across these intervals, but less dramatically so. Non-financial firms' spreads begin the sample period at a higher level of 50 basis points in the pre-crisis period, and increase to 126 basis points in the crisis. The larger increases in financial firms' CDS spreads are accompanied by the sharpest increases in estimated default probabilities. Average implied default probabilities estimated from CDS spreads (assuming that recovery rates vary across firms) for financial firms more than double during the crisis, from 1.9% to 4.7%; average implied default probabilities estimated from the equity option market also increase from 3.9% to 7.6%. For non-financial firms, the increases are significant, but smaller in magnitude. Default probabilities for non-financial firms estimated from CDS spreads increase by slightly less than a factor of 2 across the two periods (from 1.5% to 2.7%), and default probabilities estimated from the equity options market increase by approximately a factor of 50% (from 3.5% to 5.0% over the two subperiods.)

The correlation in the implied default probabilities estimated from the CDS spreads and equity options are higher during the crisis interval for both financial and non-financial firms. Again, these correlations differ across firms: they are higher for financial firms at 71% compared to between 58% (non-crisis) and 64% (crisis) for non-financial firms. Changes in the correlation between these default probabilities may be related to time-series variation in the recovery rates within each interval; we examine the dynamics of recovery rates in a subsequent section of the paper. We see evidence of variation in recovery rates in Figure 2, with recovery rates declining for all firms in the crisis. Recovery rates for financial firms drop more steeply, declining from 81% in the pre-crisis period to 68% in the crisis interval. The recovery rates for non-financial firms decline as well, but by a smaller percentage: from 78% to 72%.

Overall, changes in CDS spreads during our sample period are particularly striking for financial firms, and appear to be associated with more dramatic shifts in *both* default probabilities and recovery rates. The combination of the two leads to sharply nonlinear effects in CDS spreads for financial firms. For all firms, the evidence suggests that default probabilities and recovery rates vary strongly across *both* firms and across time. In addition, for both non-financial and financial firms, default probabilities estimated from the CDS market during the crisis appear to correspond more closely with default probabilities estimated from the equity options market.

Overall, the univariate correlations between default probabilities estimated from the two markets suggest two implications. First, there appears to be a strong link between the markets' estimates of default over the full sample period, with the relation tightening, at least for non-financial firms, as the crisis developed. Second, and more interestingly, these results suggest that the time-variation in recovery rates differs through the crisis across sectors, or that the links between the CDS market and the equity option market differs for financial firms, or both. We explore this relation, and these differences, in more detail below.

4.2 Empirical Specification

The results in Table 1 indicate a significant relation between expected default measures estimated from the CDS market, and those estimated using equity options prices. In this section, we explore the relation between daily changes in these two measures of default probability at the firm level, while controlling for other characteristics of the economic environment. Since the CDS and option-implied default probabilities are very close to non-stationary, we use an error-correction specification to model changes in these probabilities across markets. Specifically, we posit that the two probabilities are cointegrated in (log) levels,

$$q^C_{i,t+1} = \theta_{0,i} + \theta_{1,i} t + \theta_{2,i} q^O_{i,t+1} + v_{i,t+1} \tag{12}$$

where the individual option probabilities are non-stationary, but the linear combination of the two, v_{t+1}, or the error correction term, is stationary. In the context of cointegration, this relation suggests that the error correction term represents transitory movements in the long-term relation between CDS and option-implied risk neutral default probabilities. In unreported results, we verify that the levels of the CDS- and option-implied default probabilities for both the financial and non-financial firms fail to reject the augmented Dickey-Fuller test null hypothesis of a unit root, but that the residual, v_{t+1} for each of these series rejects the non-stationary null. In these expressions, q^C_{t+1} represents the log of the risk neutral probability implied by credit default swaps and q^O_{t+1} is the risk neutral default probability implied in the options market.

We also test whether the relation between estimates of default probability in these two trading venues is affected by variables which might be associated with aggregate risk. Specifically, we investigate the following empirical specification:

$$\Delta q^k_{i,t} = \alpha_{k,i} + \beta_{k,i} \Delta q^j_{i,t} + \boldsymbol{\gamma}'_{k,i} \mathbf{x}_t + \delta_{k,i} v_{i,t-1} + \epsilon_{k,i,t}, \tag{13}$$

where the $k = \{O, C\}$, to indicate risk neutral probabilities obtained from the option or CDS market respectively and $j \neq k$ indicates the risk neutral probability obtained from the alternate market. The vector $\mathbf{x}_t$ is a set of covariates largely corresponding to determinants of defaultable bond yields investigated in Collin-Dufresne, Goldstein, and Martin (2001). The vector comprises $r_t(5.0)$, the log of the five year constant maturity treasury yield, $r_t^2(5.0)$, the log of the five-year yield squared, s_t, the slope of the yield curve measured by the difference in the five-year yield and the 3-month secondary market Treasury Bill yield, ted_t, the difference in the 3-month Eurodollar deposit rate and the 3-month secondary market Treasury Bill yield, $r_{m,t}$, the return on the S&P500 in week t, and vix_t, the log VIX index. Data on the five-year constant maturity yield, 3-month secondary market Treasury Bill yield, and Eurodollar deposit rate are taken from the H.15 report at the Federal Reserve. The stock returns are from the CRSP daily stock files.

Our covariates differ from those used in Collin-Dufresne, Goldstein, and Martin (2001) along a few dimensions. First we do not include leverage in our analysis, since we examine weekly data over the span of three years. Changes in the book value of debt will be available at most at a quarterly frequency, and so the majority of the variation in any market measure of leverage will be attributable to changes in market value of equity. Second, we incorporate a new variable, ted_t. Our rationale for including ted is that the Treasury-Eurodollar spread is thought of as a measure of counterparty credit risk. During the crisis, it was widely perceived that CDS spreads and accompanying default probabilities were affected by counterparty credit risk in the market.

4.3 Estimation Results

Results of our estimation are shown in Table 2. We estimate results for financial and non-financial firms separately, across the overall sample period (Panel A), as well as the non-crisis (Panel B) and crisis intervals (Panel C). The estimates presented are averages across the estimates for firms in each subset of firms with accompanying cross-sectional t-statistics.

Throughout the table, the results from the error-correction model indicate that differences in default probability estimates across the two markets are strongly contemporaneously related. Estimates of β_i, the coefficient on the alternate market's default probability, are positive and typically strongly statistically significant across both sectors and time. In addition, across all periods and for both financial and non-financial firms, the error correction term $v_{i,t-1}$, significantly affects next period's estimate of default probability in both the CDS and the equity option market. The sign of the coefficient on $v_{i,t-1}$ in these regressions is consistent with the interpretation that the markets are adjusting their estimate of default probability to reflect the information in the CDS market. That is, if the option-implied default probability is higher than the CDS implied default probability, then next period's option-implied default probability declines, and the estimate in the CDS market increases. We do see some differences across CDS and option-implied default probabilities. In general, the evidence for error-correction is somewhat stronger for option-implied default probabilities–the coefficient on contemporaneous changes in the CDS market is larger, and the coefficient on the error-correction term in the option equation is also larger in magnitude than the coefficient on error-correction in the CDS equation.

The relations between the two markets' default probabilities are similar for financial and non-financial firms during the non-crisis period in Panel B. As shown in Panel C, the influence of changes in default probability estimates taken from the equity options market are significantly larger in the crisis period (the point estimate of the coefficient increases from 0.09 in non-crisis to 0.19 during the crisis); the magnitude of the effect of the error-correction term is also larger in the CDS equation. This suggests that, during the crisis, information flowing from the equity options market had a larger effect for financial firms. In contrast, the effect of contemporaneous changes in the CDS market's default probabilities on options market estimates declines substantially (the coefficient value drops from 0.33 to 0.17), while the effect of the error-correction term is largely unchanged, during the credit crisis compared to the non-crisis interval. In our sample of financial firms, we find no evidence that the influence of the credit derivatives market on the equity market was enhanced during the credit crisis.

In the sample of non-financial firms, we continue to find strong evidence of contemporaneous and error-correction effects across both markets, with the sign of the coefficient on the error-correction terms consistent with convergence between the two markets. Similar to the result for financial firms, we find no evidence that credit derivative markets' estimates of default probabilities had stronger effects in the crisis. Indeed, the coefficients on contemporaneous changes in CDS' market estimates of default probabilities, as well as error-correction terms, declines in the crisis interval. During the crisis interval, there is stronger evidence of an error-correction between the two markets for financial, than non-financial, firms. Moreover, the addition of control variables changes the results very little.

The influence of covariates on changes in implied default probabilities differ somewhat across the two markets, but there are some notable similarities in the results. For example, the effect of market return on changes in default probabilities in both markets tends to be negative and significant–that is, increases in market return are associated with declines in default probabilities. This effect holds for both the crisis and non-crisis periods as well across financial and non-financial firms. Changes in treasury yield are negatively related to default probabilities extracted from both markets, with a stronger influence on CDS-implied probabilities. Increases in the TED spread, which is a measure of counterparty risk, have a positive and significant effect on default probabilities in the CDS market, although not on default probabilities taken from the options market. Finally, the effect of VIX on changes in default probability estimated from CDS tends to be positive and significant, while its effect on option-implied default probability is mixed.

Overall, the results in this section provide a more formal analysis of the hypothesis that the option-implied and CDS-implied risk neutral default probabilities are linked. The results of the error-correction model suggest that, particularly during the crisis and for financial firms, the link between the two markets is not simply contemporaneous. In particular, both contemporaneous and lagged information flows from the options market to the credit markets becomes stronger during the credit crisis for financial firms. Over time, however, it appears that the default probabilities in different markets contain similar information and that much of this information is independent of aggregate covariates that have been shown to affect credit spreads. In the next section, we analyze the shared information content of these default probabilities. Specifically, we examine the dynamics of recovery rates implied jointly by the option- and CDS-implied default probabilities.

5 Information in Implied Default Probabilities Across Markets

5.1 Implied Recovery Rates

The strong relation between default probabilities across markets, observed in Table 1 and Table 2, motivates our use of option-implied default probabilities to extract recovery rates from CDS spreads. The summary statistics in Table 1 indicate that recovery rates differ substantially across both time and firms, and that the conventional assumption that recovery rates are constant at 0.4 is not consistent with the information in either the CDS or the options market. In this section, we examine our estimates of recovery for evidence of systematic effects.

