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Insider trading in credit derivatives☆

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Abstract

Insider trading in the credit derivatives market has become a significant concern for regulators and participants. This paper attempts to quantify the problem. Using news reflected in the stock market as a benchmark for public information, we find significant incremental information revelation in the credit default swap market under circumstances consistent with the use of non-public information by informed banks. The information revelation occurs only for negative credit news and for entities that subsequently experience adverse shocks, and increases with the number of a firm's relationship banks. We find no evidence, however, that the degree of asymmetric information adversely affects prices or liquidity in either the equity or credit markets.

JEL classification: G12; G13; G14; G20; D8

Keywords: Adverse selection; Bank relationships; Credit derivatives

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1. Introduction

> [B]anks must not use private knowledge about corporate clients to trade instruments such as credit default swaps (CDS), says a report [by] the International Swaps and Derivatives Association and the Loan Market Association...[M]any banks and institutions are trading CDS instruments in the same companies they finance – sometimes because they want to reduce the risks to their own balance sheets. (Financial Times, April 25, 2005)

Credit derivatives have been perhaps the most significant and successful financial innovation of the last decade. The use of credit derivatives has been cited as an important reason for the observed robustness of banks and financial institutions to the historically high global levels of corporate defaults during the period 2000–2004. As Alan Greenspan recently observed, "The new instruments of risk dispersion have enabled the largest and most sophisticated banks in their credit-granting role to divest themselves of much credit risk by passing it to institutions with far less leverage. These increasingly complex financial instruments have contributed, especially over the recent stressful period, to the development of a far more flexible, efficient, and hence resilient financial system than existed just a quarter-century ago."[1] In addition, markets for credit derivatives have helped banks create synthetic liquidity in their otherwise illiquid loan portfolios.[2] Not surprisingly, the growth in the size of this market continues unabated as products are expanding to cater to emerging markets, and indices such as iBoxx and iTraxx are becoming industry benchmarks for credit conditions.

If credit derivatives are to seamlessly provide insurance and liquidity-creation roles, then the orderly functioning of these markets becomes an important policy objective. Credit derivatives, however, like all forms of insurance, are subject to moral hazard (see Duffee and Zhou, 2001) and asymmetric information risks. In this paper, we are concerned with the latter of these risks. Specifically, if a creditor of Company X has private information about the likelihood of default, or can itself influence default, then this creditor might try to exploit its privileged information by buying credit insurance on X from a less-informed counterparty. Or if loan officers who deal directly with X pass on inside information to the traders buying credit derivatives, the institution on the other side of the trade could get a rotten deal. If fears of such behavior are widespread, the liquidity of the market could be threatened.

Of course, asymmetric information and insider trading problems potentially exist in most markets. But the credit derivatives market may be especially vulnerable since, almost by definition, most of the major players are insiders. Firms have a much closer relationship with their private financiers, such as banks, than with investors in their public securities such as stocks and bonds. In particular, firms often provide material and price-sensitive information, such as revenue projection updates or acquisition and divestiture plans, to relationship banks well in advance of release to the public. Trading desks of many banks

[1] From Greenspan's speech "Economic Flexibility" before Her Majesty's Treasury Enterprise Conference (London, 26 January 2004). A contrasting view is that if regulations such as capital requirements are ill-designed, then credit derivatives can result in inefficient transfers of risk between banks and insurance companies (Allen and Gale, 2005).

[2] In an important recent example, Citigroup distributed a large portion of its exposure to Enron through issuance of credit-linked notes at regular intervals in the two-year period preceding the default of Enron; as a result, Enron's collapse had a minor effect on Citigroup's balance sheet.

and financial institutions act as intermediaries in the credit derivatives market, quoting prices for protection written on corporations to which they have loan exposures. In the absence of perfect "Chinese walls" within banks, the credit derivatives market provides the trading desks of relationship banks a mechanism through which the information possessed by loan officers about a firm can be exploited and, in turn, transmitted in public markets.

Indeed, some recent episodes in the credit derivatives markets reveal that this issue may have potentially important implications for the efficiency of credit-risk transfer across institutions. In striking recent episodes, managers of Pacific Investment Management Co. (PIMCO), the largest bond investor in the U.S., have cited in their white papers several cases of insider trading in companies such as Household International Inc., AT&T Wireless, and Sprint Corp.: "Credit default markets are a mechanism with which friendly commercial bankers ... can profit by betraying and destroying their clients through the use of inside information," and "... firms with large lending departments would always come in and buy protection at exactly the right moment." Such events have also often been acknowledged in press (e.g., *The Economist*, "Pass the Parcel – Credit Derivatives," January 18, 2003.)

From an academic standpoint, the credit derivatives market is a particularly attractive laboratory for the testing of hypotheses pertaining to insider trading for several reasons: first, the potentially informed players, namely the banks, are well identified; second, the nature of private information (the likelihood of default) is unambiguous; third, incentives to exploit information (i.e., the magnitude of loan exposure and credit risk) are also measurable; and, finally, unlike much of the corporate bond market, daily data on prices of most widely traded credit derivatives are available since the start of the century.

Given this motivation, we study the market for trading in credit default swaps (CDS), the most common credit derivative instrument, in order to measure the prevalence of informed trading and then to assess its effects on price and liquidity. We use data on the quoted CDS levels and bid-ask spreads for a cross-section of U.S. firms over the period January 2001 through October 2004. Using news reflected in the stock market as a benchmark for public information, we report evidence of significant incremental information revelation in the CDS market, consistent with the occurrence of informed revision of quotes or insider trading. We show that the information flow from the CDS market to the stock market is greater for subsamples where we expect a priori that insider trading would be a more significant issue: entities that experience credit deterioration during the sample period, and whose CDS levels are generally high. Absent these conditions, there is no such incremental information revelation in the CDS market.

Having identified a measure of information flow from the CDS market to the stock market, we next link this directly to a proxy for the number of informed insiders: banking relationships of a firm, calculated using the Loan Pricing Corporation's data. We find that the degree of information flow increases with the number of banks that have ongoing lending (and hence monitoring) relationships with a given firm. This finding is robust to controls for non-informational trade, liquidity of stock and CDS markets, short-sale constraints, and the level of firm risk. Crucially, information revelation in the CDS market is asymmetric, consisting exclusively of bad news. This finding is consistent with the greater incentives of banks to exploit private information upon adverse credit news, that is, in times when they seek to hedge their underlying loan exposures.

If insider trading does exist in these markets, then it is possible that market makers will be less willing to make prices in these derivatives in situations where they perceive the likelihood of private information to be high. In particular, in volatile conditions or when default risks rise, the risk of insider trading could rise, resulting in a loss of liquidity precisely when hedging needs are greatest. Furthermore, the one-sided nature of insider trading risk in this market (i.e., default risk) suggests that the price level at which insurance is purchased could also be affected.

These effects could, however, be counteracted by alternate considerations. The threat of information asymmetry might also induce gains in liquidity provision, depending on the market structure. First, since informed banks are also market makers, they could play a liquidity-provision role to learn about order flow in the relatively opaque markets for credit derivatives, along the lines of the experimental evidence in Bloomfield and O'Hara (1999, 2000). Second, an increase in the number of banking relationships could increase not only information-based trading but also uninformed trading from portfolio rebalancing and regulatory arbitrage activities of banks. Finally, an increase in the number of insiders could cause them to compete, revealing information into prices rapidly and without much loss of market liquidity (Holden and Subrahmanyam, 1992). These mechanisms could render the potential harm of insider trading insignificant.

