Why is Price Discovery in Credit Default Swap Markets News-Specific?

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Abstract:

We document a stark asymmetry in price discovery in equity and CDS markets: equity markets robustly lead CDS markets following aggregate and positive news but tend not to do so following other news. While difficult to reconcile with standard asset pricing theories, asymmetric price adjustment is common in goods markets, arising from intermediary power. We provide an explanation for the asymmetry based on dealers exploiting informational advantages vis-à-vis investors with hedging motives. In support of this we find that the equity-lead and its news-specificity are related to firm-level proxies for hedging demand as well as economy-wide measures of information asymmetries.

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1. Introduction

A key interest of the finance profession is in understanding how new information is incorporated into securities prices. One approach is the study of *price discovery* across markets. If new information is simultaneously priced into different markets, this is evidence of informational efficiency. Evidence of one market pricing information faster than another by contrast suggests market inefficiencies. Studies on price discovery abound and often find some sort of inefficiencies in that one market leads in price discovery.[3]

In this paper we explore the idea that price discovery may in fact be news-specific. Traders in different markets may not be universally informed or uninformed. Rather, traders choosing to operate in one market may have an advantage (or disadvantage) with respect to one type of information but not necessarily with respect to other innovations.[4] This could cause price discovery not to be unconditionally in favour of one market but to depend upon the type of innovation. It would also suggest a more nuanced view on the informational efficiency of markets – in that it may only hold conditional on specific information.

We focus our analysis on price discovery in equity and CDS markets. The evidence on whether equity returns lead CDS price changes is mixed. Longstaff, Mithal and Neis (2005) suggest that both markets move simultaneously (but that both lead the corporate bond market) while Norden and Weber (2009) and Hilscher, Pollet and Wilson (2012) find that equity returns lead CDS price changes much more frequently than the other way around.[5]

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[3] For example, Chan (1992) shows that equity index futures tend to lead the cash index, Hou (2007) and Chordia, Sarkar and Subrahmanyam (2011), along with many others, examine lead-lag effects between large and small cap equities, while Hotchkiss and Ronen (2002) consider lead-lags between corporate bonds and equities.

[4] In Easley, O'Hara and Srinivas (1998) traders choose the market where they wish to make a trade conditional on each piece of information they receive. Here we take the view that certain investor groups may have a general preference for one market over another.

[5] There is solid evidence that with very few exceptions CDS markets price information faster than corporate bond markets, although arbitrage relationships tie credit spreads and CDS prices together in the long run (Blanco, Brennan and Marsh, 2005). There is also evidence that the corporate bond market lags the stock market (Kwan, 1996; Downing, Underwood and Xing, 2009).

Acharya and Johnson (2007) demonstrate that under certain market conditions (typically bad news about the credit quality of specific firms) changes in CDS prices lead equity returns, a phenomenon they ascribe to insider trading by banks with access to non-public information about their customers.

We first analyze unconditional price discovery. We use daily panel data on U.S. firms larger in both cross-section and time series dimensions than typically examined previously to study the lead-lag relationships between equity returns and CDS price changes. We find that equity returns robustly lead CDS price changes. There is very little support for the thesis that CDS price changes lead equity returns. This is strong evidence in favour of an unconditional informational advantage of equity markets – in particular since we have constructed our sample to include only the most liquid CDS entities and thus have effectively biased the sample against finding an equity lead.

The key focus of our paper is to investigate more precisely the nature of the information that is priced faster in equity rather than CDS markets. Does the equity-lead arise for all type of information or only in response to some information? We first ask whether common and firm-specific information are priced at different speeds. The evidence, based on alternative factor decompositions, is clear – the CDS market is slow at pricing common information while it prices firm-specific news at about the same speed as the equity market. The dominant component of systematic information in equity returns that is priced slowly by the CDS market is, rather surprisingly, the (equity) market factor. One might have expected the (single) market factor to be more efficiently priced than news specific to individual firms.

Second, we look at whether the lead-lag depends on whether there is positive or negative news in the equity market. We find that positive and negative equity market returns appear to be priced at different speeds by the CDS market. Most of the lagged response of CDS prices is driven by slow CDS price changes in response to positive equity market returns. Our findings are therefore complementary to Acharya and Johnson (2007). Acharya and Johnson argue that CDS markets can lead equities when there is bad news about a specific company, while our results suggest that CDS markets lag equities in pricing good news about the general economy.

What can account for the news-specific nature of price discovery? We bring forward an explanation based on different investor groups being important in the two markets. While a wide range of investors with very diverse trading interests are active in equity markets, participation in the CDS market is much more limited. A key reason for the development of CDS markets was institutional investors' demand (predominantly by banks) for an instrument capable of hedging credit risks. The prevalence of hedgers in CDS markets can explain both the aggregate-idiosyncratic news and the positive-negative news asymmetries. As these investors are likely to be well informed about news specific to the firms in their portfolio, CDS markets respond efficiently to such news. However, hedgers of firm risks are likely to focus less on macro-news. In response to positive equity market news dealers in the CDS market can thus keep prices high and exploit their informational advantage. This dampens price adjustment in the CDS market and causes an equity-lead specific to positive macro news. In the event of bad equity market news, conversely, CDS prices rise immediately since in this case rapid adjustment is in the interest of dealers.[6]

If this explanation is correct, we would expect the lead-lag and its asymmetries to depend on proxies for the hedging demand for a firm's debt. We consider three proxies for hedging demand on the firm level: the amount of outstanding debt, default risk, and the variability

[6] Asymmetric responses to positive and negative price shocks are widespread in goods markets (Bacon, 1991) where the phenomenon is driven by consumers facing search costs which afford intermediaries a degree of market power. Recently, Green, Li and Schürhoff (2010) – interpreting search costs as informational asymmetries – show that such asymmetries can also occur in financial markets (municipal bond markets).

default risk. We find that these proxies for hedging demand are positively and significantly related to observed lead-lag asymmetries, supporting the idea that the lead-lag relationship is driven by the hedging focus of investors in the CDS market.[7] We consider this to be a key contribution of our paper: to our best knowledge this is the first evidence linking the informational efficiency of markets to differences in trading motives across markets.

A second implication of our explanation is that in periods of high informational asymmetry the CDS market's lag should be longer – because dealers then have greater pricing power vis-à-vis uninformed investors. We capture variations in levels of information asymmetry through the behaviour of equity market bid-ask spreads and by examining major macroeconomic news announcements. We show that when information asymmetry is high – identified by either larger than usual bid-ask spreads or in days immediately preceding major macroeconomic news announcements – CDS returns are particularly sensitive to lagged positive equity returns.

Summarizing, this paper contributes to our understanding of the informational efficiency of markets by showing that price discovery can be predominantly news-specific: for equity and CDS markets there is a stark and robust asymmetry in the pricing of new information. We attribute this asymmetry to the fact that traders in one market may only be informed with respect to some type of innovation. Evidence using proxies for hedging demands in CDS markets supports the idea of the asymmetries being connected to investor clienteles with different information sets operating in both markets.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 contains the empirical analysis. Section 4 concludes.

[7] We also find evidence that the inefficiency of the CDS market is linked to limits to arbitrage, which provides an explanation for why dealers are able to exploit market power vis-à-vis hedgers.

2. Data Sources and Descriptive Statistics

The CDS data used in our analysis come from Markit Group, a leading industry provider of credit derivatives pricing. Markit collects CDS prices from over 30 contributing market makers and applies a screening process to remove outliers, stale prices and other inconsistent data. Markit then computes the mean price from those contributions that pass their data quality tests and releases a price when it has two or more contributors.[8] We use daily five-year maturity single-name CDS prices on U.S. reference entities with publicly traded equity prices for the period 1st January 2004 through 14th October 2008.

Each reference entity is matched to a traded equity identifier (Bloomberg ticker) which we then translate into a CRSP identifier (permno). Matched daily closing equity mid-market prices are extracted from CRSP. We use daily returns, calculated as changes in the log of these CDS and equity prices, as the key variables in our analysis.

Many of the reference entities' CDS are very illiquid. These are flagged as such in the database (this indicator refers to liquidity at the point in time when the database was created). To concentrate our analysis on the most liquid firms, we retain only those reference entities flagged as liquid in the database and with non-zero daily CDS returns for at least 90% of the sample period analysed. We also only retain entities with CDS (and equity) prices available for the full sample period and we exclude companies with significant merger and acquisition activities. The final data set comprises 193 reference entities, each with 1,208 daily return observations for both equities and CDS. The firms retained are detailed in Appendix B.