There are several reasons why recovery rates may have declined, particularly for financial firms, as the crisis deepened. First, and most obviously, the market's estimates of the fundamental values of the assets likely changed for the worse as market values deteriorated across the board. Second, adverse changes in market liquidity in some segments of asset markets may cause recovery rates to decline; such effects are described in Brunnermeier and Pedersen (2008). In addition, particularly for financial firms, the prospect of future fire sales may reduce the current value of the institution, as the (limited set of) investors who might purchase the asset at a fire-sale price in the future demand a lower price to purchase it today; this is the model in Diamond and Rajan (2010). And, in their model, the discounted values today can extend to the entire market segment, implying that there may be an adverse feedback loop across firms between future recovery rates and today's default probabilities. As a consequence, we investigate the time-series of estimated recovery rates for subsamples of financial and non-financial firms, for commonalities in the pre-crisis and crisis subperiods. For each firm, we regress the change in recovery rate on the same covariates, or proxies for aggregate risk, as in regression (13). We first-difference all covariates with the exception of equity returns. The results are presented in Table 3. Panel A has the results for financial firms, and Panel B has the results for non-financial firms. As above, estimates reported are averages across individual firms.

We find that measures of aggregate risk have some significant explanatory power for changes in recovery rates. In particular, several results stand out. The first is that, for the overall sample period, the recovery rates of financial firms declines significantly with increases in TED, a measure of counterparty risk. When we examine the two subperiods, it is clear that this result is driven by the crisis period–the coefficient on TED is insignificant in the pre-crisis period, and the coefficient on TED in the crisis period is identical to the coefficient in the overall sample period. Second, recovery rates are significantly positively related to market returns; this result is also driven by the crisis period. The weaker effect of these covariates during the non-crisis period is also consistent with more stable recovery rates during the pre-crisis, as reflected in Figure 2.

In Panel B, we see that the market return also has a positive influence on recovery rates for non-financial firms, and this result is also driven by the crisis period. However, TED has no significant effect on recovery rates for non-financials–that is, counterparty risk does not appear to influence market estimates of the value of assets in the 'real' economy.

Overall, the estimates of recovery rates that we generate through a comparison of default probabilities in the CDS and equity option market are plausible in magnitude, and present clear evidence that recovery rates are not constant across firms or across time. In addition, estimated recovery rates for financial firms are sensitive to measures of counterparty risk, while recovery rates for non-financial firms are not significantly related to these measures. Equity market returns are positively associated with recovery rates for both financial and non-financial firms. Since the recovery rates used in this analysis were estimated by comparing default probability information from both CDS and equity options market, we interpret this evidence of significant, intuitive relations between our estimates of recovery rates and economic variables as further evidence that the credit and equity derivative markets are linked in their information on an underlying firm's probability of default.

5.2 VARs in Sectors

To examine the relation between recovery rates and implied default probabilities, we begin with a dynamic VAR estimation on default probabilities and recovery rates for non-financial and financial sectors in the economy. As mentioned earlier, we use the Global Industrial Classification Scheme (GICS) to divide firms into sectors.

We estimate the VAR system of default probabilities and recovery rates for financial firms paired with firms in each of the nine sectors. Since, as mentioned in earlier sections, implied default probabilities and estimated recovery rates are very persistent, we first difference both of these variables. The specification posits the following relations between changes in the CDS-implied log risk neutral default probability, and the change in the recovery rate $\hat{R}_t$ (calculated from taking the option-implied default probability q^O_{it} and solving equation (11)):

$$\mathbf{y}_t = \boldsymbol{\mu} + \boldsymbol{\Phi}\mathbf{y}_{t-1} + \boldsymbol{\eta}_t \tag{14}$$

where $\mathbf{y}_t$ is a 4×1 vector, constructed by stacking the change in the option-implied default probabilities, and changes in recovery rates for non-financial firms on the same variables for financial firms.[5]

Results of the VAR estimation are presented in Table 4. We present the cross-sectional average of estimates for the within sector and across sector VAR coefficients for the full sample period. We also report the cross-sector VAR coefficients in the non-crisis and the crisis sub-periods. Across all sectors, we see fairly strong reversals in changes in short-term recovery rates in the full sample period: an increase in the recovery rates in the past week is corrected in the following week, indicating highly persistent implied recovery rates. There is relatively weaker persistence in the default probabilities. In unreported results, we find that the within-sector persistence in default probabilities and recovery rates is present in both non-crisis and crisis sub-periods, with slightly stronger persistence during the non-crisis interval.

We note several similarities in the cross-sector effects in default probabilities and recovery rates between financial firms and firms in each of the other sectors that make-up the non-financial group in our sample. For the full sample period, lagged changes in implied default probabilities and recovery rates in the financial industry predicts implied default probabilities or recovery rates in almost every sector in the economy. For example, an increase in the default probabilities in the financial sector significantly increases the next period's default probabilities in Consumer Staples, Information Technology and Telecommunication Services sectors. Across all these sectors, the implied default probabilities in the Telecommunication sector appears to be most affected, with significant positive (negative) reactions to changes in lagged default probabilities (recovery rates) in the financial sector. We also find that decreases in lagged recovery rates in the financial sector significantly worsen the current implied recovery rates in Materials, Industrials, and Health Care industries. In the case of the Utilities sector, significant cross-effects from the financial sector appear in the sub-periods.

[5]Note that we do not include the error correction term in the VAR model for the option-implied default probability. However, the lagged recovery rate, calculated as the difference between lagged values of the CDS and option-implied default probabilities, conveys very similar information; intuitively, it can be thought of as a restricted version of the error correction term v_{t+1}, where we place a specific restriction on the form of the linear combination of the CDS and option-implied default probabilities.

Comparing the results across sub-periods, the cross-effects we observe in the full sample period are stronger during the crisis than the non-crisis period. In fact, many of the significant coefficients reflecting the cross-sector transmission of distress in the financial sector during the full sample come solely from the crisis period. Our cross-sector effects of expected changes in default risks during the crisis are related to findings in Kelly, Lustig, and vanNieuwerburgh (2011). Kelly et al provide evidence of large divergence of individual and index put prices for the financial sector and suggests that this reflects a small aggregate tail risk in anticipation of future government bailout of the sector (but not each individual bank) during the recent crisis. They also report that sectors that are likely to benefit from implicit government guarantees for the financial sector also exhibit low sector tail risks during the crisis.

The reverse cross-effect of other sectors on the financial group's default probabilities and recovery rates are mostly insignificant, in the full sample and in both sub-periods. However, we note two exceptions. We find that lagged changes in the default probabilities in the Consumer Discretionary sector are significant and positively related to changes in the default probabilities in the financial sector. The other exception is that variations in recovery rates in the Energy sector have a similar positive effect on the recovery rates of the financial firms in the next period. It is interesting to note that the spillover in distress risks from these sectors to the financial industry is present only in the non-crisis sub-period. It is possible that the latter results may be evidence that shocks to industry-wide credit risks have adverse effects on the financial sector, particularly in the post-crisis period. The Consumer Discretionary sector, for example, includes firms in the automobile (Ford), retail (Eastman Kodak, Office Depot) and home construction (KB Home, D R Horton) industries that have experienced large negative shocks in consumer spending during the recent years.

Overall, our findings in Table 4 reinforce the notion that the financial crisis of 2007-2009 propagated distress in the financial sector, both by increasing the implied default probabilities and worsening the asset values in the other sectors. Changes in the prospects of financial firms have significant (and potentially deleterious) consequences for the real economy. Evidence of the influence of firms in non-financial firms on the health of firms in the financial sector is much more sparse. This result suggests that the shocks to the health of the financial sector have more significant repercussions to the health of other firms, and may as a consequence be evidence of systematic risk.

5.2.1 VARs in Subsectors

The results in Table 4 show that the credit crunch in the financial sector had significant spillover effects on the real sector. In this section, we analyze whether these spillover effects differ across different types of firms in the financial sector.

Using four-digit GICS industry classifications of firms in the financial sample, we break financial firms into four subsectors: Banks, Diversified Financials, Insurance and Real Estate. VARs are estimated for firms in each of these four subsectors paired with firms in all non-financial sectors. We then report the average across firms of the coefficients with accompanying cross-sectional t-statistics.

Table 5 reports the results. We find that the systemic effect of the financial sector on the real sector comes primarily from banking firms. There is a significant positive effect of lagged changes in default probabilities in the banking sector on all other firms. The coefficient estimate of the influence of lagged default probability of banks on default probabilities of other firms more than doubles, from 0.06 in the full sample to 0.13 during the crisis. However, this cross-effect is insignificant in the non-crisis period. Moreover, a rise in the default probabilities of banks has a negative effect on the recovery rates of other firms during the crisis, emphasizing the systemic influence of the banking sector on the real economy.

In contrast, the cross-effects arising from the changes in the default probabilities of other financial sub-sectors appear muted. Although we find some significant cross-effects stemming from changes in implied recovery rates in the insurance industry on the default probabilities of non-financial firms, the impact does not persist during the crisis period. In addition, the changes in default probabilities among diversified financials and real estate firms are affected by lagged changes in the non-financial group, reinforcing the view that the cross-effects stemming from the financial sector during the crisis may be restricted to a subset of financial firms.

Overall, the evidence suggests that an anticipated increase in default probabilities in the banking firms during the crisis has a strong negative impact on the survival rates for firms in the real economy.

6 Cross-Firm Effects

The preceding section indicates that, at the aggregate level, there are interesting interactions in the default probabilities and recovery rates among and between the set of financial and non-financial firms. In particular, we provide evidence to suggest that innovations in financial firms' default probabilities impact the recovery rates of both financial and non-financial firms, and that innovations in recovery rates of financial firms impact recovery rates and default probabilities in non-financial firms, particularly during the crisis. The results also suggest that some firms within the financial sector, particularly banks, had more systemic influence.

In this section, we analyze the interactions in the default probabilities and recovery rates between individual firms in the financial industry. In particular, we examine the degree to which firms' default probabilities and recovery rates are affected by other firms within the financial industry, and identify individual firms which had the biggest effects.

We concentrate our analysis on the 36 firms in the financial sector with available data during our sample period. For each firm, we construct a time series of the change in the log option-implied default probability ($dq^O_{i,t}$), the log recovery rate ($r_{i,t}$), and the lag of each of these variables. If in a given week a firm does not have two contiguous weeks of both of these variables, the observation is set to missing. Additionally, if the lag of each variable is not available in the contiguous week, the observation is set to missing. Put differently, for each observation there must be three contiguous weeks of data to permit the calculation of $dq^O_{i,t}$, $dq^O_{i,t-1}$, $r_{i,t}$, and $r_{i,t-1}$, where t indexes weeks.