To investigate this issue, we study whether liquidity providers in the CDS markets charge greater bid-ask spreads when insider-trading risk is greater, and whether this insider-trading risk affects the level of prices in credit derivatives markets. Answering these questions is important to understanding whether insider-trading risk in the CDS markets is a significant concern for the liquidity and orderly functioning of these markets.

We find no evidence that the degree of insider activity, proxied by the number of banking relationships, adversely affects prices or liquidity in either the equity or the credit markets (after controlling for their standard determinants). If anything, the reverse appears to be true: CDS markets for corporate entities that have a large number of banking relationships tend to have smaller bid-ask spreads, on average. Furthermore, even the direct measure of illiquidity, the percentage bid-ask spread, has no explanatory power for the level of CDS fees.

While our results highlight the complexity of the process of liquidity determination, they may have important implications for regulators. The institutional response to complaints of insider trading in CDS markets has been to issue voluntary guidelines on information sharing inside banks (issued by agencies such as the Joint Market Practices Forum and the Financial Stability Forum in North America), and on how "material non-public information should be handled by credit portfolio managers in European Union member states", issued by the International Swap Dealers' Association (ISDA), the Bond Market Association, and the Loan Market Association. Our results suggest that while the complaints against insider trading in CDS markets probably have merit, it is unclear whether there should be any regulatory action to curb insider trading if the objective of such action is to prevent the loss of liquidity or to avoid adverse pricing in credit derivatives markets. In particular, although we find that the CDS markets appear to be transmitting non-public information into publicly traded securities such as stocks, we do not find any evidence that insider trading in CDS markets is directly harmful.

1.1. Related literature

Our study integrates two different strands of literature (and also synthesizes analysis of the respective datasets): banking – the specialness of banks in possessing private information about their borrowers (Fama, 1985; James, 1987); and market microstructure – the strategic use of private information by insiders potentially affecting prices and bid-ask spreads (Kyle, 1985; Glosten and Milgrom, 1985).

Viewed in another light, our study also integrates the literature on information asymmetries and financial innovations. It is well known theoretically that in economies with information asymmetries, financial innovations that would otherwise improve risk-sharing can in fact be welfare-reducing (see, e.g., Marin and Rahi, 2000, and references therein). In practice, however, investigation of such effects is rendered difficult by the fact that a researcher is generally unable to identify the exact nature of asymmetric information, whose effects could get exacerbated by specific innovation. Our investigation helps fill this important gap in the literature.

More generally, analysis of the effects of asymmetric information on contracting and trade is also hampered by the same identification issue. Like Garmaise and Moskowitz (2004), we contribute an exogenous measure of such asymmetry and directly test for its effects on financial decisions.

Insider trading has been the focus of a large body of research in equity markets which has found that insider trading lowers liquidity and increases trading costs (see, e.g., Easley, Kiefer, O'Hara, and Paperman, 1996; Chun and Charoenwong, 1998; Bettis, Coles, and Lemmon, 2000; Brockman and Chung, 2003; Fishe and Robe, 2004), raises the cost of equity capital (Bhattacharya and Daouk, 2002), and increases volatility (Du and Wei, 2004). We are not aware of a study that has examined the effects of insider trading in credit markets.

Recent important work has begun to document and examine patterns of cross-market information flows, as we do here. Hotchkiss and Ronen (2002) focus on how quickly the information in equity markets is incorporated into bond markets, the opposite of the phenomenon we report. Blanco, Brennan, and Marsh (2005) report that for a sample of high-grade credits there is greater price discovery in the CDS market than in the bond market, although the reverse occurs as well. Norden and Weber (2004) study the co-movement of CDS, bond, and stock markets during 2000–2002. They find that the stock market generally leads the CDS and bond markets, that the CDS market is more responsive to the stock market than is the bond market, and that the CDS market plays a more important price discovery role than the bond market. Longstaff, Mithal, and Neis (2003) examine weekly lead-lag relations between CDS spread changes, corporate bond spreads, and stock returns of U.S. firms in a VAR framework. They find that both stock and CDS markets lead the corporate bond market. However, in their sample there is no clear lead of the stock market with respect to the CDS market and vice versa.

Relative to these papers, our contribution is to probe further into the causes of these sometimes complex patterns of leads and lags, and to examine their implications for pricing and liquidity. In particular, we show that these complex lead-lag patterns are related in the cross-section of firms to the adversity of future credit news and the number of ongoing banking relationships, that is, to the likelihood of informed trading.

The remainder of the paper is organized as follows. Section 2 presents our overall approach to identifying informed activity in CDS markets, describes the CDS data we employ, and presents initial evidence consistent with the conditional occurrence of insider trading. Section 3 links the information flow effects to direct measures of the number of parties with access to non-public information. Section 4 examines the effect of insider trading risk on the liquidity of CDS and equity markets, and discusses possible interpretations of our findings. Section 5 concludes.

2. Evidence of informed trading in credit derivatives

The most direct way of detecting insider trading is to know who the insiders are and identify their trades. For instance, in the case of corporate officers and directors, Section 16(a) of the 1934 Securities Exchange Act requires disclosure of individual stock trades. There is no equivalent requirement to report activity in credit derivatives, and, in any case, trading by *individuals* in the CDS market is minimal. The informed parties we are concerned with (i.e., banks) face no disclosure requirement when they trade in derivatives of companies with which they have relationships. Moreover, information about the identities of parties trading and posting quotes through the broker from whom our data is collected is privileged, and their agreements with the participating institutions do not allow them to reveal it.

A second approach relies on patterns in volume or signed order flow. In an event-study context, unusual volume prior to a price move is commonly interpreted as news "leakage." More generally, Easley, Kiefer, O'Hara, and Paperman (1996) argue that the probability of insider activity in any stream of trades is monotonically related to the imbalance (in absolute value) of customer-initiated buys over sells. Similarly, the microstructure literature has also used price impact measures to gauge informativeness of individual trades. Trades that lead to ex post permanent price changes can be viewed as having been informed. (Note that "informed" trades, by these definitions, are insider trades because, if the information were public, the market price would have adjusted prior to the orders.) Again, however, these techniques are not possible given our data. Our quote provider does not possess sufficient information to identify buyer-initiated or seller-initiated transactions. (Indeed, we have no transaction information at all.) And overall volume is not an available statistic, since, as in many OTC markets, there is no centralized reporting of trades.

To summarize, data limitations imply that the quantification of insider activity in the CDS markets poses a challenge. Our approach to meeting this challenge utilizes the fact that the securities we study are derivatives, whose worth depends primarily on the value of the underlying reference company. Since all the companies in our sample have actively traded equity, we use this primary market to identify the arrival of relevant public information.

If agents in credit markets in fact possess insider information, and they occasionally trade on that information, then this would cause credit markets to react before equity markets at least some of the time. We exploit this implication to identify the prevalence of insider trading. More specifically, we maintain the following hypotheses:

1. Stock market prices reflect all available public information.
2. Information flow from the CDS market to the stock market implies a permanent impact of CDS innovations on stock prices.
3. Not all such information flow is instantaneous.