[8] Markit data is widely used in the literature (see, for example, Acharya and Johnson (2007), Jorion and Zhang (2007) and Zhang, Zhou and Zhu (2009)).

Table 1 reports some basic descriptive statistics. Univariate statistics suggest equity and CDS daily returns are broadly comparable, although the standard deviation of CDS returns is higher. CDS prices on average increased in the sample and the distribution of returns is positively skewed. Equity prices fell, on average, and the distribution of equity returns is negatively skewed. More important patterns emerge from the correlation statistics. Equity returns exhibit very low autocorrelations, while those for the CDS market are much larger in magnitude, especially at the first lag. Cross-autocorrelations also differ markedly. Lagged CDS returns are only weakly (negatively) correlated with equity returns but the first lag of equity returns is strongly negatively correlated with CDS returns. The magnitude of this correlation is similar to the magnitude of the contemporaneous correlation. The magnitude of the correlation with the second lag of equity returns is markedly smaller. Together, the significantly positive autocorrelation and significantly negative correlation with lagged equity returns are indicative of inefficiencies in the CDS market.

3. Analysis

3.1 Equity-CDS Lead-Lag Relationships

Several papers have noted that, in general, equity returns lead CDS returns. There are occasions when the reverse appears to be true but these are not long-lasting periods of time, nor are they necessarily common for all entities. The first goal of this paper is to establish the robustness of the unconditional lead-lag relationship between equities and CDS for our panel. We emphasise that our data selection procedure produces a sample of reference entities with the most liquid CDS markets. As such, any evidence of a lag in the price discovery process for these firms would be suggestive of even more pronounced lags for less liquid entities.

We model the returns of equities and CDS in a standard bivariate vector autoregression (VAR) system of lag order k:

$$r_{i,t}^{e} = \alpha_0 + \sum_{j=1}^{k} \alpha_{1j} r_{i,t-j}^{e} + \sum_{j=1}^{k} \alpha_{2j} r_{i,t-j}^{c} + \varepsilon_{i,t}^{e} \qquad \textbf{(1a)}$$

$$r_{i,t}^{c} = \beta_0 + \sum_{j=1}^{k} \beta_{1j} r_{i,t-j}^{e} + \sum_{j=1}^{k} \beta_{2j} r_{i,t-j}^{c} + \varepsilon_{i,t}^{c} \qquad \textbf{(1b)}$$

where the dependent variables are the returns (r) on the equity (e) or CDS (c) of firm i at time t. Lag lengths are chosen according to the Akaike information criterion (but our results are not sensitive to changes in lag lengths). Not surprisingly, given the autocorrelation patterns described in Table 1, in the vast majority of cases the criterion selects just one lag. CDS returns would be deemed to lag equity returns for firm i if the β_1 coefficients are jointly non-zero, and equities would lag CDSs if the α_2 coefficients are jointly non-zero.[9]

Panel A of Table 2 summarises the results of estimating VARs for each reference entity individually and for all entities pooled together. The dominant finding is that lagged equity returns contain information for current CDS price changes, while the reverse is rarely the case. Specifically, we find that of the 193 reference entities studied, lagged equity returns are significant in explaining current CDS returns in 149 cases at the five percent level. Lagged CDS returns explain equity returns for only 12 entities. The results of estimating the pooled VAR are fully consistent. The results in Panel A are based on regressions at the firm level. In Panel B we show that the same findings hold when we analyse returns from equally weighted equity and CDS portfolios.

[9] Acharya and Johnson (2007) use a different specification in their VAR which includes interactions of the stock returns (both contemporaneous and lagged) with the inverse CDS level to capture the likely non-linear relation between CDS and equity returns. However, this interaction term is not significant for 155 of the 193 firms in our data set and so we do not include it in our specifications. Our main findings are not sensitive to this decision.

In sum, unconditionally, equity returns lead CDS price changes. These results are very robust to alternative specifications of equation (1) and to splitting the data in various ways (details are provided in Appendix A).

3.2 Asymmetric response to common and firm-specific information

In this sub-section we explore further the nature of the information that is being incorporated faster into equity prices than CDS prices. The consistency of the firm and portfolio level lead-lag results detailed in section 3.1 suggests that it is not just idiosyncratic information that is priced slowly in CDS markets and that there appears to be a systematic component. We therefore use several techniques to split equity and CDS returns into common factor and idiosyncratic components to determine the contribution of each to the delay in CDS pricing.

We begin with a statistical decomposition of returns based on principal components (PC) analysis. Using the full sample of data we extract *p* principal components for equity returns and *q* components for CDS returns. We then regress equity returns on the *p* equity principal components and collect, for each entity, a fitted series and a residual series. We view the fitted series as capturing the systematic or common component of each firm's equity returns while the residual series is assumed to capture the firm-specific component. We do the same for each firm's CDS returns using the *q* CDS principal components.

We then perform a VAR analysis using these decomposed returns (we also perform regressions using common and idiosyncratic components of CDS returns as dependent variables for completeness):

$$r_{i,t}^{ecom} = \alpha_{10} + \alpha_{11} r_{i,t-1}^{ecom} + \alpha_{12} r_{i,t-1}^{eidio} + \alpha_{13} r_{i,t-1}^{ccom} + \alpha_{14} r_{i,t-1}^{cidio} + \varepsilon_{i,t}^{ecom} \qquad \textbf{(2a)}$$

$$r_{i,t}^{eidio} = \alpha_{20} + \alpha_{21} r_{i,t-1}^{ecom} + \alpha_{22} r_{i,t-1}^{eidio} + \alpha_{23} r_{i,t-1}^{ccom} + \alpha_{24} r_{i,t-1}^{cidio} + \varepsilon_{i,t}^{eidio} \qquad \textbf{(2b)}$$

$$r_{i,t}^{ccom} = \beta_{10} + \beta_{11} r_{i,t-1}^{ecom} + \beta_{12} r_{i,t-1}^{eidio} + \beta_{13} r_{i,t-1}^{ccom} + \beta_{14} r_{i,t-1}^{cidio} + \varepsilon_{i,t}^{ccom} \qquad \textbf{(2c)}$$

$$r_{i,t}^{cidio} = \beta_{20} + \beta_{21} r_{i,t-1}^{ecom} + \beta_{22} r_{i,t-1}^{eidio} + \beta_{23} r_{i,t-1}^{ccom} + \beta_{24} r_{i,t-1}^{cidio} + \varepsilon_{i,t}^{cidio} \qquad \textbf{(2d)}$$

Significant values for β_{11} (β_{12}) would suggest that the common (idiosyncratic) component of firm i's lagged equity returns is important in explaining the common component of i's CDS returns. Similarly, significant values for β_{21} (β_{22}) would imply that the common (idiosyncratic) component of lagged equity returns is important in explaining the firm-specific CDS return for the firm.

The choice of how many principal components to retain is rather arbitrary and we do not take a firm stand on the issue. If too few components are retained then components of the returns which are actually common are incorrectly labelled as idiosyncratic. Retain too many components and idiosyncratic elements of returns are incorrectly thought to be common. Thankfully, the tenor of our results is not sensitive to the exact number of components retained as long as the number of common components is at least one for both equities and CDS returns.

We report results based on three retained components for both equity and CDS returns in Panel A of Table 3. The results are quite stark. For 173 of the 193 companies, the lagged common component of equity returns significantly predicts the current common component of CDS returns. By contrast, the lagged common CDS component is never significant in predicting the common equity component.

Second, there is some relatively weak evidence that lagged idiosyncratic equity returns predict idiosyncratic CDS returns (significant at 5% level for 28 companies, or 14.5% of the sample). The CDS market leads in the pricing of idiosyncratic information for 11.4 percent of the sample (22 companies).

Third, and as we would expect, there is little evidence that idiosyncratic equity returns predict common CDS returns, or that common equity returns predict idiosyncratic CDS returns.

The lead-lag relations between equity and CDS returns seen in the literature and confirmed in section 3.1 are hence almost entirely driven by the equity market's ability to incorporate common information faster than the CDS market. To a much lesser extent, the equity market also appears able to incorporate firm-specific information faster, although there are also cases where the CDS market leads in pricing idiosyncratic information. This final point probably reflects the insider trading issues raised in the conditional analysis of Acharya and Johnson (2007).