We then estimate VARs for each firm pair as follows:

$$\begin{pmatrix} \Delta q_{i,t} \\ \Delta r_{i,t} \\ \Delta q_{j,t} \\ \Delta r_{j,t} \end{pmatrix} = \begin{pmatrix} \mu_{q,i} \\ \mu_{r,i} \\ \mu_{q,j} \\ \mu_{r,j} \end{pmatrix} + \begin{pmatrix} \phi_{qq,ii} & \phi_{qr,ii} & \phi_{qq,ij} & \phi_{qr,ij} \\ \phi_{rq,ii} & \phi_{rr,ii} & \phi_{rq,ij} & \phi_{rr,ij} \\ \phi_{qq,ji} & \phi_{qr,ji} & \phi_{qq,jj} & \phi_{qr,jj} \\ \phi_{rq,ji} & \phi_{rr,ji} & \phi_{rq,jj} & \phi_{rr,jj} \end{pmatrix} \begin{pmatrix} dq^O_{i,t-1} \\ r_{i,t-1} \\ dq^O_{j,t-1} \\ r_{j,t-1} \end{pmatrix} + \begin{pmatrix} \eta_{q,i,t} \\ \eta_{r,i,t} \\ \eta_{q,j,t} \\ \eta_{r,j,t} \end{pmatrix}, \quad (15)$$

for $i \neq j$. The coefficient $\phi_{qq,ii}$ has the interpretation of the sensitivity of firm i's default probability to innovations in its own default probability. In contrast, the coefficient $\phi_{qq,ij}$ is the sensitivity of firm i's default probability to innovations in firm j's default probability. The coefficients $\phi_{qr,ii}$ and $\phi_{qr,ij}$ represent sensitivities of firm i's default probability to innovations in firm i's and firm j's recovery rates, respectively. Our main interest is in the cross-effects in this system: the coefficiente measuring the sensitivity of firm i's default probability and recovery rates to innovations in the default probabilities and recovery rates of firm j.

We calculate the average impact of *each firm*'s default probabilities and recovery rates on other firms' default probabilities and recovery rates. For each average, we also present t-statistics and report separate results for VARs estimated over the full sample as well as the non-crisis subsamples.[6]

The estimates of cross-effect for each of the 36 financial firms for the full sample period are presented in Table 6. We find strong evidence of sensitivity of default probabilities of financial firms to innovations in default probabilities of other firms in the same industry. Of the 36 financial firms in our full sample, 14 firms have significant positive $\bar{\phi}_{qq,ij}$ coefficients, with the highest coefficients estimated for Sallie Mae (SML) and Ambac Financial (ABK). The point estimates are invariably positive for almost all firms, indicating that default probabilities are highly interdependent among the financial firms, emphasizing the common, industry-wide nature of defaults. This is consistent with the evidence presented in Jorion and Zhang (2007), where large CDS spread changes (jumps)

[6]To be included in the analyses, we require that there are at least 52 valid weekly observations for each pair of firms. The final set of firms includes firms that fail (e.g., Lehman, Washington Mutual, etc.) and others that merged during the sample period.

are used to measure within-industry credit contagion arising from defaults.

Similarly, we find evidence of changes in recovery rates in financial firms positively affecting the innovations in the recovery rates of other financial firms. The changes in recovery rates at Citigroup (C), Lehman (LEH) and Wells Fargo (WFC) carry the largest impact on other financial firms. The predictive effect of changes in anticipated recovery rates in these institutions is consistent with the fear of counterparty defaults that worsened the credit crisis immediately following the September 2008 bankruptcy filing by Lehman.

Our paper also contributes to the evidence in Jorion and Zhang (2009), who find significant credit contagion among industrial corporations with business links. Independent of whether the cross-effects within the financial sector are due to an increase in counter-party risks, or non-credit risk related contagion in expected default risks and expected loss given default, we find significant cross-firm effects in the default probabilities and recovery rates estimated from options and CDS markets.

In addition to the apparent contagion in default probabilities, we also see evidence that increases in the default probabilities of financial firms reduce the implied recovery rates at other financial firms. The point estimates of these coefficients are largely negative, with the highest estimate observed for Lehman. Similarly, a higher expected recovery rate predicts a drop in default probabilities in the next period. These findings are consistent with the 'fire-sale' intuition in Diamond and Rajan (2010), where increases in the *ex ante* likelihood that firms will default lowers next period's recovery rate for other firm's assets.

Table 6 also presents the firm level cross-effects for the non-crisis and crisis sub-periods. There are several interesting features of the sub-period estimates. Lagged changes in default probabilities of financial firms have a smaller impact during the non-crisis period. Specifically, only four out of 36 firms have highly significant cross effects in default probabilities of other financial firms during the non-crisis period, including two financial industry bellwether firms Goldman Sachs and Morgan Stanley. The number of firms with significant cross-effects in default probabilities grows to seven firms during the crisis, with the biggest impact coming from insurance firms, Genworth Financial and MBIA. In terms of cross-effects in recovery rates, there are six firms with significant average coefficients, but only one firm, Citigroup, has significant strong effects (at 95% confidence interval) on other financial firms during the non-crisis period. The significant cross-effect on expected recovery rates spreads more widely during the crisis period to 10 financial firms, with the biggest impact exerted by changes in expected recovery rates at Lehman.

We also uncover an intriguing result about the cross-effects of AIG, which was the subject of intervention by the US government during the crisis. While increases in the expected recovery rate at AIG had a small but significant positive effect on the recovery rates in other financial firms during the non-crisis, we observe an inverse cross-effect during the crisis: decreases in expected recovery rates (and deterioration in expected default probabilities) at AIG had a significant, but *positive* impact on the prospects of other financial companies. This counter intuitive result may be consistent with distortions in the no arbitrage relation between the option and CDS markets related to government interventions that guaranteed the liabilities on CDS contracts but not the investment value of equities (extracted from the options market). That is, if AIG was deemed 'too big to fail' and, as a consequence, any deterioration in AIG increased the probability of government intervention, this might in turn improve the prospects of other financial firms. This interpretation of our findings is consistent with recent evidence on the effects of anticipated government bailout during the financial crisis. Schweikhard and Tsesmelidakis (2011), for example, document that the default risks implied by debt and equity markets decoupled during the crisis as a result of government intervention to rescue debt obligations of financial firms deemed 'too big to fail'.

7 Conclusion and Future Work

We analyze the joint relation in default probabilities implied across different derivative markets, and sectors of the economy, over different time periods which include the credit crisis of 2007-2009. Specifically, we use the information in credit default swap spreads and options to retrieve measures of implied default probabilities. We compare the default probabilities implied by the different markets and find that these probabilities are closely linked. Changes in these default probabilities are more tightly linked during the financial crisis, and are robust to controlling for alternative aggregate determinants of credit spreads. Using this empirical link and the information in both measures of default probability, we extract measures of recovery rates for financial and non-financial firms. These recovery rates exhibit significant time series patterns, declining substantially during the crisis. They are also related to macroeconomic indicators, such as measures of counterparty risk.

Across sectors and markets, we find interesting patterns in the dynamics of default probabilities and recovery rates. In particular, during the financial crisis, innovations in default probabilities in financial firms tend to lead innovations in default probabilities of non-financial firms; the effect of non-financial firms on the prospect of firms in the financial sector is much weaker. As in Brunnermeier and Sannikov (2011), frictions in the financial economy appear to lead to variation in the real economy. Further, innovations in default probabilities for financial firms appear to forecast rates of recovery for financial firms; this result is driven largely by the crisis period. These results also suggest that systemic risks are transmitted from the financial system to the remainder of the economy; in addition, these results are consistent with the fire sale effects suggested in Diamond and Rajan (2010).

The results and framework in this paper are important for future research in understanding the dynamics of default probabilities and systemic risk in several ways. First, we provide evidence to suggest important no-arbitrage links between different derivative markets, suggesting that information in one market can be used to refine information in another. Second, we propose what we believe to be a novel approach to extracting recovery rates, which we show vary not only by firm, as suggested in Pan and Singleton (2008), but also across time. Finally, our results suggest that there are systemic effects in default and recovery that transmit from financial firms to non-financial firms in times of crisis.

Appendix

The scale-invariant NIG distribution is characterized by the density function

$$f(x;\alpha,\beta,\mu,\delta)=\frac{\alpha}{\pi\delta}\exp\left(\sqrt{\alpha^2-\beta^2}-\frac{\beta\mu}{\delta}\right)\frac{K_1\left(\alpha\sqrt{1+\left(\frac{x-\mu}{\delta}\right)^2}\right)}{\sqrt{1+\left(\frac{x-\mu}{\delta}\right)^2}}\exp\left(\frac{\beta}{\delta}x\right). \tag{16}$$

In this expression, $x\in\Re$, $\alpha>0$, $\delta>0$, $\mu\in\Re$, $0<|\beta|<\alpha$, and $K_1(\cdot)$ is the modified Bessel function of the third kind with index 1. The formal properties of the distribution are discussed in greater detail in Eriksson, Forsberg, and Ghysels (2004). As shown, the density is characterized by the four parameters α, β, μ, and δ.

As discussed above, a principal advantage of this density function is that it is completely characterized by its first four moments. More specifically, let the mean, variance, skewness, and excess kurtosis be denoted as $\mathcal{M}$, $\mathcal{V}$, $\mathcal{S}$, and $\mathcal{K}$. The parameters are nonlinearly related to the moments by

$$\alpha = \frac{3\left(4\rho^{-1}+1\right)}{\mathcal{K}\sqrt{(1-\rho^{-1})}} \tag{17}$$

$$\beta = sign\,(\mathcal{S})\,\frac{3\left(4\rho^{-1}+1\right)}{\mathcal{K}^{-1}\sqrt{\rho-1}} \tag{18}$$

$$\mu = \mathcal{M}-sign\,(\mathcal{S})\sqrt{\frac{3\left(4\rho^{-1}+1\right)\mathcal{V}}{\mathcal{K}\rho}} \tag{19}$$

$$\delta = \sqrt{\frac{3\left(4\rho^{-1}+1\right)\left(1-\rho^{-1}\right)\mathcal{V}}{\mathcal{K}}} \tag{20}$$

where $\rho=3\mathcal{K}\mathcal{S}^{-2}-4>1$ and $sign\,(\cdot)$ is the sign function. Thus, given risk neutral moments, one can compute the risk neutral density.