In short, as in many microstructure studies, we will use predictive regression coefficients to measure information flow. Several points about this approach bear elaboration. First, it implicitly assumes a monotonic (in fact, negative) relation between the response to news of stock prices and CDS fees. This is typically true in practice, since good news about firm value lowers credit spreads. But to the extent that it fails sometimes – as with news that is good for stocks and bad for bonds – our assumptions imply that we will under-detect information flows. (The period following our sample saw a dramatic increase in news of this type, such as rumors of LBOs.) Second, we will also under-detect these flows to the extent that they sometimes occur within a day. Indeed, the huge rise in capital committed to cross-market arbitrage could invalidate our technique in more recent data. Even if insider trading had grown, we would discern less of it. For both reasons, then, our approach can detect only part of the actual informed trading that takes place.

It is, also worth stressing why an informed creditor might (at least occasionally) prefer CDS markets to stock markets in order to trade on private information and/or to hedge its exposures. First, the risks of detection in the stock market are higher due to active surveillance and severe penalties, both of which are largely absent in the CDS market. Second, the CDS contract is designed precisely to provide a good hedge on debt-like exposures to the underlying firm: a creditor can hedge itself *statically* by buying protection through the CDS market, whereas hedges performed through the stock may require *dynamic rebalancing* and thus incur greater transaction costs. Third, buying protection in the CDS market is easier (in terms of market liquidity) than taking an equivalent position by shorting corporate bonds. If, however, informed traders do choose alternative markets, our assumptions will again lead us to understate the degree of insider activity in credit derivatives.

Summarizing, our stance is that the presence of information flow from daily CDS returns to daily stock returns is sufficient to identify the presence of informed revision of quotes (if not actual trades) in the CDS markets. We then reinforce the supposition that such occurrences are based on informed hedging activity by conditioning our measures of information flow according to the following hypotheses:

1. Insider trading should imply greater information flow from the CDS market to the stock market for firms and in times for which the likelihood of distress is greater.
2. Insider trading should imply greater information flow from the CDS market to the stock market when there is a larger number of potentially informed insiders.

It turns out that we find significant information flow *only* when there are a large number of insiders or the potential gains to hedging are large. This provides the basis for interpreting information flow as evidence of insider trading. The conditional measures then further allow us to assess the effects of the prevalence of the insider trading risk on the markets themselves.

2.1. Data

Our primary data set for this study comes from daily closing CDS quotes for the most widely traded, North American reference entities ("benchmarks") from January 1, 2001 through October 20, 2004. The bid-ask quotes are obtained from CreditTrade, an online trading platform for credit derivatives that attracts a significant portion of trade and quotes in these markets and has participation from all the top players and market-makers (numbering more than 20). A subset of the CreditTrade data has also been employed by

Table 1
Summary statistics
The table describes the firm characteristics for our sample of credit derivatives. Sample statistics are computed across all observations, except average stock trading statistics which are computed across firms.

	Low	Median	High
CDS level (mid price, BP)	13	81	2,400
CDS bid-ask spread (BP)	1	20	2,000
CDS bid-ask percent spread	1.9	24	107
Credit rating	Ba3/BB-	Baa1/BBB+	AAA/Aaa2
Firm size (equity mkt val, $mm)	720	15,820	412,900
Firm debt (book val, $mm)	9	8,874	312,684
Firm leverage (debt at book val)	0.00	0.21	0.65
Average stock volume (mm shrs/day)	0.14	2.65	76.1
Average stock turnover (pct/day)	0.2	0.56	2.68
Average stock volatility (ann std dev)	0.24	0.39	0.83
Number of bond issues	0	9	71
Observations/day	9	46	62

Blanco, Brennan, and Marsh (2005) in their study of the difference between CDS fees and bond market yields.

A firm enters the set of benchmarks when CreditTrade believes its CDS market has become sufficiently liquid to quote a daily closing price. Daily closing bid and ask prices are obtained by polling market-makers at the end of the day. Thus, the benchmark prices supplied by CreditTrade are not "matrix" prices (estimated algorithmically) but are widely perceived to be a generally accurate indication of where the CDS markets traded and closed for that day. We note that the "closing" in this market is defined as no later than 4:15 p.m. New York time, and hence that our CDS prices are collected prior to the end of trading for U.S. stocks. If anything, this timing biases against detecting information flow from credit markets to equity markets.

A firm that enters the list of benchmark CDS names does not leave unless it defaults during the sample period (e.g., Enron), undergoes a merger, or is acquired. In particular, there is no back-filling of data when a benchmark name is added to the data, and, in turn, there is no look-ahead bias.

The CDS levels are calculated as mid-prices based on the bid-ask quotes. The quotes are for U.S. $10 million notional transactions of five-year maturity with the underlying reference credit being senior unsecured. We focus on a total of 79 North American benchmark corporate credits. The names of these entities are listed in Appendix A. Matching information for stock market data and balance sheet data is obtained for these firms from the Center for Research in Security Prices (CRSP) and Compustat. While limited in a time-series and a cross-sectional sense, these are some of the best data available on CDS prices. Furthermore, the sample period is among the most interesting in recent history since it witnessed defaults of large U.S. corporations such as WorldCom, Enron, and Sprint, and significant credit deterioration for others such as Tyco.

Table 1 provides summary statistics for the credits in our sample. The median CDS level is 81 basis points (bps) with a high of 2,400 bps (for Enron close to its bankruptcy).

Interestingly, although the median bid-ask spread in CDS markets is 20 bps, the high is 2,000 bps representing a trading cost that is comparable in magnitude to the highest observed CDS level. The median Moody's (S&P) credit rating of firms in our sample is Baa1 (BBB+), median market capitalization is U.S. $15.82 billion, median book debt is U.S. $8.88 billion, and the median ratio of book debt to assets is 21%. The median number of firms for which quotes are observed on a day is 46, reflecting the gradual increase in the number of liquid benchmarks over the sample period.

Since most firms in our sample are large, trading in their equity market is quite liquid: the median volume is 2.65 million shares per day and the median turnover is 0.56% of the outstanding shares per day. The median (annualized) stock return volatility based on daily stock returns is 39% with a high of 83% and a low of 24%. Interestingly, there are firms with no public bond issues outstanding, that is, our sample includes firms whose debt is entirely bank-financed. The median number of public bond issues for firms in our sample is nine with a high of 71. The data on corporate bonds include issues that are either in the Merrill Lynch Corporate Master index or the Merrill Lynch Corporate High Yield index, and were employed in Schaefer and Strebulaev (2003).[3]

2.2. *Preliminary evidence*

To illustrate the relation between information flow and informed trading, we examine the cross-correlation structure of returns in CDS and equity markets. As mentioned above, our maintained assumption is that the stock market reaction is coincident with public release of information about the firm. Hence, if there is insider trading in CDS markets, then we should at least sometimes observe a flow of information from CDS markets to equity markets. This offers a nice counterpart to the much-studied response of bond prices to stock moves, where the literature has generally found a slow adjustment to stock innovations, with bond returns having a negative cross-correlation with up to several days' lag of stock returns. This finding of is most likely due to the poor quality of bond data.[4]

We provide a graphical representation of the cross-correlation structure between daily stock returns and CDS changes in Fig. 1. Specifically, the figure shows the cross-correlation between percent changes in CDS prices at time t and stock returns at time $t+k$ as a function of $k = -5, -4, \ldots, +5$. In the first panel, results are shown for the whole sample, and the second panel show results for the four largest cases of corporate distress in our sample: WorldCom, Enron, Sprint, and Tyco. In each panel, the cross-correlations for individual firms are averaged across firms.