To confirm the results using equity factors motivated by the literature, rather than statistically derived principal components, we repeat the analysis using the three Fama-French factors.[10] Since there is no recognised factor model for CDS returns we revert to using total CDS returns in the regressions. Results are reported in Panel B of Table 3. Lagged fitted equity returns based on the three Fama-French factors are significant for CDS returns for 178 companies (92% of the sample) while the lagged residual equity returns not explained by these factors are significant for 40 firms (21% of the sample). We find almost exactly the same results if we use three principal components instead of Fama-French factors – lagged fitted returns are significant for 179 firms, and lagged residual returns are significant for 18 firms. Correlation analysis between the largest principal components for equity returns and Fama-French factors suggests that the first principal component is a very close proxy for the

[10] The returns on the Fama-French factors were sourced from Ken French's website.

market. However, none of the other principal components correlate strongly with the Fama-French factors.

The similarity of the lead-lag results from PC and Fama-French-based analyses combined with the fact that these two approaches only appear to share one common factor suggest that the equity market return is behind most of the results. We proxy the equity market return in three ways – the first principal component, the return on an equally weighted portfolio of the equities in our sample, and the market return from the Fama-French database. Panel C of Table 3 reports the results of using lagged fitted values and lagged residuals from all three measures to explain CDS returns (with lagged CDS returns also included in the regressions). The results are quite consistent. Lagged equity market returns significantly explain CDS returns for a very large proportion of firms. Lagged idiosyncratic equity returns are much less frequently significant. It appears that the lead-lag relationship between equities and CDSs is mainly driven by a single common equity component – the market return.[11]

3.3 Asymmetric response to positive and negative news

So far we have imposed symmetrical responses of CDS returns to positive and negative lagged equity returns. We now relax this constraint and allow positive lagged equity returns to bear a different coefficient to negative returns. We regress the common component of CDS returns for each firm on lags of itself, lagged positive equity market returns and lagged negative equity market returns. Market returns are proxied by the return on an equally

[11] Although the focus of this paper is on the cross asset-class information spillover, the autoregressive coefficient for CDS returns is very large, suggesting that while there is some information in lagged equity returns there appears to also be even more information in lagged CDS returns. Table 3, panel A confirms the inability of the CDS market to incorporate common information quickly. For all 193 companies, the lagged common component of CDS returns is significant in explaining the current common component. Lagged idiosyncratic CDS returns are also significant in explaining the current idiosyncratic component of CDS returns for around 42% of the firms.

weighted portfolio of the equities in our sample but our results are not sensitive to alternative measures. Specifically, we use the following specification

$$r_{i,t}^{ccom} = \beta_0 + \beta_1 r_{i,t-1}^{ccom} + \beta_2 r_{m,t-1}^{epos} + \beta_3 r_{m,t-1}^{eneg} + \varepsilon_{i,t}^{ccom} \quad \textbf{(3)}$$

The results are reported in Table 4. For all 193 firms, the coefficient of common CDS returns on lagged positive equity market returns is negative and significantly different from zero. The cross-sectional mean of the coefficient on lagged positive equity returns is -0.5.[12] The coefficient on lagged negative equity returns is also generally negative, averaging -0.16, but is significant for just 106 firms (55% of the sample). The restriction that the coefficients on positive and negative equity returns are equal is rejected in 56 cases (29% of the sample) although in every case the coefficient on lagged positive equity returns is larger in absolute terms than the coefficient on negative returns. We obtain very similar results if we use total CDS returns as the dependent variable – coefficient values barely change and while the coefficient on positive equity returns is statistically significant, that on negative equity market returns is not.

The p-values reported in the first row of Table 4 are from a test that the average coefficient value is zero. This test assumes independence across firms, which is unlikely to be valid. As an alternative, we pool the data and run a single regression for the whole sample with standard errors clustered by time (double clustering by time and firm, or including firm fixed effects leave the results essentially unchanged). We report these results in the second row. The coefficient on lagged positive equity returns is larger in magnitude than that on lagged negative equity returns. The test of coefficient equality is not significant but note that by pooling the data we impose the same coefficients on all firms. As we expand upon later,

[12] If we use raw CDS returns rather than the common component the average coefficient is essentially unchanged (-0.56) although significance levels fall.

there is important coefficient heterogeneity in the cross section and hence the clustered standard errors are likely to be too large.

Finally, we run a version of this equation using equally-weighted portfolio returns. We regress portfolio CDS returns on a lagged dependent variable and lagged positive and negative portfolio equity returns series:

$$r^{c}_{m,t} = \beta_0 + \beta_1 r^{c}_{m,t-1} + \beta_2 r^{epos}_{m,t-1} + \beta_3 r^{eneg}_{m,t-1} + \varepsilon^{c}_{m,t} \qquad \textbf{(4)}$$

The coefficients on both positive and negative equity returns are significantly negative, though only marginally so in the case of negative returns (see the last row of Table 4). The absolute value of coefficient is much larger for positive returns than negative returns (-0.49 compared with -0.17) and equality of these coefficients is rejected. Partitioning lagged CDS returns into positive and negative components also has no effect on our results since they bear effectively the same coefficient.

3.4 The lead-lag relationship, hedging demand and informational asymmetries

We have so far established three robust sets of results: i) the equity markets leads the CDS market in price discovery but this lead is specific to ii) common news, and, iii) positive news.

The presence of lead-lag relationships across markets documented in sections 3.1-3.3 is at odds with market efficiency. Moreover, the news-specific nature of the lead-lags demonstrated in sections 3.2-3.3 rules out standard explanations such as arbitrage risk or transactions cost since these would be expected to apply regardless of the type of news.[13] Hilscher, Pollet and Wilson (2012) for example, argue that the CDS lag reflects a separating

[13] McQueen, Pinegar and Thorley (1996) also emphasise this point in their discussion of asymmetric cross serial correlations for large and small cap stock returns.

equilibrium where informed traders only trade in equities due to high bid-ask spreads in CDS markets. This explanation is not consistent with our findings that firm-specific and negative equity market news is priced approximately equally rapidly by both markets.[14]

While relatively unexplored in the finance literature, asymmetric adjustment of prices to changes in fundamentals is a frequent phenomenon in goods markets, termed "rockets and feathers" (Bacon, 1991). In a study of 242 goods markets, Peltzman (2000) finds that in two-thirds of the markets the upward adjustment of prices in response to a positive (cost) shock is faster than the downward response of prices to a negative shock of similar magnitude. Prices thus rise like rockets but fall like feathers. While smacking of collusive actions by intermediaries, such price setting behaviour is consistent with profit-maximizing behaviour of imperfectly competitive intermediaries who face customers that are rational but only partially-informed (Tappata, 2009). In most goods markets the intermediary buys in wholesale markets against well-informed participants but sells in retail markets to consumers that are less informed about the nature of costs in the market. Since search costs prevent consumers from locating the lowest available price for the good, intermediaries can set relatively high prices following cost reductions, exploiting their market power and extracting rent. When costs rise, conversely, they immediately pass on these increases to consumers and so prices rise accordingly.

Such behaviour has recently also been documented in the finance literature. Green, Li and Schürhoff (2010) find that there is an asymmetric response by U.S. municipal bond yields to Treasury bond yield shocks. They show that muni bond prices rapidly rise when Treasury bonds prices increase yet they fall very slowly following a drop in T-bond prices. Green et al. argue that asymmetries in the clientele in muni bonds – with the buy side dominated by

[14] The relatively good ability of the CDS market in pricing negative (equity) news may arise from short-selling constraints in the equity market. However, short-selling constraints cannot explain the differential response to common and idiosyncratic news and are also inconsistent with evidence provided later in this section.

retail customers while the sell side includes both retail and institutional sellers – are behind these results. They translate the search costs faced by retail consumers in goods markets into information asymmetries in asset markets such that the sell side is, on average, better informed than the buy side due to the presence of informed institutions in the former.

As we have demonstrated, the CDS market displays similar pricing behaviour. In the remainder of the paper we explore whether the rockets and feathers hypothesis can explain our results. The hypothesis relies on there being an asymmetry in the clientele faced by dealers on different sides of the market, with one side likely to be less informed than the dealer and the participants on the other side of the market. We will argue below that while the CDS market is dominated by institutional traders, there is a class of customers present predominantly on the protection-buying side of the market – credit risk hedgers – who may be less focussed on the consequences of some types of news.