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Table 1: Descriptive Statistics

Table 1 presents descriptive statistics for credit default swap- (CDS-) implied risk-neutral default probabilities, option-implied risk neutral default probabilities, and recovery rates implied by equating CDS-implied and option-implied risk neutral default probabilities in percentage points. CDS spreads are obtained from CMA and Bloomberg and are used to calculate implied default probabilities under the assumption that the recovery rate is a constant 40% across firms and time. Option-implied default probabilities are computed using the Bakshi, Kapadia, and Madan (2003) procedure to retrieve risk neutral moments from option prices and then using these moments to determine the probability that the value of the equity is less than or equal to zero using the Normal Inverse Gaussian (NIG) distribution of Ericsson, Forsberg, and Ghysels (2009). Panel A presents the mean across time and firms, the mean time series standard deviation across firms, and the global minimum and maximum of the default probabilities and recovery rates. Additionally, we report the mean time series correlation of the option-implied and CDS-implied default probabilities. We separately analyze two subperiods and two subsets of firms. Our subperiods are during the financial crisis ('Crisis'), which we date from the BNP Paribas event in August, 2007 until the NBER end of recession in June, 2009, and for time periods prior-to and subsequent to the crisis ('Non-Crisis'). The subsets of firms are 'Financial' firms, defined as firms with Global Industrial Classification Standard sector code (GICS) from Compustat of 40, and 'Non-Financial' firms, defined as those with GICS sector code not equal to 40. Panel B presents statistics for the subsamples of financial and non-financial firms for the full sample. Panel C presents statistics for all firms for the subsamples of the crisis and non-crisis periods. Panel D presents results for non-financial firms separated into subsamples for the crisis and non-crisis periods. Panel E presents statistics for financial firms for the two subperiods. In order to be included in the sample, a firm must be a constituent of the S&P 500 index as of January 1, 2006 and have one year (52 weeks) of observations. There are 260 total firms in the sample; 223 non-financial firms and 37 financial firms. Options data are obtained from OptionMetrics with maturities closest to, but less than 365 days. Data are sampled at the daily frequency and aggregated to weekly, covering the period January 1, 2006 through July 23, 2010 for 238 weekly observations.

Panel A: All Firms, Full Sample

	CDS	$q^{C,0.4}$	q^O	R	ρ_{q^C,q^O}
Mean	1.301	2.135	4.322	0.751	0.699
Std	0.943	1.521	2.107	0.121	0.199
Min	0.023	0.038	0.001	0.000	-0.468
Max	35.292	49.908	21.410	0.990	0.945

Panel B: Non-Financial and Financial Firms, Full Sample

Non-Financial Firms

	CDS	$q^{C,0.4}$	q^O	R	ρ_{q^C,q^O}
Mean	1.209	1.989	4.145	0.750	0.684
Std	0.779	1.263	1.843	0.116	0.203
Min	0.023	0.038	0.001	0.000	-0.468
Max	35.292	49.908	17.768	0.990	0.945

Financial Firms

	CDS	$q^{C,0.4}$	q^O	R	ρ_{q^C,q^O}
Mean	1.857	3.018	5.394	0.756	0.791
Std	1.930	3.078	3.695	0.150	0.138
Min	0.080	0.133	0.054	0.010	0.170
Max	32.119	46.166	21.401	0.974	0.933

Table continued on next page.

Panel C: All Firms, Subperiods

Non-Crisis	CDS	$q^{C,0.4}$	q^{O}	R	ρ_{q^C,q^O}
Mean	0.934	1.537	3.535	0.780	0.600
Std	0.566	0.921	1.380	0.103	0.308
Min	0.023	0.038	0.001	0.003	-0.770
Max	23.496	35.168	18.239	0.990	0.974

Crisis	CDS	$q^{C,0.4}$	q^{O}	R	ρ_{q^C,q^O}
Mean	1.825	2.984	5.405	0.710	0.650
Std	0.974	1.562	2.226	0.112	0.237
Min	0.053	0.088	0.245	0.000	-0.284
Max	35.292	49.908	21.410	0.980	0.977

Panel D: Non-Financial Firms, Subperiods

Non-Crisis	CDS	$q^{C,0.4}$	q^{O}	R	ρ_{q^C,q^O}
Mean	0.899	1.483	3.467	0.776	0.582
Std	0.489	0.799	1.286	0.100	0.316
Min	0.023	0.038	0.001	0.003	-0.770
Max	20.924	31.774	15.039	0.990	0.951

Crisis	CDS	$q^{C,0.4}$	q^{O}	R	ρ_{q^C,q^O}
Mean	1.648	2.700	5.037	0.716	0.640
Std	0.807	1.301	1.947	0.108	0.245
Min	0.053	0.088	0.245	0.000	-0.284
Max	35.292	49.908	17.768	0.980	0.977

Panel E: Financial Firms, Subperiods

Non-Crisis	CDS	$q^{C,0.4}$	q^{O}	R	ρ_{q^C,q^O}
Mean	1.142	1.864	3.944	0.807	0.711
Std	1.030	1.661	1.947	0.117	0.225
Min	0.080	0.133	0.054	0.010	0.097
Max	23.440	35.168	18.239	0.974	0.975

Crisis	CDS	$q^{C,0.4}$	q^{O}	R	ρ_{q^C,q^O}
Mean	2.877	4.671	7.596	0.675	0.706
Std	1.960	3.105	3.882	0.134	0.172
Min	0.208	0.346	0.267	0.018	0.125
Max	32.119	46.166	21.410	0.944	0.926

Table 2: Contemporaneous Regressions with Error Correction

Table 2 presents results of regressions of default probabilities implied by CDS spreads on those implied by option prices and vice versa. Specifically, we present results of the following regressions:

$$\begin{aligned}\Delta q^C_{i,j,t} &= \alpha_{i,j,1} + \beta_{i,j,1}\Delta q^O_{i,j,t} + \boldsymbol{\gamma}'_{i,j,1}\mathbf{x}_t + \delta_{i,j,1}v_{i,j,t-1} + \epsilon_{i,j,1,t}\\ \Delta q^O_{i,j,t} &= \alpha_{i,j,2} + \beta_{i,j,2}\Delta q^C_{i,j,t} + \boldsymbol{\gamma}'_{i,j,2}\mathbf{x}_t + \delta_{i,j,2}v_{i,j,t-1} + \epsilon_{i,j,2,t},\end{aligned}$$

where $i = \{1, ..., N\}$ indexes firms and $j = \{F, NF\}$ indexes sector. where $\Delta q^C_{i,t}$ represents the first difference in the log average (across firms) of the risk neutral probability implied by credit default swaps, assuming a recovery rate of 0.4 and $\overline{q}^O_{i,t}$ is the average risk neutral default probability implied in the options market. The vector $\mathbf{x}_t$ is a vector of covariates: Δy_t, the first difference in the log of the five year constant maturity treasury yield, $(\Delta y_t)^2$, log yield innovation squared, Δs_t, the first difference in the slope of the yield curve measured by the difference in the five-year yield and the 3-month secondary market Treasury Bill yield, ted_t, the difference in the 3-month Eurodollar deposit rate and the 3-month secondary market Treasury Bill yield, $r_{S,t}$, the log stock return on the S&P 500 index, and Δvix_t, the first difference in the log VIX index. Data on the five-year constant maturity yield, 3-month secondary market Treasury Bill yield, and Eurodollar deposit rate are taken from the H.15 report at the Federal Reserve. Stock returns and the VIX are from the CRSP daily stock files. The variable $v_{i,t-1}$ is an error correction term from a regression of log levels of CDS probabilities on a time trend and log levels of option probabilities,

$$q^C_{i,j,t} = \theta_{i,0} + \theta_{i,j,1}t + \theta_{i,2}q^O_{i,t} + v_{i,t}.$$

The table presents average coefficients across firms and t-statistics calculated using cross-sectional standard errors for the parameters. In Panel A, we present results for the full sample period, where firms are grouped by sector. Financial sector firms ($j = F$) have Global Industrial Classification Standard (GICS) sector code 40, obtained from Compustat. Non-Financial firms ($j = NF$) are firms with GICS sector codes other than 40. Results for two subperiods are presented in Panels B and C. In Panel B, we present results for the 'Non-Crisis' period, defined as periods prior to the BNP Paribas event in August, 2007, and subsequent to the NBER end recession date in June, 2009. 'Crisis' refers to the subperiod between August, 2007 and June, 2009. Data are sampled at the daily frequency and aggregated to weekly, covering the period January 1, 2006 through July 23, 2010 for 238 weekly observations.

Panel A: Full Sample

Dep. Var.	Const.	$\Delta q^{O/C}_{i,j,t}$	$v_{i,t-1}$	Δy_t	$(\Delta y_t)^2$	Δs_t	ted_t	Δvix_t	$r_{S,t}$
$\Delta q^C_{i,NF,t}$	-0.012	0.064	-0.050	-0.226	1.957	0.008	0.019	0.103	-0.011
T-Stat	-5.708	11.066	-18.608	-11.316	2.409	4.229	5.077	12.536	-24.080
$\Delta q^O_{i,NF,t}$	0.063	0.164	0.148	-0.141	-1.897	-0.039	-0.013	0.091	0.000
T-Stat	11.739	10.361	18.837	-3.606	-1.717	-7.672	-1.660	5.894	-0.565
$\Delta q^C_{i,F,t}$	-0.004	0.086	-0.049	-0.343	2.053	0.004	0.107	0.089	-0.018
T-Stat	-1.282	7.390	-7.584	-3.958	1.186	1.451	5.638	4.196	-11.337
$\Delta q^O_{i,F,t}$	0.070	0.177	0.159	0.027	0.107	-0.047	-0.026	0.020	-0.004
T-Stat	8.714	7.773	12.723	0.286	0.051	-6.467	-1.648	0.852	-1.980

Panel B: Non-Crisis

Dep. Var.	Const.	$\Delta q_{i,j,t}^{O/C}$	$v_{i,t-1}$	Δy_t	$(\Delta y_t)^2$	Δs_t	ted_t	Δvix_t	$r_{S,t}$
$\Delta q_{i,NF,t}^{C}$	-0.016	0.085	-0.067	-0.450	6.570	0.010	0.110	0.064	-0.009
T-Stat	-4.226	4.145	-11.662	-11.933	5.672	2.591	6.732	4.899	-12.380
$\Delta q_{i,NF,t}^{O}$	0.085	0.222	0.222	0.090	5.071	-0.042	-0.003	-0.101	-0.021
T-Stat	7.481	7.400	12.558	1.013	2.733	-5.866	-0.072	-4.954	-11.772
$\Delta q_{i,F,t}^{C}$	-0.014	0.087	-0.046	-0.607	13.265	0.022	0.132	0.013	-0.016
T-Stat	-1.792	5.900	-5.679	-5.230	4.464	1.228	3.672	0.593	-6.609
$\Delta q_{i,F,t}^{O}$	0.104	0.334	0.181	0.025	2.074	-0.021	0.173	-0.164	-0.021
T-Stat	5.313	7.662	8.283	0.133	0.458	-0.962	3.170	-3.855	-4.866