In each of the two panels, there is a negative cross-correlation between CDS changes and lagged equity returns, reflecting a flow of information from equity market to the CDS market: when stock returns are positive, there is a decrease in contemporaneous and subsequent price of default protection. In the panel where the entire sample is employed, the cross-correlation between CDS changes and *future* equity returns is essentially zero. In striking contrast, in the panel with the four firms of our sample that experienced significant deterioration in credit quality, this cross-correlation structure is different: there is on average a negative cross-correlation between CDS changes and future equity returns, the

[3]We are grateful to those authors for generously providing us with this data.

[4]Hotchkiss and Ronen (2002) employ daily data on corporate bond prices from NASDAQ, and find the bond market to be as informationally efficient as the stock market.

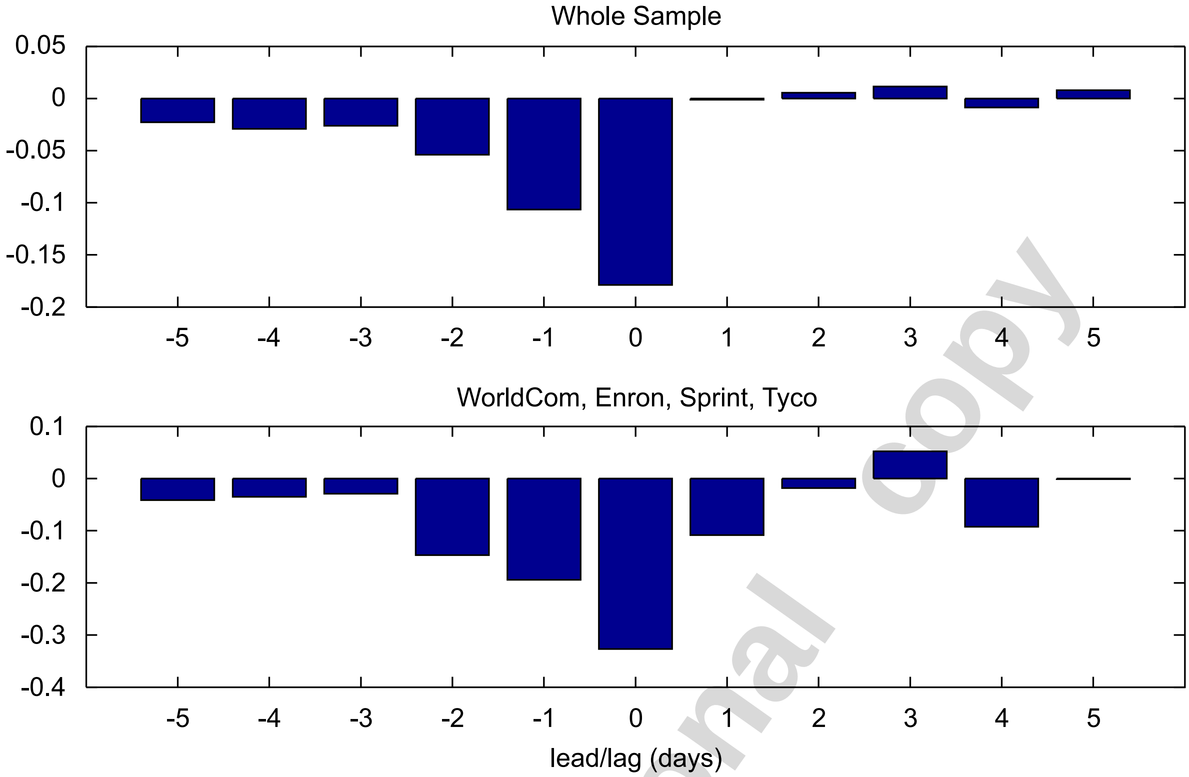

Fig. 1. The figure shows the cross-correlation between percent changes in credit default swap prices at time t and stock returns at time $t+k$ as a function of k. The top panel uses all the "benchmark" firms in our sample; the bottom uses only the four companies shown. In each panel the cross-correlations for individual firms are averaged across firms.

correlation being highest in magnitude for future date $t+1$. In other words, for firms for which there is adverse credit information during our sample period, we do find evidence of an information flow from today's CDS price to future stock returns. Indeed, for these firms information apparently flows both ways between these markets.

This preliminary evidence is consistent with the hypothesis that if insiders are active in our sample, then firms that experience severe credit deterioration should exhibit significant cross-correlation of CDS changes with *future* stock returns. In other words, insiders appear to be exploiting information in the CDS market only when there is significant negative information.

2.3. Econometric analysis

Isolating the pure effect of a CDS market innovation at time t on the stock return at time $t+k$ requires, among other things, controlling for CDS innovations between t and $t+k$. We now seek to establish rigorously whether or to what extent credit markets actually acquire information prior to the stock market (that is, the market as a whole). First we describe our methodology for identifying innovations in the CDS prices. Then we establish the basic finding that, while there is little unconditional spillover of these innovations to the stock market, there are strong conditional effects linked to certain firms at certain times.

2.3.1. Constructing CDS innovations

Since credit and equity markets are highly dependent, the first step in our analysis is to regress changes in our CDS prices on contemporaneous stock returns in order to extract the residual component. We do this by means of separate time-series regressions for each firm, also including five lags of both the CDS changes and stock returns to absorb any lagged information transmission within the credit market.

Two points about this step are worth clarifying. First, the CDS changes are defined as log differences in credit spread, or percentages of percentages. Second, we anticipate that the relation between these changes and stock returns should be inherently nonlinear. This can be seen in the context of any structural model of credit spreads. To illustrate, Fig. 2 plots the elasticity of credit spreads with respect to stock prices under the Merton (1974) model of risky debt. This elasticity represents the theoretical relation that should, under that model, relate percentage changes in stock prices to percentage changes in credit spreads. The figure shows that there is a roughly linear relation between this elasticity and the inverse level of the credit spread itself.

Guided by this, our specification of expected CDS returns includes interactions of the stock returns (both contemporaneous and lagged) with the inverse CDS level. We could impose the functional form of the Merton (1974) or any other structural model in this stage. But we choose to remain agnostic about the degree of the nonlinearity. As a result, we are in effect purging the credit market innovations of any level-dependent dynamics.