Following this, we test two implications of the rockets and feathers hypothesis. First, the larger the market share of the relatively uninformed participants, the longer the CDS market lag as dealers can exploit their market power to a greater extent. Since we argue that the relatively uninformed are likely to be credit risk hedgers, we relate the magnitude of the CDS market's lag in the cross-section to several proxies for hedging demand. Second, if information asymmetries are behind the lead-lag relationships then longer CDS market lags should be observed when information asymmetries are high. To examine this prediction, we analyze the impact of variations in two types of information asymmetries across time on the lead-lag.

3.4.1 The lead-lag relation, limits to arbitrage, and the demand for hedging credit risks

A key difference between equity and CDS markets arises from different motivations for trading in these markets and (ultimately related) the types of investors that are active in these markets. Equity markets are characterized by a wide group of investors – private investors and most types of institutional investors trade equities – and the motives for trading are manifold. Furthermore, investors are, on average, equally active on both the buy and sell side of the equity market. There is no pronounced asymmetry in clientele in equity markets.

Credit derivatives markets are much more limited in scope. Participants in this market are almost exclusively institutional investors, with banks forming the largest group: 60% of CDS protection in 2006 (the mid-year in our sample) was bought by banks, 28% by hedge funds and 6% by insurance companies (source: BBA, 2006). A key motive for banks taking CDS positions is to hedge (about one third of their credit derivatives positions are held in the loan book). This hedging demand is largely passive as it is determined by the lending business of banks, which is governed by medium-to-long term considerations. The importance of the hedging motive in CDS markets creates a natural asymmetry.

We hypothesise that the trading desks of banks and other potentially well-informed participants both buy and sell credit protection through CDS contracts. However, the credit risk management (CRM) desks of banks concentrate their trading on just one side of the market, buying credit protection. Due to the information generated by their banks' lending activities, they are possibly well-informed about firm-specific news (as discussed by Acharya and Johnson, 2007) but we argue that they may be relatively uninformed with respect to credit risk implications of market-wide information. One explanation for the CRM desk's lack of focus on market-wide information may be that it considers its bank to be (independently) hedged against broad market movements, leaving the desk free to concentrate on managing firm-specific risks.

The presence of a large group of uninformed participants in a market ought not have important efficiency implications if dealers are competitive. However, CDS dealers have market power for at least two reasons. First, the CDS market is a bilateral over the counter market with no centralised quote disclosure mechanism. As there is no central counterparty system, counterparties need to enter into an ISDA Master Agreement before they can trade against each other. It is unlikely that hedgers enter into agreements with all dealers and hence they are limited in who they can trade against at any point in time. Second, protection bought on Firm X from Bank A is different from protection bought on Firm X from Bank B since the probability of joint default of Firm X and the protection writing bank differs.[15] There is therefore a degree of product differentiation across dealers. Product differentiation has been identified as a contributory factor to asymmetric price adjustment in goods markets.

The consequences of information asymmetry across participants and a less than fully competitive dealer networks are as follows. When firm-specific news arrives, all participants in the CDS market are well informed. They cannot be exploited by market makers, resulting in an efficient pricing in the CDS market. When macro news occurs, hedgers tend to be relatively less well informed. CDS prices will still be efficient in the case of bad news, as in this case it is in the interest of market makers to pass on the higher cost of protection to the hedgers. However, in the case of good economic news, market makers can exploit their informational advantage vis-à-vis hedgers and delay lowering the cost of protection. Pricing in the CDS market then becomes inefficient.

If our explanation has any bearing, we would expect the CDS lag in the presence of good news to depend on the importance of uninformed hedgers. In particular, if there is no hedging demand for a specific firm, the response of CDS prices to good and bad news ought to be equivalent. The higher the demand by hedgers, the slower the response is when good

[15] Arora, Gandhi and Longstaff (2010) show that these risk differences are priced in CDS markets.

news occurs, although there ought not be much cross-sectional variation in the response to bad news.[16] We therefore next study whether various proxies of hedging can explain cross-sectional variations in the lead-lag to equity market news.[17]

We consider three determinants of hedging demand on the firm level:

1. *Outstanding debt*. The higher the debt of the firm, the higher should be the demand for hedging. We measure debt by the log of the average total outstanding long-term debt of a firm, which we extract from Compustat at a quarterly frequency.

2. *Default risk*. Qiu and Yu (2012) posit a non-linear relation between hedging demand and the level of default risk. Briefly, their argument runs as follows. Top-quality credits face little hedging demand since insurance is deemed unnecessary, but as credit quality falls hedgers increasingly purchase credit protection. Once assets fall below investment grade, however, the cost of insurance becomes excessive. In addition, many investors have already been forced to sell the asset due to mandates and remaining investors are likely to bear the risk of further deterioration. We use the numerical long-term S&P credit rating variable as a proxy for firm risk (whereby a AAA rating translates to 1, AA to 2 etc).[18] We compute a time-weighted average rating level for each firm in the cross-section. We allow for non-linearity in the relationship by including a quadratic term.

3. *Default risk volatility*. A firm whose default risk varies substantially tends to require more frequent adjustments in hedging positions. Hedging-motivated trading should

[16] Alternatively, one may look whether a firm's lead-lag is related to the actual trading of banks in the firm's CDS. However, data on banks' CDS positions on a firm-basis are not available.

[17] There may also be variations in hedging demand over time. In particular, we would expect higher hedging demand during times of crises. This is consistent with our findings in Section 3.1 that the equity-CDS lead-lag is higher during the crisis of 2007-2008.

[18] It might be argued that risk increases demand for trading in the CDS of a firm generally (and regardless of whether it is for speculative or hedging purposes). However, in this case we would expect the lead-lag and the asymmetries to decrease in firm risk as more trading should increase the efficiency of the CDS market.

be more important for such a firm. We proxy this effect by the (log of the) standard deviation of CDS returns in the sample.

It should be pointed out that any importance of passive hedgers for price formation requires limits to arbitrage across the two markets. However, Kapadia and Pu (2012) document significant short-term pricing discrepancies across equity and CDS markets, and ascribe these to limited arbitrage capital flows between the two. In our analysis, we include two proxies for arbitrage costs as controls for limits to arbitrage:

1. *Transactions costs*. Illiquidity constrains the actions of an arbitrageur since entering into or unwinding a position in a timely manner will impact price and make arbitrage costly. A lower level of liquidity is therefore expected to reduce arbitrage activity. We use the average bid-ask spread on the equity of the firm as a simple measure of illiquidity.

2. *Idiosyncratic risk*. Shleifer and Vishny (1997) and Pontiff (2006) argue that exposure to idiosyncratic risk deters arbitrage. In the case of CDS-equity arbitrage, Kapadia and Pu (2012) note that an imperfect hedge caused by an incorrect or out of date hedge ratio leaves the arbitrageur with an unhedged position in the firm. Arbitrage flows are hence less likely for firms with high idiosyncratic risk. We measure idiosyncratic risk as the (log of the) standard deviation of the residuals from a regression of daily equity returns on the market return.

Since higher limits to arbitrage should lead to more pronounced efficiencies, we expect the arbitrage cost proxies to be positively associated with cross-market lead-lags. Importantly, significance of the limit to arbitrage proxies also provides an explanation for why dealers are able to exploit informational asymmetries across markets.

We study the cross-sectional relation between a firm's CDS lag and hedging demand by running the following regression:

$$LagCoeff_i = \alpha + \gamma_1 H_i + \gamma_2 A_i + \gamma_3 C_i + \varepsilon_i \qquad \textbf{(5)}$$

The dependent variable (the CDS lag) is one or more of the coefficients obtained from firm-by-firm estimation of equation (4). The explanatory variables fall into three categories: *H* refers to the set of hedging proxies, *A* refers to a set of arbitrage costs and *C* refers to general control variables. As a control, we first use the (log of) average equity market capitalisation to capture size effects. In addition, we include the average level of the CDS price. This variable may proxy for various factors such as the market's attention to a specific firm (higher attention is expected for firms with a higher CDS price) or the extent to which a firm is subject to informational asymmetries (for a firm with a low CDS price there is limited potential to gain from information acquisition and hence asymmetries are expected to be low).