Panel C: Crisis

Dep. Var.	Const.	$\Delta q_{i,j,t}^{O/C}$	$v_{i,t-1}$	Δy_t	$(\Delta y_t)^2$	Δs_t	ted_t	Δvix_t	$r_{S,t}$
$\Delta q_{i,NF,t}^{C}$	-0.012	0.087	-0.064	-0.131	-0.522	0.014	0.020	0.213	-0.010
T-Stat	-3.111	7.192	-12.721	-4.683	-1.327	5.685	1.901	16.437	-18.179
$\Delta q_{i,NF,t}^{O}$	0.043	0.176	0.135	-0.163	-1.528	-0.031	-0.005	0.012	0.002
T-Stat	6.150	9.511	11.754	-3.901	-2.762	-6.844	-0.697	0.644	2.548
$\Delta q_{i,F,t}^{C}$	0.018	0.189	-0.098	-0.101	4.487	-0.003	0.102	0.334	-0.013
T-Stat	1.050	5.480	-6.928	-0.851	1.054	-0.277	4.526	5.693	-5.350
$\Delta q_{i,F,t}^{O}$	-0.007	0.166	0.194	-0.030	-4.190	-0.009	-0.025	-0.047	-0.001
T-Stat	-0.349	6.202	10.194	-0.298	-1.031	-0.797	-1.404	-0.767	-0.638

Table 3: Determinants of Recovery Rates

Table 3 analyzes aggregate determinants of implied recovery rates. Recovery rates are determined by using information in CDS-implied and option-implied risk-neutral default probabilities. Specifically, we solve for the recovery rates that set these two probabilities equal:

$$q^{O}_{i,t}(\tau) = 1 - \left(1 - \frac{0.25 s_{i,t}}{1 - \hat{R_{i,t}} + s_{i,t}/8}\right)^{4\tau}.$$

We regress the log first difference of these recovery rates on aggregate variables:

$$\Delta \ln \hat{R}_{i,t} = \alpha_i + \beta_{i,1}\Delta y_t + \beta_{i,2}\left(\Delta y_t\right)^2 + \beta_3 \Delta s_{i,t} + \beta_{i,4} ted_t + \beta_{i,5} r_{S,t} + \beta_{i,6}\Delta VIX_t + \epsilon_{i,t},$$

where Δy_t is first difference of the log five year constant maturity treasury yield, Δs_t is the first difference of the slope of the yield curve measured by the difference in the five-year yield and the 3-month secondary market Treasury Bill yield, ted_t is the spread between the 3-month Eurodollar deposit rate and the 3-month secondary market Treasury Bill yield, $r_{S,t}$ is the log return on the S&P 500 at time t, and Δvix_t is the change in the log VIX index. Data on the five-year constant maturity yield, 3-month secondary market Treasury Bill yield, and Eurodollar deposit rate are taken from the H.15 report at the Federal Reserve. The return on the S&P 500 and market values are from the CRSP daily stock files. The table reports the cross-sectional average of firm-level regression coefficients with cross-sectional t-statistics underneath the averages.financial firms in Panel A, as determined by S&P GICS code and non-financial firms in Panel C. In each panel, we analyze the regressions for the full sample, the non-crisis period, defined as the pre-BNP Paribas (August, 2007) and after NBER recession (June, 2009) subperiods, and the crisis period. Data are aggregated to weekly and cover the period January 1, 2006 through July 23, 2010, for 238 weekly observations.

Panel A: Financial Firms

	Constant	Δy_t	$(\Delta y_t)^2$	Δs_t	ted_t	Δvix_t	r_S
Full Sample Coeff.	0.008	-0.089	-7.516	0.002	-0.156	0.092	0.013
T-Stat	1.077	-0.331	-1.167	0.413	-3.765	1.905	3.725
Non-Crisis Coefficient	-0.015	-0.260	-6.489	0.004	-0.006	-0.002	0.003
T	-0.925	-0.629	-1.281	0.487	-0.097	-0.028	0.951
Crisis Coefficient	0.031	0.001	-8.665	-0.011	-0.156	0.044	0.015
T	1.646	0.007	-1.157	-1.426	-3.189	0.302	2.763

Panel B: Non-Financial Firms

	Constant	Δy_t	$(\Delta y_t)^2$	Δs_t	ted_t	Δvix_t	r_S
Full Sample Coeff.	-0.002	-0.127	1.692	0.001	0.011	-0.002	0.008
T-Stat	-1.105	-2.132	1.056	1.273	0.810	-0.065	5.397
Non-Crisis Coefficient	0.007	0.269	-1.518	0.000	-0.016	-0.043	-0.004
T	0.856	2.302	-0.671	0.113	-0.567	-1.539	-1.536
Crisis Coefficient	0.019	-0.199	2.327	-0.012	0.009	-0.109	0.009
T	1.666	-3.132	1.715	-1.621	0.542	-2.184	6.487

Table 4: Sector Vector Autoregressions of Default and Recovery Rates

Table 4 presents results of vector autoregressions (VARs) for aggregate measures of risk neutral default probabilities and recovery rates across sectors. The VAR that we investigate is of the form $\mathbf{y}_{t+1} = \boldsymbol{\mu} + \boldsymbol{\Phi}\mathbf{y}_t + \boldsymbol{\eta}_{t+1}$,

$$\begin{pmatrix} \Delta q_{i,t+1} \\ \Delta r_{i,t+1} \\ \Delta q_{f,t+1} \\ \Delta r_{f,t+1} \end{pmatrix} = \begin{pmatrix} \mu_{i,q} \\ \mu_{i,r} \\ \mu_{f,q} \\ \mu_{f,r} \end{pmatrix} + \begin{pmatrix} \phi_{qq,ii} & \phi_{qr,ii} & \phi_{qq,if} & \phi_{qr,if} \\ \phi_{rq,ii} & \phi_{rr,ii} & \phi_{rq,if} & \phi_{rr,if} \\ \phi_{qq,fi} & \phi_{qr,fi} & \phi_{qq,ff} & \phi_{qr,ff} \\ \phi_{rq,fi} & \phi_{rr,fi} & \phi_{rq,ff} & \phi_{rr,ff} \end{pmatrix} \begin{pmatrix} \Delta q_{i,t} \\ \Delta r_{i,t} \\ \Delta q_{f,t} \\ \Delta r_{f,t} \end{pmatrix} + \begin{pmatrix} \eta_{i,q,t+1} \\ \eta_{i,r,t+1} \\ \eta_{f,q,t+1} \\ \eta_{f,r,t+1} \end{pmatrix},$$

where $\Delta q_{i,t+1}$ is the change in log CDS-implied default probability for sector i, $\Delta r_{i,t+1}$ is the change in log recovery rates for sector i, and $\Delta q_{f,t+1}$ and $\Delta r_{f,t+1}$ are the corresponding changes in log default probabilities and recovery rates for the financial sector. Sectors are defined by two-digit Global Industrial Classification Standard (GICS) code from Compustat. VARs are estimated at the firm level and coefficients reported are means across firms with accompanying cross-sectional t-statistics. For each sector, we report own effects (the block diagonals of the matrix $\boldsymbol{\Phi}$) for the full sample and cross effects (the block off-diagonals of the matrix $\boldsymbol{\Phi}$) for the full sample, crisis, and non-crisis subperiods. Data cover the period January 1, 2006 through July 23, 2010, for 238 weekly observations.

Panel A: Energy

	Own Effects		Cross Effects					
	Full Sample		Full Sample		Non-Crisis		Crisis	
	Default	Recovery	Default	Recovery	Default	Recovery	Default	Recovery
$\Delta q_{i,t+1}$	0.0009	-0.1282	-0.0299	-0.0838	-0.0286	-0.2835	0.1568	-0.0389
	0.0089	-0.7448	-0.3122	-0.9999	-0.1980	-1.7512	1.1317	-0.4427
$\Delta r_{i,t+1}$	0.1419	-0.2609	-0.0877	0.0083	-0.1106	-0.0894	0.0438	0.0437
	2.6488	-2.8960	-1.7479	0.1890	-1.7732	-1.2780	0.4472	0.7029
$\Delta q_{f,t+1}$	-0.1782	-0.1512	0.1008	-0.1330	0.0528	0.1090	0.1401	-0.2835
	-1.8730	-1.8182	0.9918	-0.7784	0.3812	0.4326	1.0526	-1.3936
$\Delta r_{f,t+1}$	-0.0452	-0.2553	-0.0222	0.2756	-0.0883	0.4977	0.1075	0.0214
	-0.6854	-4.4335	-0.3149	2.3294	-1.0556	3.2731	0.8409	0.1097

Panel B: Materials

	Own Effects		Cross Effects					
	Full Sample		Full Sample		Non-Crisis		Crisis	
	Default	Recovery	Default	Recovery	Default	Recovery	Default	Recovery
$\Delta q_{i,t+1}$	-0.3644	0.1804	0.1607	0.0152	0.1309	-0.2757	0.0520	0.2637
	-5.4188	1.2989	1.7940	0.1608	1.0651	-1.4979	0.3927	2.9971
$\Delta r_{i,t+1}$	0.0375	-0.2125	-0.0479	0.1127	-0.0130	-0.0468	-0.2628	0.3019
	0.9621	-2.6379	-0.9227	2.0509	-0.3063	-0.7380	-1.8585	3.2124
$\Delta q_{f,t+1}$	-0.1587	-0.1481	0.0713	-0.1344	0.0885	0.0763	-0.0783	-0.0692
	-2.0836	-1.8377	1.2472	-1.1377	1.3512	0.3395	-0.5364	-0.5143
$\Delta r_{f,t+1}$	-0.0029	-0.2159	-0.0149	-0.0460	-0.0351	0.1498	0.1113	-0.1859
	-0.0542	-3.8135	-0.3721	-0.5549	-0.8523	1.0588	0.7998	-1.4492

Table continued on next page

Panel C: Industrials

	Own Effects		Cross Effects					
	Full Sample		Full Sample		Non-Crisis		Crisis	
	Default	Recovery	Default	Recovery	Default	Recovery	Default	Recovery
$\Delta q_{i,t+1}$	-0.1276	-0.3463	-0.0555	0.1195	-0.0104	-0.0485	-0.1215	0.0404
	-1.2525	-2.5575	-0.4954	1.2209	-0.0579	-0.2174	-1.0336	0.5592
$\Delta r_{i,t+1}$	0.0346	-0.3958	-0.0626	0.1393	0.0699	-0.0024	-0.2084	0.1429
	0.6524	-5.6199	-1.0738	2.7356	1.0358	-0.0282	-1.7520	1.9554
$\Delta q_{f,t+1}$	-0.0627	-0.1203	-0.0698	-0.1533	-0.1488	0.1371	0.1885	-0.3260
	-0.6477	-1.4236	-0.7936	-1.3117	-1.3329	0.7396	1.2160	-2.3054
$\Delta r_{f,t+1}$	0.0542	-0.1582	-0.0730	-0.1872	-0.1670	-0.1452	0.2958	-0.3608
	0.8124	-2.7136	-1.2041	-2.3220	-2.4709	-1.2942	2.0161	-2.6969