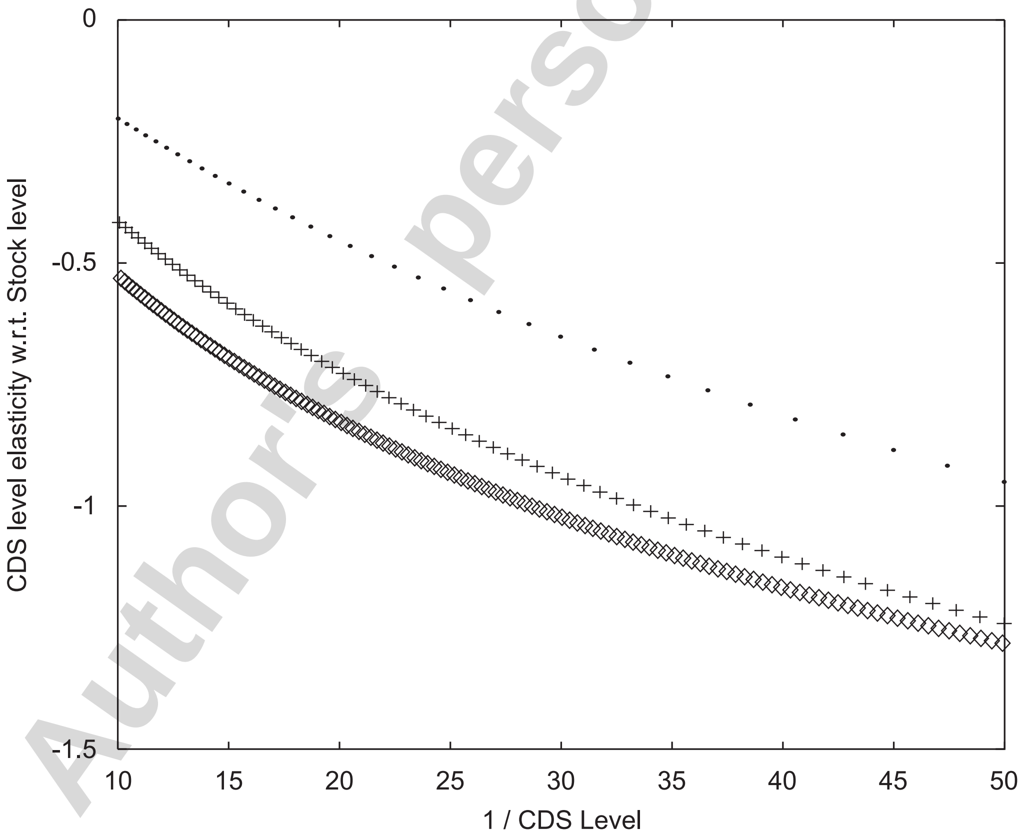

Fig. 2. The figure plots the elasticity of the credit spread s with respect to equity value E under the Merton (1974) model. Specifically, zero-coupon debt with face value of 100 maturing in five years is considered, with risk-free interest rate set to 4%. Three values for firm-value volatility are considered: 12.5%, 25% and 37.5%. The firm value V is varied in order to generate different values of the credit spread s and equity value E. The credit-spread elasticity is calculated as $(\frac{ds}{dV}/s)$ divided by $(\frac{dE}{dV}/E)$. This elasticity is plotted against the reciprocal of the credit spread s for different values of V.

This limits our ability to separately identify such level-dependent effects in the cross-market dynamics studied below.

To summarize, for each firm i, we run a regression of CDS percentage changes on a constant, five lags of CDS percentage changes, the contemporaneous stock return, the product of that return and the inverse CDS level, and five lags of the latter two terms:

$$\begin{aligned}(\text{CDS return})_{i,t} = \alpha_i + \sum_{k=0}^{5}[\beta_{i,t-k} + \gamma_{i,t-k}/\ (\text{CDS level})_{i,t}](\text{Stock return})_{i,t-k} \\ + \sum_{k=1}^{5}\delta_{i,t-k}(\text{CDS return})_{i,t-k} + u_{i,t}. \qquad (1)\end{aligned}$$

We view the residuals $u_{i,t}$ from each of these regressions as independent news arriving in the credit markets that is either not relevant or simply not appreciated by the stock markets at the time.

It is worth noting that these credit innovations are not small. Although the debt and equity returns are highly correlated, and although our specification errors on the side of imposing too few restrictions, the R^2 from our regressions are mostly in the single digits.[5]

2.3.2. Information flows from credit markets to stock markets

In this section, we study the information flow from CDS markets to equity markets under different credit conditions. We allow the information flow to vary depending on whether (i) firms experience significant credit deterioration on some day during our sample period; (ii) firms experience a general widening of their credit spread during our sample period; and (iii) credit rating of firms is low. Specifically, we estimate the following panel specification:

$$\begin{aligned}(\text{stock return})_t = a + \sum_{k=1}^{5}[b_k + b_k^{\mathrm{D}}(\text{Credit-condition Dummy})_t](\text{CDS innovation})_{t-k} \\ + \sum_{k=1}^{5}[c_k + c_k^{\mathrm{D}}(\text{Credit-condition Dummy})_t](\text{stock return})_{t-k} + \varepsilon_t. \qquad (2)\end{aligned}$$

Note that we allow the own lag effects on stock returns to also vary conditionally, in order to ensure that any apparent CDS lag effects are not artifacts of unmodeled dynamics in the share price itself.

We estimate this specification for three credit-condition dummies in Table 2. In specification (A), the dummy is one if the firm experiences a one-day decline in credit spread level exceeding 50 basis points between time t and end of the sample period. In specification (B), the dummy is one whenever the firm's credit spread level remains at a level greater than 100 basis points between time t and end of the sample period. Finally, in specification (C), the dummy is one if the credit rating of the firm at time t is low (A3/A- or worse). We examine $\sum_{k=1}^{5} b_k$ and $\sum_{k=1}^{5} b_k^{\mathrm{D}}$ as measures of unconditional and conditional permanent information flows from the CDS market to the stock market, respectively.

[5]This, in itself, is a somewhat surprising finding which perhaps points to the inherent limitations of the explanatory power of structural models.

Table 2
Information flow from CDS market to stock market for different credit conditions

The table shows OLS panel estimates and t-statistics for the coefficients of a regression of daily stock returns on a constant, lagged CDS innovations, and lagged stock returns, as follows:

$$\begin{aligned}(\text{stock return})_t = a + \sum_{k=1}^{5} [b_k + b_k^{\mathrm{D}}(\text{Credit-condition Dummy})_t](\text{CDS innovation})_{t-k} \\ + \sum_{k=1}^{5} [c_k + c_k^{\mathrm{D}}(\text{Credit-condition Dummy})_t](\text{stock return})_{t-k} + \varepsilon_t.\end{aligned}$$

That is, the regression also includes interaction terms of the lagged CDS innovations and stock returns with an indicator equal to one for firm i at date t if (i) the firm experiences a credit deterioration of more than 50 basis points between date t and the end of the sample (specification A); (ii) the firm's credit spread level remains at a level greater than 100 basis points between time t and end of the sample period (specification B); and (iii) the credit rating of the firm at time t is low, that is, A3/A- or worse (specification C).