The first column of Table 5 reports regression results where the CDS lag is the estimated coefficient on lagged positive equity market returns from equation (4) (that is, β_{2i}). Since the dependent variable in (5) is an estimated coefficient, we use weighted least squares for the estimation (with weights inversely proportional to the variance of the coefficient estimates in the first-stage regression).

The hedging proxies are all significant and have the expected sign. In particular, long term debt enters negatively, indicating that larger hedging demand due to higher debt exposures increase inefficiencies in the CDS market. The rating variable is significantly negative while rating squared is significantly positive. Thus, as firm quality declines the CDS lag initially becomes more pronounced but at a sufficiently high degree of default risk the relationship reverses. Interestingly, the coefficients imply that this happens at a single-A rating. This non-linear relation is consistent with the argument put forward in Qiu and Yu (2012) that hedging demand is maximised near the boundary between investment grade and non-investment grade. Finally, the standard deviation of CDS returns has the expected negative sign, indicating that more frequent adjustments in hedging behaviour lead to a reduced CDS lag.

Among the proxies for arbitrage costs, illiquidity in the equity market is associated with a significantly larger CDS lag, consistent with higher inefficiencies when arbitrage becomes more costly. The second arbitrage limit proxy, idiosyncratic volatility, however, does not significantly affect the CDS lag. Turning to the general control variables, it can be seen that market capitalization (the size proxy) significantly reduces the CDS lag. This is consistent with the notion that asset markets for larger firms are generally more efficient. The average CDS price is negatively associated with the CDS lag – but the relationship is only marginally significant. The negative sign may reflect that the scope for informational asymmetries is larger for firms that have higher CDS prices.

A potential concern is that the hedging results may be driven by multicollinearity between the hedging and the arbitrage cost proxies. However, the correlation among these groups of proxies is modest; the highest correlation arises between the rating variable and equity illiquidity and is -0.20. We also ran a regression excluding the arbitrage cost proxies (unreported); the results do not change in any important way. Finally, it should be noted that the explanatory power coming from the hedging variables is substantial: while the R^2 in column 1 is 0.345, the R^2 drops to 0.004 when hedging variables are excluded.

The results from this regression are supportive of the rockets and feathers hypothesis since they confirm that the CDS market's slow incorporation of positive equity market news is related to hedging demand. However, we can exploit this setting further. The hypothesis suggests that, while the lag with respect to positive stock market news should be related to hedging proxies, the lag following *negative* news should not. This provides us with an important placebo test. The second column in Table 5 reports the results when the dependent variable is the coefficient on the CDS response to lagged negative equity news. We see that there is no longer significance for any of the hedging proxies (only the squared rating variable enters with marginal significance).

Finally, the third column in Table 5 reports results where the dependent variable is the difference between positive and negative equity market news (that is, β_{2i}-β_{3i} from equation (5)). The results are largely unchanged from those reported in the first column. In particular, the hedging proxies are all significant and signed as expected.

Taken together, the results in this section corroborate the idea that the asymmetry in the lead-lag relationship is driven by the presence of passive hedgers which allow CDS dealers to maintain high protection prices in the advent of positive news.

3.4.2 The lead-lag relation and information asymmetries

The rockets and feathers hypothesis relies on participants on one side of the market being, on average, less informed about the true value of the asset than the dealers and the participants on the other side. We have established that variation in proxies for hedging demand are correlated with the magnitude of the CDS market's lag in the face of good equity market news. In this section we test whether the lag is also related to informational asymmetries, exploiting time-series variations.

Chordia, Sarkar and Subrahmanyam (2011) argue that an important economic announcement ought to resolve uncertainty. Hence, information asymmetries ought to be high immediately prior to this news announcement, and lead-lags should be relatively large. Our previous results suggest that macroeconomic rather than firm-specific information is important in explaining the equity lead over the CDS market. Consequently, we focus on three key U.S. macroeconomics announcements: the release of advanced GDP estimates, the employment situation announcement (which includes non-farm payroll figures), and the producer price index release.[22] We construct three indicator variables: *DAY* takes the value of one on the day that one of these announcements was made (and zero otherwise); *PRE* takes the value of one on the day immediately prior to an announcement (and zero otherwise); *NONE* takes the value of one if the other two indicator variables both equal zero (and is zero otherwise).[23] Since the previous results suggest that good news is critical to understanding the lagged response of the CDS market we interact these three indicators with the lagged positive component of the return on an equally-weighted portfolio of equity returns. The lagged negative component of equity returns is included but is not interacted with the indicator variables.[24] We run the following regression:

$$r^{c}_{m,t} = \alpha_0 + \alpha_1 PRE_t \times r^{epos}_{m,t-1} + \alpha_2 POST_t \times r^{epos}_{m,t-1} + \alpha_3 r^{epos}_{m,t-1} + \alpha_4 r^{eneg}_{m,t-1} + \alpha_5 r^{c}_{m,t-1} + \varepsilon^{c}_{m,t} \qquad \textbf{(6)}$$

If information asymmetries are important in explaining the magnitude of the CDS market's lag behind the equity market then we would expect $\alpha_1 < \alpha_3 < \alpha_2$ since the coefficient on lagged good equity market performance should be more negative than usual on days immediately preceding announcements, and less negative than usual on announcement days.[25]

Coefficient point estimates reported in the first column of Table 6 are supportive of the hypothesised relationship in that the coefficient orderings are correct, and all three

[22] In some months the consumer price index was announced before the producer price index. In these months we use the day of the consumer price index release.
[23] In the few instances where announcements occur on successive days, *PRE* takes the value of one only on the day prior to the first announcement.
[24] Interaction terms with the negative component are insignificant when included.
[25] The uninteracted indicator variables are each far from significant when added to equation (6).

coefficients are significantly negative suggesting that CDS returns are slow to incorporate good news irrespective of information asymmetries. However, the test of equality between the three coefficients cannot be rejected at conventional significance levels as the standard errors on these coefficients are relatively large.[26] To increase the power of the test we pool data on individual firms and rerun the regression.[27] Results are reported in the second column of the table. Again, the coefficient estimates are supportive of the hypothesis and the p-value of the equality of coefficients restriction is just 0.06. We interpret these results as (weakly) confirming that information asymmetries are behind the CDS market's lag relative to the equity market.

Our second time-series based test is also derived from Chordia, Sarkar and Subrahmanyam (2011). They reason that increased information asymmetry will result in widening bid-ask spreads and decreased liquidity in the lead market – equities in our case. Increases in the bid-ask spreads for equities then predict slower adjustment of CDS returns to (positive) stock market returns.[28] We measure stock-level illiquidity using the daily proportional bid-ask spread on each firm in our sample (sourced from CRSP) and construct a daily equally-weighted average spread across stocks (denoted *SP*). We interact SP_t with positive and negative components of equity market returns, and include these interactions as additional regressors in portfolio-level regressions:

[26] The standard errors on all three coefficients are larger than the standard error on the single coefficient on lagged positive equity market returns reported in the final row of Table 4, particularly for the relatively infrequently occurring announcement day dummy.

[27] Pooling in this way risks reducing power as the cross-sectional variation in coefficients on lagged equity market news is large. An alternative approach to improve the precision of the estimates of α_1 and α_2 might be to increase the number of announcements included in the analysis. However this risks pooling important macroeconomic releases with less important ones, which reduces our ability to discriminate between days with high and low information asymmetries.

[28] Note that a negative correlation between equity market illiquidity and the magnitude of the lagged response of CDS returns would be suggested by Barberis and Shleifer's (2003) model in which random liquidity demands with systematic components are traded first in large cap stocks and later in other assets. Such liquidity trading would decrease equity market illiquidity while increasing the magnitude of the lead-lag relationship. This could be viewed as an alternative hypothesis to the one we propose.

$$r^{c}_{m,t} = \beta_0 + \beta_1 r^{epos}_{m,t-1} + \beta_2 r^{eneg}_{m,t-1} + \beta_3 r^{epos}_{m,t-1} \times SP_{t-1} + \beta_4 r^{eneg}_{m,t-1} \times SP_{t-1} + \beta_5 r^{c}_{m,t-1} + \varepsilon^{c}_{m,t} \qquad \textbf{(7)}$$

Results are reported in Table 7 for portfolio CDS returns and for pooled individual returns. The coefficients on the interaction of spreads with positive equity market movements are negative and statistically significant, supporting the idea that information leading to widening equity spreads and a rising equity market is incorporated into CDS prices with a relatively long lag. Importantly, the results suggest that it is not the direction of news per se that drives the asymmetry since restricting the coefficients on lagged positive and negative equity market to be equal is not rejected and barely alters the goodness of fit. Rather it is the direction of news combined with high levels of asymmetric information that drive the asymmetry in the lead-lag relationship. Conversely, the coefficients on the interaction of spreads with negative equity news are significantly positive, although the coefficient magnitude is much smaller than for positive news. This suggests that bad news actually reduces the lag of the CDS market.