Panel D: Consumer Discretionary

	Own Effects		Cross Effects					
	Full Sample		Full Sample		Non-Crisis		Crisis	
	Default	Recovery	Default	Recovery	Default	Recovery	Default	Recovery
$\Delta q_{i,t+1}$	0.1546	-0.1139	-0.0027	-0.1136	-0.0337	-0.1232	0.1702	-0.1203
	1.6578	-1.5149	-0.0443	-2.0589	-0.4009	-1.1271	1.6788	-2.0574
$\Delta r_{i,t+1}$	0.2359	-0.2333	-0.1202	0.0336	-0.1113	0.0695	-0.0875	0.0411
	2.6965	-3.3052	-2.0675	0.6497	-1.8804	0.9028	-0.6443	0.5239
$\Delta q_{f,t+1}$	-0.2731	-0.1027	0.4665	-0.4849	0.6251	-0.5066	0.0318	-0.2691
	-3.0925	-1.3067	3.5117	-4.5250	3.3937	-2.0653	0.1703	-2.5819
$\Delta r_{f,t+1}$	-0.1332	-0.1656	0.3510	-0.3156	0.4943	-0.4151	0.0625	-0.2207
	-2.1481	-3.0017	3.7638	-4.1953	4.4008	-2.7754	0.3445	-2.1784

Panel E: Consumer Staples

	Own Effects		Cross Effects					
	Full Sample		Full Sample		Non-Crisis		Crisis	
	Default	Recovery	Default	Recovery	Default	Recovery	Default	Recovery
$\Delta q_{i,t+1}$	-0.0991	0.1291	0.0909	-0.0435	-0.0118	0.0457	0.3293	-0.1185
	-1.1716	1.2785	1.8610	-0.9020	-0.1994	0.5727	3.3930	-1.8804
$\Delta r_{i,t+1}$	0.1149	-0.2483	-0.0218	-0.0161	-0.0445	-0.0220	0.0550	-0.0250
	1.9774	-3.5824	-0.6503	-0.4869	-1.5375	-0.5625	0.6515	-0.4567
$\Delta q_{f,t+1}$	-0.1093	-0.1753	-0.0611	0.0776	-0.1286	0.0011	0.0447	0.0893
	-1.3144	-2.1343	-0.4241	0.4519	-0.5869	0.0030	0.2700	0.5818
$\Delta r_{f,t+1}$	0.0708	-0.2062	-0.2665	-0.0259	-0.3648	-0.1038	-0.1296	-0.0122
	1.2394	-3.6508	-2.6923	-0.2195	-2.7639	-0.4580	-0.8181	-0.0835

Table continued on next page.

Panel F: Healthcare

	Own Effects		Cross Effects					
	Full Sample		Full Sample		Non-Crisis		Crisis	
	Default	Recovery	Default	Recovery	Default	Recovery	Default	Recovery
$\Delta q_{i,t+1}$	-0.0719	0.0310	0.0155	0.0017	-0.0404	0.1083	0.1044	-0.1257
	-1.0193	0.3044	0.3097	0.0317	-0.6083	1.0778	1.1297	-2.0382
$\Delta r_{i,t+1}$	0.1648	-0.4003	-0.0815	0.1705	-0.0687	0.1326	-0.0775	0.1433
	3.3456	-5.6292	-2.3370	4.5668	-1.4555	1.8606	-1.2615	3.4960
$\Delta q_{f,t+1}$	-0.1840	-0.1622	0.2114	-0.0352	0.1492	-0.0520	0.0974	-0.0017
	-2.4673	-2.0310	2.0067	-0.2313	1.0245	-0.2532	0.6707	-0.0083
$\Delta r_{f,t+1}$	-0.0248	-0.2046	0.0399	-0.1308	0.0205	-0.1183	0.0304	-0.1548
	-0.4716	-3.6323	0.5377	-1.2201	0.2248	-0.9178	0.2190	-0.7934

Panel G: Information Technology

	Own Effects		Cross Effects					
	Full Sample		Full Sample		Non-Crisis		Crisis	
	Default	Recovery	Default	Recovery	Default	Recovery	Default	Recovery
$\Delta q_{i,t+1}$	-0.1463	-0.0397	0.1443	0.0807	0.1090	0.2069	0.2112	-0.0226
	-2.0340	-0.5162	2.3685	1.2399	1.3867	1.8312	1.8086	-0.2844
$\Delta r_{i,t+1}$	-0.0025	-0.2566	0.0278	0.0604	0.1161	-0.0515	-0.0822	0.1066
	-0.0329	-3.1853	0.4354	0.8868	1.7411	-0.5379	-0.5421	1.0346
$\Delta q_{f,t+1}$	-0.1393	-0.1761	0.0340	0.0195	-0.0981	0.0344	0.1219	-0.0258
	-1.7831	-2.1095	0.3683	0.1974	-0.7462	0.1780	1.0779	-0.2573
$\Delta r_{f,t+1}$	-0.0291	-0.2087	0.0364	-0.0326	-0.0609	0.0612	0.1660	-0.1238
	-0.5321	-3.5718	0.5631	-0.4723	-0.7395	0.5061	1.5419	-1.2963

Panel H: Telecommunications

	Own Effects		Cross Effects					
	Full Sample		Full Sample		Non-Crisis		Crisis	
	Default	Recovery	Default	Recovery	Default	Recovery	Default	Recovery
$\Delta q_{i,t+1}$	-0.0654	-0.0249	0.2680	-0.4031	0.1228	-0.0288	0.4483	-0.4736
	-0.6844	-0.2320	2.7872	-2.9708	0.9306	-0.0799	2.3386	-3.1379
$\Delta r_{i,t+1}$	0.0587	-0.0710	0.1247	-0.2164	0.0362	-0.0680	0.2175	-0.2177
	0.6868	-0.7379	1.4496	-1.7820	0.4419	-0.3046	0.9661	-1.2283
$\Delta q_{f,t+1}$	-0.1420	-0.1379	0.1413	-0.1675	0.0659	0.0152	0.0493	-0.1930
	-1.7034	-1.1725	1.7061	-1.7979	0.5586	0.0918	0.4350	-1.9538
$\Delta r_{f,t+1}$	-0.0963	-0.3442	0.0194	0.0082	-0.0295	0.1317	-0.0208	-0.0223
	-1.7851	-4.5221	0.3622	0.1367	-0.5309	1.6921	-0.1854	-0.2280

Panel I: Utilities

$\Delta q_{i,t+1}$	0.0379	-0.0147	0.0040	-0.0046	-0.0432	0.0004	0.1958	-0.0682
	0.5281	-0.4093	0.0760	-0.0801	-0.6311	0.0031	1.9947	-1.0433
$\Delta r_{i,t+1}$	0.2028	0.0049	-0.1016	0.1129	-0.0921	0.2250	-0.2028	0.0858
	1.7925	0.0875	-1.2352	1.2567	-1.2972	1.8280	-0.9540	0.6062
$\Delta q_{f,t+1}$	-0.1631	-0.0647	0.0249	-0.1195	0.1063	-0.2733	-0.1108	-0.0486
	-2.0496	-0.7448	0.2283	-2.2116	0.6011	-1.7759	-0.8957	-1.0283
$\Delta r_{f,t+1}$	-0.0196	-0.2306	0.0234	-0.0770	-0.0401	-0.1792	0.1300	-0.0675
	-0.3426	-3.7005	0.2992	-1.9876	-0.3648	-1.8729	1.0928	-1.4845

Table 5: Industry Vector Autoregressions of Default and Recovery Rates

Table 5 presents results of vector autoregressions (VARs) for aggregate measures of risk neutral default probabilities and recovery rates across 36 firms in the financial sector. The VAR that we investigate is of the form $\mathbf{y}_{t+1} = \boldsymbol{\mu} + \boldsymbol{\Phi}\mathbf{y}_t + \boldsymbol{\eta}_{t+1}$,

$$\begin{pmatrix} \Delta q_{i,t+1} \\ \Delta r_{i,t+1} \\ \Delta q_{f,t+1} \\ \Delta r_{f,t+1} \end{pmatrix} = \begin{pmatrix} \mu_{i,q} \\ \mu_{i,r} \\ \mu_{f,q} \\ \mu_{f,r} \end{pmatrix} + \begin{pmatrix} \phi_{qq,ii} & \phi_{qr,ii} & \phi_{qq,if} & \phi_{qr,if} \\ \phi_{rq,ii} & \phi_{rr,ii} & \phi_{rq,if} & \phi_{rr,if} \\ \phi_{qq,fi} & \phi_{qr,fi} & \phi_{qq,ff} & \phi_{qr,ff} \\ \phi_{rq,fi} & \phi_{rr,fi} & \phi_{rq,ff} & \phi_{rr,ff} \end{pmatrix} \begin{pmatrix} \Delta q_{i,t} \\ \Delta r_{i,t} \\ \Delta q_{f,t} \\ \Delta r_{f,t} \end{pmatrix} + \begin{pmatrix} \eta_{i,q,t+1} \\ \eta_{i,r,t+1} \\ \eta_{f,q,t+1} \\ \eta_{f,r,t+1} \end{pmatrix},$$

where $\Delta q_{i,t+1}$ is the change in log CDS-implied default probability for non-financial firm i, $\Delta r_{i,t+1}$ is the change in log recovery rates for non-financial firm i, and $\Delta q_{f,t+1}$ and Δr_{ft+1} are the corresponding changes in log default probabilities and recovery rates for firms in financial industries. The financial industries, $f = \{BK, DF, IN, RE\}$ represent Banks, Diversified Financials, Insurance, and Real Estate, respectively. Financial industries are defined by four-digit Global Industrial Classification Standard (GICS) code from Compustat (GICS code 40). VARs are estimated at the firm level and coefficients reported are means across firms with accompanying cross-sectional t-statistics. For each industry, we report own effects (the block diagonals of the matrix $\boldsymbol{\Phi}$) for the full sample and cross effects (the block off-diagonals of the matrix $\boldsymbol{\Phi}$) for the full sample, crisis, and non-crisis subperiods. Data cover the period January 1, 2006 through July 23, 2010, for 238 weekly observations.