	(A)	(B)	(C)
a	0.0003	0.0003	0.0003
	(2.19)	(2.21)	(2.04)
$\sum_{k=1}^{5} b_k$	0.0033	0.0050	0.0111
	(0.44)	(0.66)	(0.91)
$\sum_{k=1}^{5} b_k^{\mathrm{D}}$	−0.0492	−0.0465	−0.0224
	(2.36)	(2.52)	(1.51)
$\sum_{k=1}^{5} c_k$	−0.0413	−0.0399	0.0183
	(3.22)	(3.00)	(0.97)
$\sum_{k=1}^{5} c_k^{\mathrm{D}}$	0.1917	0.1338	−0.0488
	(5.90)	(4.68)	(2.02)

Table 2 shows that the evidence is consistent with there being greater information flow from CDS to equity markets for firms that experience, or are more likely to experience, "credit events" in the future. In each of the three specifications, there is no unconditional flow from CDS to equity markets ($\sum_{k=1}^{5} b_k$ is essentially zero). However, conditional on the credit-condition dummies, the flow is present and is significant. For firms that actually experience credit deterioration (specifications A and B), the sum of the coefficients on lagged CDS innovations, $\sum_{k=1}^{5}(b_k + b_k^{\mathrm{D}})$, is negative. The flow measure ($\sum_{k=1}^{5} b_k^{\mathrm{D}}$) is both negative and statistically significant and represents around 5% transmission of information in CDS innovation to future stock market returns. For firms that are more likely to experience credit deterioration (the low-rated firms), the flow is negative but not as statistically significant. Overall, this provides some evidence that CDS prices impound information about adverse credit developments before that information is reflected in stock prices.

A feature of the panel estimation described above is that it forces all firms to have the same dynamic properties, except as captured by the conditioning introduced in the lagged response terms. We also estimate separate dynamics for each firm and then study the cross-firm variation in response to credit market information. This analysis addresses the possibility that our previous finding of a significant conditional effect from the CDS innovations is actually driven by uncaptured variation in the other terms (the intercept and stock lag coefficients).

Here we follow the methodology of Hou and Moskowitz (2005) who study cross-firm variation in lagged response to market news. Specifically, for each firm i we run the time-series regression

$$(\text{stock return})_{i,t} = a_i^{\text{f}} + \sum_{k=1}^{5} b_{i,k}^{\text{f}}(\text{CDS innovation})_{i,t-k} + \sum_{k=1}^{5} c_{i,k}^{\text{f}}(\text{stock return})_{i,t-k} + \varepsilon_t. \tag{3}$$

We then define a measure of the permanent information flow from CDS market to the stock market for firm i as

$$\theta_i = \sum_{k=1}^{5} b_{i,k}^{\text{f}}. \tag{4}$$

For firms for which the information flow is large and permanent, θ should be large and negative; if the information flow is partially reversed within five days, then θ should be less negative; and for firms for which there is not much information flow in the first place, θ should be close to zero. Panel A of Table 3 shows the summary statistics for the estimated θ_i's. The mean is 0.0043 and statistically insignificant. That is, there is not much of an unconditional effect once the full dynamics are allowed to be firm specific.

Next we sort our firms into quintiles based on their lagged response and examine the average firm characteristics of each. Panel B of Table 3 reveals that the main evidence of insider activity is confined to the lowest θ quintile. Firms in this set are on average larger, more actively traded, and somewhat more volatile than the sample as a whole. (Note that the table reports medians, and is thus not sensitive to individual outliers.) Neither credit rating nor leverage varies much across quintiles. However, credit risk, as measured by CDS level, does rise monotonically as θ falls, echoing the observation that trading on the basis of adverse non-public information about a firm's credit prospects responds to the incentive represented by increased risk to bank portfolios.

In terms of the magnitude of the information flow documented here, we note that while a θ of -0.11 (e.g., for a lowest-quintile firm) is economically significant, it does not imply a gross violation of market efficiency. The time-series standard deviation of weekly CDS changes for these firms is roughly 5%, implying a predictable stock return of about half a percent, which is on the order of the round-trip trading costs in these stocks. We do not regard numbers of this size as implausible. It is also worth noting that the magnitudes themselves are not important for our analysis. We simply use the cross-sectional variation in these information flow measures to study patterns in, and effects of, information asymmetry.

To summarize, our empirical methodology provides a way of identifying insider trading or at least informed revision of quotes in the CDS markets. We have shown that such activity is present, and is concentrated in the firms for which credit risk is highest. However, we have not yet tied this to any direct measure of asymmetric information. The next section explores the banking relationships of our sample of borrowers to establish this link.

3. Information flow and bank relationships

The evidence in the last section suggests that, under certain market conditions, information revelation (or price discovery) in the credit markets precedes that in the equity

Table 3
Information flow from CDS market to stock market for different credit conditions (two-stage cross-sectional estimation)

Panel A shows univariate properties of θ, the firm-specific measure of permanent information flow from CDS innovations to stock markets. In the first stage, we run for each firm i the time-series regression

$$(\text{stock return})_{i,t} = a_i^{\text{f}} + \sum_{k=1}^{5} b_{i,k}^{\text{f}}(\text{CDS innovation})_{i,t-k} + \sum_{k=1}^{5} c_{i,k}^{\text{f}}(\text{stock return})_{i,t-k} + \varepsilon_t.$$

Then θ_i is a measure of permanent information flow from CDS market to the stock market for firm i, defined as $\theta_i = \sum_{k=1}^{5} b_{i,k}^{\text{f}}$. For Panel B, firms are ranked into quintiles based on the first-stage estimates of θ, Q1 being the quintile with the smallest (most negative) estimates and Q5 being the quintile with the largest estimates. The summary statistics reported for each quintile are the medians (across firms) of the time-series means of the characteristics for each firm.

Panel A: *Properties of* θ
Mean = 0.0043
t-stat = 0.4600
Min = −0.1961
Max = 0.3262

	Q1	Q2	Q3	Q4	Q5
Panel B: *Properties (medians) of firms in different* θ*-quintiles*					
Average θ (%)	−11	−2	1	4	8
CDS level (mid-price, BP)	185	108	101	79	68
CDS bid-ask spread (BP)	26	21	20	18	17
Credit rating (Moody's)	Baa1	Baa1	Baa2	Baa1	Baa2
Credit rating (S&P)	BBB+	BBB+	BBB	BBB+	BBB
Firm size (equity mkt val, $mm)	28,021	12,477	9,663	12,677	13,862
Firm debt (book val, $mm)	12,785	7,178	4,136	6,864	6,380
Firm leverage (debt at book val)	0.28	0.32	0.33	0.33	0.27
Average stock volume (mm shrs/day)	8.07	2.10	1.37	1.71	2.49
Average stock turnover (pct/day)	5.4	6.4	4.8	5.0	5.6
Average stock volatility (ann std dev)	0.40	0.37	0.33	0.33	0.33
Number of bond issues	12.6	7.1	5.2	12.0	5.8

markets. If this is due to the activity of insiders with access to non-public information, we would expect the effect to be bigger when there are more players with access to such information. In addition, if our interpretation of information flow as evidence of informed hedging activity is correct, a secondary hypothesis is that this relationship-driven flow should occur primarily for negative firm-specific news. In this section, we identify a key class of insiders – commercial banks with an ongoing lending relationship with the company – and test these predictions.

While it seems natural to conjecture that more insiders would lead to more insider trading, it is worthwhile to articulate precisely why this should be so.

One view is that more insiders would imply more information gathering. In our case, the lending banks have both an incentive and a responsibility to actively monitor each borrower. Indeed, some theories of banking (e.g., Fama, 1985) postulate that the differential monitoring ability of banks is the primary reason for their existence, and that firms undertake bank loans precisely to commit an outsider to monitor them (among other reasons). It could then be that the technology of monitoring is such that more monitors with a sufficient incentive produce more information than do fewer monitors with larger incentives; or that a larger number of relationships would be optimal ex ante precisely when this is true.