This sub-section has focussed on demonstrating that information asymmetries lie behind the equity market lead over the CDS market. In line with the rockets and feathers hypothesis we show that at times of high information asymmetry, such as immediately prior to important macroeconomic announcements or when market-wide equity bid-ask spreads are high and the news is positive, the equity market's lead is maximised. Conversely, when asymmetries are low, the lead is small.

Conclusions

This paper has analyzed lead-lag patterns in equity and CDS markets. Using a large dataset we have documented a strong and robust advantage of the equity market over the CDS market in pricing new information. We have also documented that this advantage is mainly due to the pricing of aggregate and positive information in the equity market. A potential explanation for this is the presence of institutional investors with hedging demands in the CDS market. While these investors may be well informed about news specific to the firms in their portfolio, they may behave relatively passively in the advent of macro news. Dealers can exploit their local market power following good equity market news and maintain relatively high CDS prices when hedgers are not fully informed about the fall in the true price of protection. Conversely, after bad equity market news, CDS prices rise much more rapidly since it is in the dealers' best interest to raise prices for protection buyers.

Consistent with this hypothesis we have shown that the lead-lag is stronger for firms for which there is larger hedging demand. We have also presented evidence in favour of the pricing advantage of the equity market being related to informational asymmetries, as the equity-lead is more pronounced at times of higher macroeconomic uncertainty (as measured by days prior to macroeconomic announcements and high bid-ask spreads). By contrast, our evidence does not lend support to alternative explanations of the lead-lag that are consistent with efficient markets.

Our paper strikes a negative note on the efficiency of CDS markets. CDS markets are widely considered to be the most efficient means of pricing credit risk. As such, one would expect them to do also relatively well compared with equity markets. However, our results show that this is not the case as we find a strong lead for equity markets. Perhaps most disturbingly, the lead arises from supposedly easy-to-price economy-wide information, such as the equity-market factor. It should also be recalled that we have centred our sample on the firms with the most liquid CDS contracts, thus effectively biasing us against finding inefficiencies in the CDS market.

Our analysis indicates that the inefficiency of the CDS market is caused by the presence of institutional investors with a passive demand for hedging. This suggests that the composition of investors in a market can have important implications for pricing inefficiencies, especially when some classes of investor are informed (or uninformed) about certain types of news. More research in this area seems warranted – in particular understanding whether the pricing properties of other markets and assets (for example, CDS versus bond markets or large versus small firm stocks) can also be linked to the presence (or lack) of certain investor groups.

Table 1

Descriptive Statistics

This table provides summary statistics of the key returns series used in the paper. The sample runs from 1st January 2004 through 14th October 2008 (1208 observations per firm), and there are 193 firms in the data set. Figures in rows denoted Autocorrelation 1, 2 and 3 give autocorrelations with one, two and three lags. Figures in rows denoted Cross-autocorrelation 1, 2 and 3 give correlations between the time *t*-dated returns of the asset in that column and returns of the other asset at times *t*-1, *t*-2 and *t*-3. Statistics are calculated from the pooled data set.

	Equity returns	**CDS returns**
Mean	-0.0003	0.0014
25th percentile	-0.0090	-0.0098
75th percentile	0.0091	0.0095
Standard Deviation	0.0238	0.0351
Skew	-6.1305	2.4295
Autocorrelation 1	0.0239	0.2137
Autocorrelation 2	-0.0530	0.1106
Autocorrelation 3	-0.0093	0.0377
Cross-correlation	-0.1886	-0.1886
Cross-autocorrelation 1	-0.0145	-0.1487
Cross-autocorrelation 2	-0.0235	-0.0255
Cross-autocorrelation 3	-0.0089	-0.0310

Table 2

Bivariate VAR Results

The table reports the results of a bivariate vector autoregression of daily equity and CDS returns with one lag. The relevant dependent variable is given in the first column of each row. The first two rows of Panel A report average OLS results (coefficient values and R^2 values) across the 193 individual firms together with a count of the number of firms with coefficients significant at the 5% level. The latter is also expressed as a percentage of the total sample of 193 firms. The p-val figure is that resulting from a test that the average coefficient value is zero. The second two rows of Panel A report pooled regression results. Panel B reports results of a bivariate vector autoregression of daily equity and CDS equally weighted portfolio returns with one lag. OLS results use standard errors robust to unspecified heteroscedasticity and serial correlation. Pooled regressions report p-values based on standard errors robust to unspecified heteroscedasticity and double clustered by day and by firm. The full sample runs from 1st January 2004 through 14th October 2008 (1208 observations per firm).

	Lagged equity returns		**Lagged CDS returns**		**R2**
	Coefficient (p-val)	Count significant (% signif.)	Coefficient (p-val)	Count significant (% signif.)	
Panel A:					
Individual firms					
Equity returns	-0.025 (0.648)	20 (10.4%)	-0.001 (0.977)	12 (6.2%)	0.008
CDS returns	-0.201 (0.011)	149 (77.2%)	0.197 (0.001)	157 (81.3%)	0.076
Pooled firms					
Equity returns	0.021 (0.517)		-0.007 (0.582)		0.001
CDS returns	-0.166 (0.000)		0.191 (0.000)		0.057
Panel B:					
Equity port. returns	-0.027 (0.599)		0.024 (0.612)		0.003
CDS port. returns	-0.306 (0.000)		0.408 (0.000)		0.279

Table 3

Factor VAR Results

The table reports the results of vector autoregressions of daily factor decomposed equity and CDS returns with one lag. The table reports average results (coefficient values and R2 values) across the 193 individual firms together with a count of the number of firms with coefficients significant at the 5% level. The latter is also expressed as a percentage of the total sample of 193 firms. The p-val figure is that resulting from a test that the average coefficient value is zero. In panel A firm-level equity and CDS returns are decomposed into common and idiosyncratic components based on principal components analysis. Specifically, the first three principal components are extracted from the equity returns of the 193 firms. The equity returns of each firm are then regressed on these three principal components, fitted values are saved as the common component of equity returns and residuals are saved as the idiosyncratic component. A similar approach is taken for CDS returns. These four components form the VAR. The relevant dependent variable is given in the first column and the explanatory variables are identified by the column headings. In panel B a similar decomposition is performed for equity returns using three Fama-French factors. CDS returns are not decomposed and the trivariate VAR is composed of the common equity return component, the idiosyncratic equity component and the total CDS return. In Panel C, the equity decomposition is performed using just one factor, alternately the first principal component, the equally weighted average return from the 193 equities, and the Fama-French market factor. Each row in Panel C reports the results of regression with the total CDS return as dependent variable. All VAR estimates are computed using OLS with standard errors robust to unspecified heteroscedasticity and serial correlation. The full sample runs from 1st January 2004 through 14th October 2008 (1208 observations per firm).