Panel A: Banks

	Own Effects		Cross Effects					
	Full Sample		Full Sample		Non-Crisis		Crisis	
	Default	Recovery	Default	Recovery	Default	Recovery	Default	Recovery
$\Delta q_{i,t+1}$	0.0486	-0.2021	0.0638	-0.0425	-0.0220	0.0406	0.1294	-0.0844
	0.6055	-1.8509	2.0870	-1.2515	-0.3852	0.3008	3.8825	-2.7162
$\Delta r_{i,t+1}$	0.0383	-0.0718	0.0318	-0.0349	-0.0193	0.0920	0.0510	-0.0521
	0.6426	-0.8849	1.4000	-1.3844	-0.7717	1.5578	1.2270	-1.3446
$\Delta q_{BK,t+1}$	-0.0830	-0.1467	0.0682	-0.3104	0.0824	-0.6204	0.0558	-0.2188
	-0.8573	-1.3649	0.2685	-0.8985	0.2689	-0.9419	0.0971	-0.4741
$\Delta r_{BK,t+1}$	0.0177	-0.3685	0.1138	-0.4247	-0.3046	0.3198	0.5280	-0.7569
	0.2098	-3.9286	0.5131	-1.4089	-2.0739	1.0131	0.8637	-1.5436

Panel B: Diversified Financials

	Own Effects		Cross Effects					
	Full Sample		Full Sample		Non-Crisis		Crisis	
	Default	Recovery	Default	Recovery	Default	Recovery	Default	Recovery
$\Delta q_{i,t+1}$	0.0749	-0.2462	-0.0152	-0.0188	0.0413	-0.0793	-0.0340	0.0117
	0.7195	-1.6959	-0.3009	-0.3072	0.5573	-0.7917	-0.5043	0.1728
$\Delta r_{i,t+1}$	0.0988	-0.0952	-0.0250	-0.0392	-0.0111	-0.0501	-0.0185	-0.0329
	1.6518	-1.1403	-0.8613	-1.1122	-0.4010	-1.3445	-0.2943	-0.5209
$\Delta q_{DF,t+1}$	-0.2033	-0.1930	0.4025	-0.6163	-0.0816	-0.4935	0.9235	-0.8184
	-1.9967	-1.5622	1.9175	-2.1045	-0.2634	-0.7713	3.7012	-3.2195
$\Delta r_{DF,t+1}$	0.0549	-0.4145	-0.0206	-0.1891	-0.2583	0.1259	0.1738	-0.3548
	0.9672	-6.0187	-0.1758	-1.1583	-1.7225	0.4066	0.8859	-1.7755

Panel C: Insurance

	Own Effects		Cross Effects					
	Full Sample		Full Sample		Non-Crisis		Crisis	
	Default	Recovery	Default	Recovery	Default	Recovery	Default	Recovery
$\Delta q_{i,t+1}$	0.0828	-0.2909	-0.0391	0.0176	-0.0671	0.0056	0.0761	-0.0173
	0.9058	-2.0164	-0.7129	0.5104	-0.9181	0.1117	0.8880	-0.3695
$\Delta r_{i,t+1}$	0.1102	-0.1806	-0.0653	0.0334	-0.0413	0.0096	-0.1102	0.0679
	2.0981	-2.1796	-2.0716	1.6866	-1.5028	0.5102	-1.3926	1.5716
$\Delta q_{IN,t+1}$	-0.1829	-0.2023	0.1641	-0.1776	0.1104	0.3326	-0.0193	-0.0734
	-2.1482	-3.7762	1.1564	-0.7933	0.5566	0.7105	-0.1047	-0.3589
$\Delta r_{IN,t+1}$	-0.0414	-0.0525	0.1384	-0.3696	0.0955	-0.4062	0.3356	-0.3343
	-0.5352	-1.0781	1.0724	-1.8156	0.5509	-0.9925	1.5113	-1.3576

Panel D: Real Estate

	Own Effects		Cross Effects					
	Full Sample		Full Sample		Non-Crisis		Crisis	
	Default	Recovery	Default	Recovery	Default	Recovery	Default	Recovery
$\Delta q_{i,t+1}$	0.0659	-0.2797	0.0086	-0.0242	-0.0297	-0.0368	0.0765	-0.0057
	0.7227	-2.0077	0.1959	-0.7622	-0.4151	-0.5896	1.4860	-0.1769
$\Delta r_{i,t+1}$	0.0819	-0.1612	-0.0033	0.0216	0.0001	-0.0276	0.0206	0.0483
	1.2964	-1.6711	-0.1092	0.9831	0.0028	-1.0829	0.3513	1.3128
$\Delta q_{RE,t+1}$	-0.1620	0.1099	0.3813	-0.6985	0.4229	-0.5145	0.6234	-0.8833
	-1.9064	1.7913	2.1622	-2.5942	1.7517	-0.9021	1.6541	-2.8054
$\Delta r_{RE,t+1}$	-0.0317	-0.0672	0.0491	0.0348	0.0076	0.5040	0.4758	-0.3454
	-0.2544	-0.7458	0.1895	0.0879	0.0288	0.8129	0.7086	-0.6157

Table 6: Firm-Level Vector Autoregressions of Default and Recovery Rates

Table 6 presents results of vector autoregressions (VARs) for aggregate measures of risk neutral default probabilities and recovery rates across sectors. The VAR that we investigate is of the form $\mathbf{y}_{t+1} = \boldsymbol{\mu} + \boldsymbol{\Phi}\mathbf{y}_t + \boldsymbol{\eta}_{t+1}$,

$$\begin{pmatrix} \Delta q_{i,t+1} \\ \Delta r_{i,t+1} \\ \Delta q_{jt+1} \\ \Delta r_{jt+1} \end{pmatrix} = \begin{pmatrix} \mu_{i,q} \\ \mu_{i,r} \\ \mu_{jq} \\ \mu_{jr} \end{pmatrix} + \begin{pmatrix} \phi_{qq,ii} & \phi_{qr,ii} & \phi_{qq,ij} & \phi_{qr,ij} \\ \phi_{rq,ii} & \phi_{rr,ii} & \phi_{rq,ij} & \phi_{rr,ij} \\ \phi_{qq,ji} & \phi_{qr,ji} & \phi_{qq,jj} & \phi_{qr,jj} \\ \phi_{rq,ji} & \phi_{rr,ji} & \phi_{rq,jj} & \phi_{rr,jj} \end{pmatrix} \begin{pmatrix} \Delta q_{i,t} \\ \Delta r_{i,t} \\ \Delta q_{jt} \\ \Delta r_{jt} \end{pmatrix} + \begin{pmatrix} \eta_{i,q,t+1} \\ \eta_{i,r,t+1} \\ \eta_{jq,t+1} \\ \eta_{j,r,t+1} \end{pmatrix},$$

where $\Delta q_{i,t+1}$ is the change in log CDS-implied default probability for firm i, $\Delta r_{i,t+1}$ is the change in log recovery rates for firm i, and $\Delta q_{j,t+1}$ and $\Delta r_{j,t+1}$ are the corresponding changes in log default probabilities and recovery rates for the firm $j \neq i$. Sectors are defined by two-digit Global Industrial Classification Standard (GICS) code from Compustat. VARs are estimated at the firm level and coefficients reported are means across firms with accompanying cross-sectional t-statistics. For each firm, we report cross effects of the firm on other firms in the financial sector (the upper right block off-diagonal of the matrix $\boldsymbol{\Phi}$) for the full sample, crisis, and non-crisis subperiods. Data cover the period January 1, 2006 through July 23, 2010, for 238 weekly observations.

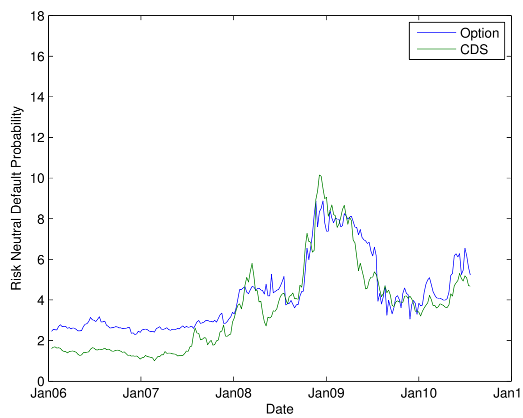
	Full Sample				Non-Crisis				Crisis			
Ticker	$\phi_{qq,ij}$	$\phi_{qr,ij}$	$\phi_{rq,ij}$	$\phi_{rr,ij}$	$\phi_{qq,ij}$	$\phi_{qr,ij}$	$\phi_{rq,ij}$	$\phi_{rr,ij}$	$\phi_{qq,ij}$	$\phi_{qr,ij}$	$\phi_{rq,ij}$	$\phi_{rr,ij}$
ABK	0.15	0.01	-0.02	0.06	-0.02	0.90	-0.06	0.81	0.16	-0.11	-0.08	0.15
	3.09	0.10	-0.71	0.80	-0.20	0.83	-2.43	1.78	1.79	-1.72	-0.72	1.03
ACE	0.03	0.26	0.04	-0.08	0.17	0.23	0.05	0.19	-0.03	0.12	-0.03	-0.20
	1.01	2.21	0.68	-0.56	1.52	0.43	0.79	1.13	-0.75	0.95	-0.37	-0.56
AIG	-0.06	-0.16	0.00	-0.24	-0.10	0.11	-0.09	0.30	-0.23	-0.19	0.65	-0.55
	-1.44	-2.48	-0.03	-1.16	-1.31	0.25	-1.84	1.73	-2.37	-1.17	1.45	-1.91
ALL	-0.01	0.15	-0.03	0.30	0.06	0.19	0.02	0.15	-0.04	0.13	-0.03	0.47
	-0.30	1.90	-0.54	3.27	1.20	0.40	0.42	0.84	-0.79	1.35	-0.31	3.13
AXP	0.01	-0.02	0.04	-0.01	0.04	-0.27	-0.06	0.40	0.02	0.00	0.14	-0.17
	0.49	-0.39	1.33	-0.09	1.20	-1.85	-1.19	1.79	0.41	-0.02	1.01	-0.74
BAC	0.03	-0.14	-0.03	-0.08	0.06	-0.44	0.02	-0.14	0.06	-0.04	-0.27	0.10
	1.95	-1.94	-2.13	-0.67	1.46	-1.32	0.66	-0.78	1.13	-0.48	-2.29	1.03
BSC	0.01	0.00	-0.05	0.09	-0.05	0.00	-0.03	0.06	0.05	-0.06	-0.25	0.29
	0.59	0.11	-2.47	2.98	-0.50	0.01	-0.96	0.75	1.22	-0.97	-3.12	3.91
BXP	0.00	-0.01	-0.06	0.00	0.00	-0.12	-0.04	-0.01	0.21	0.03	-0.11	0.04
	0.06	-1.25	-1.89	-0.50	0.05	-0.52	-1.18	-0.09	1.16	0.36	-0.67	0.65
C	0.12	0.13	-0.05	0.70	0.07	0.49	-0.03	0.59	-0.13	0.02	0.03	0.71
	4.09	0.90	-1.14	2.90	1.54	1.61	-0.69	3.49	-0.44	0.12	0.34	2.40
CB	0.07	0.06	0.00	0.36	0.08	-0.11	0.03	0.27	0.44	-0.01	0.73	0.58
	2.86	0.63	-0.03	1.88	1.51	-0.23	0.44	1.10	1.37	-0.07	1.38	1.64
CFC	0.06	-0.06	-0.01	0.10	-0.01	-0.42	-0.01	-0.18	4.05	-0.56	5.28	-0.55
	2.69	-1.89	-1.00	3.60	-0.09	-1.90	-0.38	-1.58	1.44	-1.61	1.07	-0.81
COF	0.04	-0.07	-0.08	0.10	0.01	0.06	-0.04	0.10	0.00	-0.03	-0.21	0.27
	1.35	-1.63	-2.92	1.95	0.18	0.48	-1.33	1.16	-0.04	-0.44	-3.68	2.97
GNW	0.08	0.05	-0.13	0.19	0.03	0.23	-0.14	0.75	0.66	-0.16	-0.40	0.18
	0.82	1.81	-1.77	2.19	0.25	0.68	-1.30	1.09	2.73	-1.75	-2.34	2.32
GS	0.08	-0.07	0.00	0.08	0.09	-0.14	0.03	-0.09	0.05	-0.05	-0.03	0.07
	3.06	-1.84	0.05	1.03	1.93	-1.49	0.98	-0.98	1.08	-1.08	-0.37	1.04
HIG	0.01	-0.03	-0.05	0.03	-0.01	-0.09	-0.07	0.04	0.03	-0.05	-0.03	0.07
	0.30	-0.69	-1.54	0.34	-0.22	-0.33	-1.61	0.27	0.63	-0.82	-0.38	0.49

Table continued on next page.