A second motivation for our hypothesis does not rely on assumptions about information gathering per se, but rather concerns the incentives *not* to exploit non-public information through trading. Whether or not such exploitation is literally illegal is probably secondary to the inhibitions that could come from damaging other relationships. Unloading dangerous exposures on the market could be seen as harmful to the banks' trading counterparties (customers and other banks) on whom the bank might rely for hedging. It could also be seen as a violation of an implicit contract with other members of the lending syndicate if the result is a lower value of the positions they continue to hold. However, the more members there are of a given syndicate, the greater is the chance that for *some* of them these implicit contracts fail to bind because the relationships that are damaged are simply not as valuable as the immediate benefits of avoiding losses.

Finally, a third view builds on the insight of the market microstructure literature that more insider trading will occur when it is easier to hide. Here the concern is not with hiding from regulators (although that could matter too), but with concealing the fact that the trading is informed so as to minimize its price impact. In this case, we might anticipate that uninformed trading volume in the credit markets would rise with the number of exposed banks (for example, due to informationless trading), eliciting greater informed trading through higher liquidity.

Our data on bank relationships are based on the Loan Pricing Corporation (LPC) DealScan database. For each borrower on a given date, we look back as far as 1996 for any syndicated loan facilities still outstanding for this entity as well as its affiliated and predecessor companies. Summing over all such active facilities, we compute on each date the number of unique banks with which the borrower has an ongoing relationship.[6] Our results are insensitive to excluding affiliated company debt, and to defining relationship length based on a fixed five-year window.

Our primary measure of relationships counts lead banks only, although we examine participant banks as well. We further focus on the top 100 large commercial and investment banks which together account for most of the market share in syndicated lending in the LPC database over our sample period. (These banks are listed in Appendix B.) We restrict attention to these banks in order not to overstate the number of informed parties, and to focus on the players most likely to possess both an informational advantage and access to the credit derivatives markets. We note, however, that *every* member of a bank syndicate has the same right to information gathered by the lead banks or any delegated member (see, e.g., Lee and Mullineaux, 2004) and that this information is actively and instantaneously disseminated via electronic networks, such as IntraLinks. Further, as stressed by Lee and Mullineaux (2004), there is a regulatory requirement that each participating bank perform independent due diligence for each loan. Also, to the extent that small players in the syndicated loan market, such as foreign banks and hedge

[6]This approach to calculating the number of bank relationships is similar to the one described in detail in Bharath, Dahiya, Saunders, and Srinivasan (2007).

funds, are the most inclined to exploit private information (as discussed above), our more restricted definition could be less appropriate.[7] When we include all banks in our relationship measure, the statistical importance of this number in the tables below generally strengthens.

The large amount of merger and acquisition activity in the banking sector over our sample period, and to some extent in the corporate sector, requires us to make careful adjustments to the LPC data. The information on bank merger and acquisition activity are obtained from the data employed and generously provided to us by Bharath, Dahiya, Saunders, and Srinivasan (2007) and Sufi (2004), and from the web site of the Federal Reserve Bank of Chicago. The data on corporate merger and acquisition activity are obtained from the Securities Data Corporation (SDC) Platinum database. Bank relationships are computed at the level of parent banks, and are assumed to merge whenever a merger takes place at the bank level or at the level of the borrowing firms.

The top panel of Table 4 gives some summary statistics on the relationships of the benchmark companies that we study. Besides the number of relationships, we also tabulate the number and notional amount of all active facilities at each date.[8] The median number of lead banking relationships is 16, with a mean of 29. There is substantial cross-sectional variation: there are firms with no syndicate banking relationships and firms with as many as 50 lead-bank relationships. The median number of loan facilities is four with a median total amount per firm of about U.S. $4 billion. The duration of active relationships has a median of 4.1 years in the sample.

In looking at bank relationships, might we inadvertently be measuring other firm-specific characteristics? Prior research (Lee and Mullineaux, 2004; Sufi, 2004) has presented evidence that larger syndicates are formed for more transparent firms, and some evidence that riskier firms tend to have larger syndicates. The bottom panel of Table 4 shows weak evidence supportive of both. Firms with more banks are slightly more volatile and leveraged than those with fewer (although there is no difference in ratings). On the Standard & Poor's transparency scale (see Patel and Dallas, 2002), which for U.S. firms effectively runs from 7 to 9, firms with more banks are marginally more transparent. The last few lines of the table show that the primary determinant of the number of banks is simply scale: not surprisingly, there is a strong monotonic relation between banks and firm size or amount of borrowing. The regressions below will control for scale effects in isolating the role of bank relationships.[9]

To start, we present the most direct tests of our main hypothesis: that the degree of informed trading in the CDS market – measured by information flow – is a function of the

[7]It also must be noted that the set of players with access to private syndicate information can change due to the rise of secondary market trading in bank loans. We have no way of tracking this, but Sufi (2004) reports that less than 10% of outstanding syndicated debt is ever traded. Still, we could be missing an important source of insider activity: hedge funds are reported to commonly purchase small syndicate stakes precisely to acquire non-public information to aid them in arbitrage trading (see "The new insider trading? Concerns mount that private information furnished to lenders is seeping into trading," *Investment Dealers Digest*, 13 June 2005).

[8]LPC data does not give a detailed bank-by-bank breakdown for each loan facility. So it is not possible to come up with a precise loan-size-weighted measure of the number of banking relationships that would incorporate actual exposure data.

[9]In the next section we will be more concerned with the endogeneity of relationships with respect to the dependent variables. In this section, where the dependent variables are stock returns, endogeneity is not a concern.

Table 4
Bank relationship summary statistics

Bank relationship statistics are reported for all firm-date observations for the sample studied in Section 3. Relationships are defined by outstanding syndicated loan commitments originated after 1996. Only the top 100 syndicated lenders are included in the count. The top panel shows the range of some relationship statistics. The bottom panel shows the average of firm characteristics when the observations are sorted into three groups based on the number of (lead) relationships.

	Low	Median	High
Panel A: *Distribution across all observations*			
Number of bank relationships (leads)	0	16	50
Number of bank relationships (all)	0	29	69
Average relationship length (yrs.)	0.3	4.1	7.2
Number of active facilities	0	4	36
Amount of active facilities ($mm)	0	4,019	66,099
	Few (0–11)	Middle (12–22)	Many (23–50)
Panel B: Firm characteristics			
Rating	Baa1/BBB+	Baa1/BBB+	Baa1/BBB+
Volatility (ann std dev)	0.36	0.38	0.39
Leverage (debt at book val)	0.18	0.26	0.22
S&P transparency (2002)	8	8	9
Size (equity mkt val, $mm)	11,478	13,470	25,845
Debt (book val, $mm)	4,463	8,120	19,168
Number of active facilities	2	4	11
Amount of active facilities ($mm)	1,642	3,636	10,206

number of informed participants. We run regressions of the following form:

$$\begin{aligned} \text{stock return}_t = a_0 &+ [b_0 + b_1(\text{number of insiders})](\text{CDS innovation})_{t-1} \\ &+ \sum_{k=1}^{5} c_k(\text{stock return})_{t-k} + \varepsilon_t, \end{aligned} \tag{5}$$

where the CDS innovation is constructed as described in the previous section. Our proxy for the number of insiders varies substantially across firms and over time. To exploit this, we estimate the model using panel data specifications.