	Lagged equity returns				**Lagged CDS returns**				**R2**
	Common returns		**Idiosyncratic returns**		**Common returns**		**Idiosyncratic returns**		
	Coefficient (p-val)	Count signif. (% signif.)	Coefficient (p-val)	Count signif. (% signif.)	Coefficient (p-val)	Count signif. (% signif.)	Coefficient (p-val)	Count signif. (% signif.)	
Panel A: PCA factors									
Equity Common	-0.026 (0.632)	0 (0.0%)	0.001 (0.989)	14 (7.3%)	0.027 (0.553)	0 (0.0%)	-0.001 (0.947)	12 (6.2%)	0.009
Equity Idiosyncratic	0.004 (0.954)	30 (15.5%)	-0.020 (0.677)	31 (16.1%)	-0.005 (0.896)	20 (10.4%)	-0.012 (0.603)	22 (11.4%)	0.017
CDS Common	-0.279 (0.000)	173 (89.6%)	-0.012 (0.816)	17 (8.8%)	0.451 (0.000)	193 (100.0%)	-0.002 (0.947)	30 (15.5%)	0.293

CDS Idiosyncratic	-0.009 (0.922)	19 (9.8%)	-0.058 (0.459)	28 (14.5%)	0.005 (0.940)	21 (10.9%)	0.078 (0.171)	81 (42.0%)	0.029
Panel B: Fama-French factors									
Equity Common	-0.086 (0.141)	57 (29.5%)	0.010 (0.787)	15 (7.8%)	0.005 (0.765)	1 (0.5%)			0.014
Equity Idiosyncratic	0.003 (0.962)	28 (14.5%)	-0.005 (0.917)	26 (13.5%)	-0.009 (0.652)	22 (11.4%)			0.015
CDS Total	-0.422 (0.001)	178 (92.2%)	-0.086 (0.354)	40 (20.7%)	0.185 (0.001)	151 (78.2%)			0.086
Panel C: Market factor									
Principal component #1	-0.470 (0.000)	184 (95.3%)	-0.065 (0.480)	31 (16.1%)	0.182 (0.002)	150 (77.7%)			0.089
Average equity return	-0.482 (0.000)	184 (95.3%)	-0.064 (0.483)	31 (16.1%)	0.181 (0.002)	149 (77.2%)			0.090
Fama-French market factor	-0.443 (0.001)	179 (92.7%)	-0.085 (0.350)	48 (24.9%)	0.184 (0.002)	152 (78.8%)			0.087

Table 4

Asymmetric Responses to Positive and Negative Equity Market News

This table reports results of regressions of CDS returns on lagged equity market returns partitioned into positive and negative components. Lagged CDS returns are also included in the regressions. The first row of the table summarizes results using common components of firm CDS returns as dependent variables. The common components were extracted using the first three principal components of CDS returns. This row reports average results (coefficient values and R2 values) across the 193 individual firms together with a count of the number of firms with coefficients or test statistics significant at the 5% level. The latter is also expressed as a percentage of the total sample of 193 firms. The p-val figure is that resulting from a test that the average coefficient value is zero. The second row reports results from the equivalent pooled regression. The final row reports regression results using equally weighted portfolio CDS returns. Equity market returns are computed as the equally weighted equity market return for our sample of stocks. All estimates are computed using OLS with standard errors robust to unspecified heteroscedasticity and serial correlation. The pooled regression results report robust double clustered (firm and time) standard errors. The sample runs from 1st January 2004 through 14th October 2008 (1208 observations per firm).

	Lagged positive equity market returns		**Lagged negative equity market returns**		**Coefficient equality test**	**R2**
	Coefficient (p-val)	Count signif. (% signif.)	Coefficient (p-val)	Count signif. (% signif.)	p-val (% signif.)	
Individual common CDS returns	-0.497 (0.000)	193 (100.0%)	-0.159 (0.092)	106 (54.9%)	0.121 (29.0%)	0.299
Pooled regression	-0.57 (0.000)		-0.34 (0.000)		0.148	0.069
Portfolio CDS returns	-0.489 (0.000)		-0.168 (0.058)		0.043	0.286

Table 5
Cross-Sectional Variation in Responses to Good and Bad News

The first column of this table reports results of cross-sectional regressions of estimated coefficients from row 2 of Table 4 on firm-specific variables. Specifically, the dependent variable is the estimated coefficient on lagged positive equity market returns from regressions of CDS returns on lags of itself, lagged positive equity market returns and lagged negative equity market returns. The second column uses the coefficient on lagged negative equity market returns from the same regression. In the third column we use *Difference*, defined as the coefficient on positive news minus the coefficient on negative news, as a dependent variable. All estimates are computed using weighted least squares with robust standard errors. Weights are inversely proportional to the variance of the estimated coefficients from the first stage regression. Coefficient estimates are reported with associated p-values in parentheses.

	Positive coefficient	**Negative coefficient**	**Difference**
Long term debt	-0.0762 (0.000)	-0.0093 (0.531)	-0.0765 (0.009)
Rating	-0.1691 (0.015)	0.1225 (0.130)	-0.2681 (0.026)
Rating squared	0.0279 (0.005)	-0.0207 (0.072)	0.0473 (0.004)
CDS volatility	-0.5398 (0.015)	0.0812 (0.207)	-0.5871 (0.000)
Equity illiquidity	-8.8434 (0.015)	2.1422 (0.405)	-10.9865 (0.035)
Idiosyncratic volatility	-0.0175 (0.694)	-0.0839 (0.011)	0.0623 (0.345)
Market capitalisation	0.0815 (0.001)	-0.0209 (0.247)	0.1132 (0.001)
Average CDS level	-0.0004 (0.070)	0.0010 (0.004)	-0.0011 (0.002)
R2	0.345	0.089	0.268

Table 6

Information Asymmetries and News Announcements

The table reports results of regressions of CDS returns on lagged positive equity market returns interacted with three indicator variables. PRE takes the value 1 on days immediately prior to important macroeconomic announcements (and 0 otherwise), DAY takes the value of 1 on the day of macro announcements (and 0 otherwise) and NONE takes the value of 1 if both other indicator variables equal 0 (and 0 otherwise). Equity market returns are computed as the equally weighted equity market return for our sample of stocks. Lagged CDS returns and lagged negative equity market returns are also included in the regressions. Results are reported for equally weighted portfolio CDS returns and for pooled individual CDS returns. The final row reports the test statistic and p-value of the test that coefficients on the three interacted variables are equal. All estimates are computed using OLS with standard errors robust to unspecified heteroscedasticity and serial correlation. The sample runs from 1st January 2004 through 14th October 2008 (1208 observations per firm).

	Portfolio CDS Returns		**Pooled Individual CDS Returns**	
	Coefficient	(p-val)	Coefficient	(p-val)
Lagged positive equity market returns × PRE	-0.641	(0.000)	-0.297	(0.000)
Lagged positive equity market returns × NONE	-0.437	(0.001)	-0.153	(0.000)
Lagged positive equity market returns × DAY	-0.401	(0.032)	-0.111	(0.000)
Lagged negative equity market returns	-0.171	(0.054)	-0.159	(0.000)
Lagged CDS returns	0.421	(0.000)	0.193	(0.000)
R2	0.287		0.058	
Coefficient equality test	0.89	(0.410)	2.85	(0.060)

Table 7

Information Asymmetries and Illiquidity

This table reports results of a regression of equally weighted portfolio CDS returns on the variables listed in the first column. The main innovation in this set of regressions is the inclusion of lagged equity market returns interacted with lagged average equity market bid-ask spreads. Equity market returns are computed as the equally weighted equity market return for our sample of stocks. Estimates are computed using OLS with standard errors robust to unspecified heteroscedasticity and serial correlation. Coefficient estimates are reported with associated p-values in parentheses. The final row reports the test statistic and p-value of the test that the sum of the coefficients on the two interacted variables is equal to zero. The sample runs from 1st January 2004 through 14th October 2008 (1208 observations).

	Portfolio CDS Returns		**Pooled Individual CDS Returns**	
	Coefficient	(p-val)	Coefficient	(p-val)
Lagged positive equity market returns	-0.247	(0.044)	-0.387	(0.000)
Lagged negative equity market returns	-0.277	(0.007)	-0.477	(0.000)
Lagged positive equity market returns × lagged spreads	-1.244	(0.026)	-0.908	(0.001)
Lagged negative equity market returns × lagged spreads	0.334	(0.004)	0.428	(0.000)
Lagged CDS returns	0.420	(0.000)	0.182	(0.000)
R2	0.290		0.070	
Coefficient equality test	5.98	(0.003)	4.99	(0.000)

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Appendix A: Robustness of Unconditional Equity Lead-CDS Lag Result

Tables 2 in the text summarises the results of estimating VARs of equity and CDS returns. The dominant finding is that lagged equity returns contain information for current CDS price changes, while the reverse is rarely the case. This appendix demonstrates the robustness of these findings.