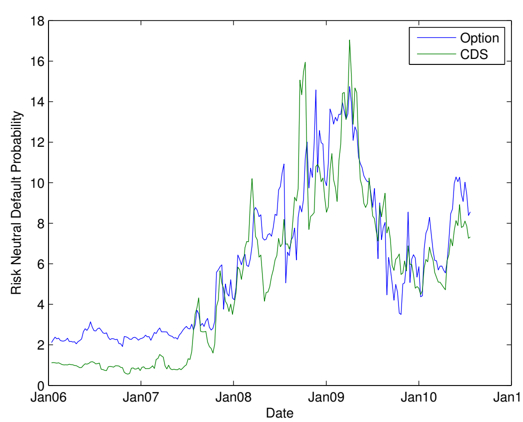
	Full Sample				Non-Crisis				Crisis			
Ticker	$\phi_{qq,ij}$	$\phi_{qr,ij}$	$\phi_{rq,ij}$	$\phi_{rr,ij}$	$\phi_{qq,ij}$	$\phi_{qr,ij}$	$\phi_{rq,ij}$	$\phi_{rr,ij}$	$\phi_{qq,ij}$	$\phi_{qr,ij}$	$\phi_{rq,ij}$	$\phi_{rr,ij}$
JPM	0.07	-0.22	-0.06	0.23	0.00	0.16	-0.01	0.22	0.04	-0.20	-0.09	0.22
	2.29	-2.89	-1.45	1.87	-0.02	0.51	-0.13	1.48	0.87	-1.98	-1.64	1.28
LEH	-0.06	0.37	-0.14	0.64	0.01	0.30	-0.05	0.32	-0.05	0.42	-0.19	1.16
	-1.43	2.15	-3.92	4.06	0.29	0.94	-1.67	1.47	-0.39	1.36	-0.95	3.22
LNC	0.05	0.04	-0.02	0.07	0.07	0.13	0.00	0.10	-0.04	0.03	-0.24	0.09
	1.37	2.09	-0.56	4.14	0.88	0.33	-0.03	0.70	-0.26	1.00	-1.17	2.16
MBI	0.08	-0.01	-0.01	-0.10	-0.07	-0.04	-0.10	0.04	0.35	-0.03	0.10	-0.11
	2.10	-0.56	-0.38	-2.54	-0.47	-0.29	-1.12	0.84	2.62	-1.34	0.64	-1.64
MER	0.04	-0.09	-0.01	-0.03	0.11	-0.71	0.03	0.07	0.02	-0.06	-0.11	0.06
	1.32	-1.71	-0.46	-0.35	1.56	-2.51	0.73	0.69	0.50	-1.06	-1.03	0.34
MET	0.02	-0.11	-0.10	-0.06	0.11	-0.82	-0.06	0.13	0.04	0.08	-0.03	-0.13
	0.32	-2.18	-1.58	-0.73	1.37	-1.83	-1.30	0.62	0.35	0.76	-0.13	-0.46
MMC	0.10	-0.02	0.04	0.44	0.68	-5.42	0.63	-4.41	0.02	0.21	0.03	0.77
	2.58	-0.14	0.70	2.34	0.94	-1.02	1.02	-0.97	0.24	0.81	0.23	1.74
MS	0.07	-0.05	0.02	0.12	0.12	-0.54	0.01	-0.12	0.09	-0.05	0.21	0.05
	2.89	-1.15	0.52	1.06	3.02	-2.98	0.29	-1.18	2.54	-0.92	1.92	0.26
MTG	0.02	-0.05	-0.02	0.04	0.08	-0.19	0.05	-0.09	-0.01	0.05	-0.10	0.11
	0.69	-1.38	-0.87	1.28	1.26	-2.24	0.94	-1.57	-0.26	0.89	-1.54	1.16
PLD	0.00	-0.05	-0.04	0.03	0.05	-0.18	-0.05	0.00	0.05	0.00	-0.44	0.05
	0.13	-2.13	-2.76	1.57	0.77	-1.23	-0.73	-0.01	0.62	0.14	-0.81	0.92
PRU	0.04	-0.11	-0.09	0.02	0.03	0.01	-0.03	-0.06	0.00	-0.08	-0.12	0.08
	1.57	-3.00	-1.43	0.18	0.42	0.06	-0.45	-0.47	0.11	-1.31	-1.62	0.64
SCHW	0.13	-0.67	0.09	-0.28	0.58	-0.55	0.47	-0.60	0.32	-1.68	0.37	-1.06
	2.82	-2.49	1.78	-0.75	1.19	-0.29	1.27	-0.35	1.09	-0.76	1.86	-1.69
SLM	0.20	-0.04	0.06	0.00	0.40	-0.24	0.01	-0.14	0.13	-0.03	0.17	-0.06
	6.89	-2.35	1.34	0.17	3.91	-0.78	0.12	-1.44	2.00	-1.24	1.51	-0.81
SPG	0.03	-0.13	-0.03	0.07	0.09	-0.32	0.00	0.02	0.05	-0.08	0.01	0.11
	1.32	-2.31	-1.05	0.85	1.47	-1.56	-0.06	0.10	0.89	-0.99	0.08	1.08
TRV	-0.01	0.31	-0.03	0.25	-0.11	0.62	-0.02	0.12	0.06	0.14	-0.02	-0.19
	-0.16	1.89	-0.62	1.62	-1.37	1.10	-0.27	0.41	1.06	0.82	-0.12	-0.74
UNM	0.04	0.00	-0.01	0.05	-0.98	0.01	-0.20	0.05	-0.04	0.07	0.14	-0.16
	1.21	0.18	-0.34	2.15	-1.08	0.02	-0.84	0.37	-0.81	1.09	1.83	-1.68
VNO	0.00	-0.01	-0.03	0.04	0.13	-0.43	-0.04	0.09	-0.23	-0.07	-0.16	-0.04
	0.23	-0.33	-1.51	0.67	2.32	-2.87	-0.80	0.60	-1.18	-0.53	-0.75	-0.35
WB	0.04	-0.02	-0.03	0.03	-0.17	1.56	-0.10	0.67	0.00	0.08	-0.11	-0.06
	1.45	-0.38	-1.38	0.34	-1.06	1.84	-1.17	1.41	-0.01	0.95	-0.70	-0.23
WFC	0.11	-0.19	-0.10	0.59	0.05	0.16	-0.07	0.14	0.09	-0.15	-0.09	0.63
	4.44	-1.94	-3.48	4.71	1.28	0.73	-1.75	1.72	2.05	-0.96	-1.49	3.15
WM	-0.03	0.13	-0.03	0.08	0.10	-0.45	0.04	-0.07	0.09	0.13	-0.27	0.27
	-1.00	1.60	-1.45	2.45	1.26	-1.50	0.90	-0.65	1.25	1.17	-2.02	3.77
XL	0.12	-0.09	-0.01	0.12	-0.01	0.42	-0.08	0.25	0.14	-0.13	0.15	0.02
	3.92	-2.79	-0.13	2.42	1.28	0.73	-1.75	1.72	2.65	-3.25	1.70	0.26

Figure 1: Risk Neutral Default Probabilities

Figure 1 depicts the time series of risk neutral default probabilities implied under different assumptions about recovery and by alternative assets. The figure presents two time series; risk neutral default probabilities implied by credit default swaps (CDS) under an assumption that recovery rates are 40%, and retrieved from option prices. Option-implied default probabilities are computed using the Bakshi, Kapadia, and Madan (2003) procedure to retrieve risk neutral moments from option prices and then using these moments to determine the probability that the value of the equity is less than or equal to zero using the Normal Inverse Gaussian (NIG) distribution of Ericsson, Forsberg, and Ghysels (2009). Panel A presents results for an average over 223 non-financial firms in the S&P 500 index sampled at the daily frequency and averaged to weekly over the period January 6, 2006 through July 23, 2010. Panel B presents results for 37 financial firms in the S&P 500 index over the same time horizon. To be included in the sample, firms must have valid default probabilities implied by CDS and options for 52 weeks. Classification as financial and non-financial firms is from the Global Industrial Classification Standard (GICS) available on Compustat. CDS data are obtained from CMA Bloomberg. Options data are obtained from IVolatility.com and represent NBBO averages of closing bid and ask quotes. The plotted series are averages of default probabilities across firms in the sample.



(a) Non Financial Firms



(b) Financial Firms

Figure 2: Implied Recovery Rates

Figure 2 depicts the time series of recovery rates implied by options and CDS spreads. We solve for the recovery rate, given the option and CDS risk neutral probability of default for a firm, that sets the probabilities equal. The figure presents two time series; recovery rates implied by data for non-financial firms and financial firms. Option-implied default probabilities are computed using the Bakshi, Kapadia, and Madan (2003) procedure to retrieve risk neutral moments from option prices and then using these moments to determine the probability that the value of the equity is less than or equal to zero using the Normal Inverse Gaussian (NIG) distribution of Ericsson, Forsberg, and Ghysels (2009). The sample of non-financial firms comprises 223 non-financial firms in the S&P 500 index sampled at the daily frequency and averaged to the weekly frequency over the period January 6, 2006 through July 23, 2010. Financial firms are represented by 37 financial firms in the S&P 500 index over the same time horizon. To be included in the sample, firms must have valid default probabilities implied by CDS and options for 52 weeks. Classification as financial and non-financial firms is from the Global Industrial Classification Standard (GICS) available on Compustat. CDS data are obtained from CMA and Bloomberg. Options data are obtained from IVolatility.com and represent NBBO averages of closing bid and ask quotes. The plotted series are averages of implied recovery rates across firms in the sample.