The VAR as specified in equations (1a) and (1b) does not control for contemporary CDS or equity returns, respectively. The delayed diffusion of information from equity to CDS markets suggested by our results may simply be due to the omission of contemporaneous equity returns from equation (1b). We test for this by incorporating the relevant contemporaneous return in each equation both for each reference entity individually and for all entities pooled together. Results are reported in panel A of Table A2. Our key finding - that CDS returns lag equity returns - is robust to the inclusion of contemporaneous equity returns.

Panel B of Table A2 summarises results when we pool the companies but split the sample according to the credit rating and equity market capitalisation of the firms. Irrespective of whether companies are rated AAA-A versus BBB-B, or whether they are in the smallest quartile or the middle 50% by market capitalization, lagged equity returns are significant in explaining current CDS returns. Lagged equity returns are not significant in pooled regressions for firms in the largest quartile but this is driven by a small number of firms since lagged equity returns are significant for the largest quintile (coefficient = -0.29, p-val = 0.000). Conversely, but irrespective of how we separate the firms, lagged CDS returns are not significant in the equity returns regressions, with the sole exception of the small firms. Even in this case, however, the magnitude of the coefficient is very small and the goodness of fit very low indicating statistical but not economic significance.

Panel C of Table A2 pools the companies but splits the sample into pre-crisis and crisis periods. The pre-crisis period runs from the start of the sample through the end of June 2007 while the crisis period runs from the start of August 2007 to the end of the sample period. Observations for July 2007 are dropped from the analysis. Again, there is a strong lag of the CDS market in both periods. It is interesting to note that the CDS predictability is higher in the crisis period (the coefficient on lagged equity returns is -0.349, compared to -0.226 before the crisis). There is some evidence of information in lagged CDS returns for the equity market prior to the crisis, but this is again statistically but not economically significant and, further, completely disappears during the crisis interval.

Table A2

Bivariate VAR Results

The table reports the results of a bivariate vector autoregression of daily equity and CDS returns with one lag. The relevant dependent variable is given in the first column of each row. The first two rows report average results (coefficient values and R^2 values) across the 193 individual firms together with a count of the number of firms with coefficients significant at the 5% level. The latter is also expressed as a percentage of the total sample of 193 firms. The p-val figure is that resulting from a test that the average coefficient value is zero. The remaining rows report pooled regression results. OLS results use standard errors robust to unspecified heteroscedasticity and serial correlation. Pooled regressions report p-values based on standard errors robust to unspecified heteroscedasticity and double clustered by day and by firm. The full sample runs from 1st January 2004 through 14th October 2008 (1208 observations per firm). In panel A the equity (CDS) equation in the VAR is augmented with contemporaneous CDS (equity) returns. In panel C, the pre-crisis period runs from 1st January 2004 through end June 2007 (877 observations per firm) and the crisis period runs from start August 2007 to the end of the sample (308 observations per firm).

	Lagged equity returns		**Lagged CDS returns**		**R2**
	Coefficient (p-val)	Count significant (% signif.)	Coefficient (p-val)	Count significant (% signif.)	
Panel A:					
Individual firms with contemporaneous 'other asset' returns					
Equity returns	-0.051 (0.392)	43 (22.3%)	0.029 (0.424)	47 (24.4%)	0.054
CDS returns	-0.208 (0.023)	154 (79.8%)	0.196 (0.001)	157 (81.3%)	0.118
Pooled firms with contemporaneous 'other asset' returns					
Equity returns	0.000 (0.998)		0.018 (0.161)		0.036
CDS returns	-0.160 (0.000)		0.190 (0.000)		0.091
Panel B:					
Credit rating					
AAA-A					
Equity returns	0.002 (0.946)		-0.003 (0.829)		0.000
CDS returns	-0.240 (0.000)		0.150 (0.000)		0.050
BBB-B					
Equity returns	-0.008 (0.677)		-0.004 (0.785)		0.000
CDS returns	-0.162 (0.000)		0.228 (0.000)		0.077
Size					
Largest 25%					
Equity returns	0.111 (0.398)		-0.014 (0.587)		0.014
CDS returns	-0.140 (0.193)		0.158 (0.000)		0.037
Middle 50%					

Equity returns	-0.015 (0.510)	-0.000 (0.974)	0.002
CDS returns	-0.189 (0.000)	0.200 (0.000)	0.064
Smallest 25%			
Equity returns	0.002 (0.885)	-0.014 (0.263)	0.003
CDS returns	-0.150 (0.000)	0.222 (0.000)	0.077
Panel C:			
Pre-crisis			
Equity returns	0.006 (0.590)	-0.004 (0.388)	0.000
CDS returns	-0.147 (0.000)	0.166 (0.000)	0.037
Crisis period			
Equity returns	0.027 (0.573)	-0.005 (0.837)	0.001
CDS returns	-0.166 (0.002)	0.210 (0.000)	0.075

Appendix B: List of Firms Analysed

Basic Materials
Alcoa
Ashland
Commercial Mtls.
Cytec Inds.
Dow Chemical
E I Du Pont De Nemours
Eastman Chemical
Intl. Paper
Monsanto
Newmont Mining
Nucor
Olin
Praxair
Weyerhaeuser

Consumer Goods
Altria Group
Archer-Danls.-Midl.
Arvinmeritor
Avon Products
Black & Decker
Borgwarner
Brunswick
Campbell Soup
Centex
Coca Cola
Coca Cola Ents.
Conagra Foods
Constellation Brands
Cooper Tire & Rub.
D R Horton
Ford Motor
Fortune Brands
General Mills
General Motors
Johnson Controls
Jones Apparel Group
KB Home
Kellogg
Kimberly-Clark
Kraft Foods
Lear
Lennar
Liz Claiborne
Newell Rubbermaid
Pepsico
Pulte Homes
Sara Lee
Sears Holdings
Smithfield Foods
Stanley Works
Standard Pacific
Toll Bros.
Tyson Foods
Universal
V F
Whirlpool

Consumer Services
Autozone
Cardinal Health
Comcast
Costco Wholesale
Dillards
Gannett
Home Depot
Interpublic Gp.
Penney Jc
Kohl's
Kroger
Limited Brands
Lowe's Companies
Marriott Intl.
McDonalds
McKesson
Nordstrom
Office Depot
Omnicom Gp.
Radioshack
Safeway
Southwest Airlines
Staples
Starwood Htls.& Rsts.
Supervalu
Target
Gap
Time Warner
Tjx Cos.
Walt Disney
Yum! Brands

Financials
Allstate
Ambac Financial
American Express
AIG
Aon
Berkshire Hathaway
Capital One Finl.
Chubb
Cit Group
CNA Financial
General Electric
Goldman Sachs Gp.
Hartford Finl.Svs.Gp.
Lincoln Nat.
Loews
Marsh & Mclennan
Mbia
Metlife
Mgic Investment
Morgan Stanley
PMJ Group
Prudential Finl.
Radian Gp.
SLM
Washington Mutual
Wells Fargo & Co

Health Care
Abbott Laboratories
Amgen
Boston Scientific
Bristol Myers Squibb
Humana
Medtronic
Merck & Co.
Pfizer
Schering-Plough
Tenet Hlthcr.
Unitedhealth Gp.
Wyeth

Industrials
3m
Arrow Electronics
Avnet
Boeing
Burl.Nthn.Santa Fe
Caterpillar
CSX
Danaher
Dover
Emerson Electric
Fedex
Goodrich
Honeywell Intl.
Lockheed Martin
Masco
Meadwestvaco
Norfolk Southern
Raytheon 'B'
Republic Svs.
Ryder System
Sealed Air
Sherwin-Williams
Temple Inland
Textron
Union Pacific
United Parcel Ser.
Waste Man.

Oil & Gas
Anadarko Petroleum
Apache
Baker Hughes
Chesapeake Energy
Chevron
Conocophillips
Devon Energy
Diamond Offs.Drl.
El Paso
Enterprise Prds.Ptns.Lp.
Forest Oil
Hess
Kinder Morgan En.Ptns.
Marathon Oil
Parker Drilling
Pioneer Ntrl.Res.
Sunoco

Technology
Amkor Tech.
CA
Centurytel
Computer Scis.
Corning
Dell
Hewlett-Packard
IBM
Motorola
Pitney-Bowes
Sun Microsystems
Texas Insts.
Xerox

Utilities
Cms Energy
Constellation En.
Dte Energy
Duke Energy
Entergy
Exelon
Oneok
Pepco Holdings
Progress Energy
Sempra En.
Teco Energy
Xcel Energy