Table 5 shows several versions of the specification. Column A shows that, unconditionally, there is a small but statistically significant spillover of yesterday's CDS innovation to today's stock return. In Column B we see that this unconditional effect is completely absorbed by the inclusion of the number of banking relationships. For a firm with ten relationships there is essentially no spillover, whereas for one with 50 relationships the spillover is around 4%. The tests in Columns C and D distinguish between the effect of positive and negative CDS innovations. In Column C there is no difference in the unconditional response: both are about the same as that found in Column A and the p value of the t test for their equality is 0.64. However, the conditional responses are quite different. Only positive CDS shocks (i.e., bad news) are now found to have a significant impact on future stock prices. The coefficient b_1^+ is around eight times larger (with p value

Table 5
Regressions of stock returns on CDS innovations

The table shows the results of regressing daily stock returns on lagged values of CDS innovations. The lag coefficient is modeled as $b_0 + b_1$(number of bank relationships) in the first two columns. The second two columns allow the coefficients to differ depending on the sign of the lagged CDS innovation. For these four specifications, OLS t-statistics appear in parentheses. The final two columns include five lags, with each constrained to have the same values of b_0 and b_1. These specifications are estimated by NLLS. Numerical standard errors are used for the t-statistics shown in parentheses. All regressions also include an intercept and five lags of the dependent variable.

	(A)	(B)	(C)	(D)	(E)	(F)
b_0	−0.0080	0.0095			−0.0057	0.0155
	(2.93)	(1.78)			(1.96)	(3.22)
b_1		−0.00094				−.00093
		(3.81)				(3.62)
b_0^+			−0.0095	0.0216		
			(2.27)	(2.793)		
b_1^+				−0.0016		
				(4.78)		
b_0^-			−0.0065	−0.0031		
			(1.52)	(0.39)		
b_1^-				−0.0002		
				(0.52)		
a_1					1.0	1.0
					NA	NA
a_2					−0.052	−0.507
					(0.10)	(1.52)
a_3					−0.110	−0.083
					(0.23)	(0.28)
a_4					−0.124	1.193
					(0.25)	(2.60)
a_5					0.082	0.226
					(0.16)	(0.68)

for no difference of 0.00) than b_1^- and implies approximately 6% spillover for a firm with 50 relationships. The fact that the information flow occurs primarily for negative news is consistent with the interpretation of hedging activity being undertaken by asymmetrically informed banks with positive loan exposures.

The last two columns augment the specification with further lags of CDS innovations, so that the conditional response term looks like

$$\sum_{k=1}^{5} a_k[b_0 + b_1(\text{number of insiders})_{t-k}](\text{CDS innovation})_{t-k}. \tag{6}$$

This specification allows us to check whether the leading relation we have identified is merely a transient effect, possibly due to some short-term price pressure from the hedging activity of debt-market participants in the stock market. The specification is estimated by nonlinear least squares (NLLS) and the a_k terms are measured relative to a_1, which is set equal to one for purposes of identification. Column E implies that there is no significant unconditional contribution to information flow at any other lag. The last column shows some evidence (though not statistically significant) of a partial reversal of the bank-related information flow at two days' lag. However, looking back a week, the total lagged conditional effect is even stronger than the one-day effect, due to a highly significant contribution at four days' lag. While we have no explanation for a four-day effect, we can conclude that the conditional information flow we have documented is not transitory.

Might the information flows that we document here be due to *late* stock market reactions to public news, rather than *early* credit market reactions to non-public news? In particular, the asymmetry found in specification D might suggest that short-sale constraints delay stock reaction to negative news (at least for firms with many bank relationships). Table 6 provides some checks on our maintained hypothesis of a weakly efficient stock market. In Columns A and C, we repeat the regression specification B from Table 5 with more flexibility in the lagged stock terms. If our stocks in general react slower to bad news, then we can capture this by allowing separate coefficients on the positive and negative parts of lagged own returns. This is done (with all five lags) in Column A. If, instead, slower stock reactions are, for some reason, more associated with firms with many banks, we can control for this by interacting the lagged stock terms with the number of banks. This is allowed in Column C. Neither specification alters the significance of the b_1 term. Moreover, when we again split the b_1 term into reactions to positive and negative CDS innovations (in Columns B and D), neither specification changes the finding that the information flow only occurs for negative credit news.

For another quick check to see if delayed stock reactions are driving our results, we compute the average autocorrelation coefficients for stocks in the lowest θ quintile (see Table 3) for five lags. This statistic is -0.01, economically and statistically insignificant. Moreover, the average coefficient on negative lags is slightly negative (and that on positive lags slightly positive), meaning that, if anything, these stocks tend to overreact to negative news, not underreact.

As a final check on the possibility that short-sale constraints play a role in our findings, we repeat these tests for a subpanel of observations for which we have specific, positive information that the stocks in question were readily borrowable. The data come from a large stock lender that is sometimes active in the firms in our sample. We record every lending transaction that coincides with our sample and throw out any for which the lending fee exceeds the 75th percentile of all outstanding loans. (There are only three such observations out of over 8,000.) Restricting attention to the remaining firm-dates, we re-run our regressions. The results, in Columns E and F, make clear that our findings are not driven by difficulties with short sales. Although *t*-statistics are lower, this is only due to having lost 75% of our sample. (The sparseness of the stock loan data is simply a reflection of the ease of borrowing these large stocks; the opportunities to lend them out are relatively infrequent.) While the asymmetry effect in Column F is now difficult to discern, this is not because the coefficient on negative news has shrunk (as the short-sale constraint argument would imply) but because, if anything, there could now also be delayed reaction to positive news.

Next, to check that the core results in Table 5 are not driven by outliers or other inferential problems, we present some alternative estimators and standard errors in Table 7. We first test the ordinary least square (OLS) estimates with robust standard errors, then we re-estimate the coefficients after some outlier controls, and, finally, we compute both the first and second stages of our estimation simultaneously in a generalized method of moments (GMM) setting to correct for the estimation error in the first stage. In each case, we report the (two-sided) p value for the test that our bank coefficient b_1 is zero.

Table 6
Stock return regressions – alternate specifications

Daily stock returns are regressed on one lag of CDS innovations using alternative specifications to control for possibly misspecified stock dynamics. In (A) and (B) the regression allows separate coefficients on the positive and negative part of each of five lagged stock return terms. In (C) and (D) a single lagged stock return is used, but is allowed to depend on the number of bank relationships. In (E) and (F) the original specification of Table 5 is used, but restricting the sample to firm-days on which we can verify that the stock was easily borrowable. OLS t-statistics are in parentheses.

	Asymmetric stock lag terms		Stock lag conditional on number of banks		Definitely borrowable subsample	
	(A)	(B)	(C)	(D)	(E)	(F)
b_0	0.0086		0.0091		0.0069	
	(1.60)		(1.69)		(0.57)	
b_1	−0.0009		−0.0009		−0.0011	
	(3.61)		(3.69)		(1.92)	
b_0^+		0.0208		0.0173		0.0088
		(2.68)		(2.10)		(0.47)
b_1^+		−0.0016		−0.0013		−0.0010
		(4.55)		(3.50)		(1.32)
b_0^-		−0.0042		0.0001		0.0067
		(0.53)		(0.02)		(0.40)
b_1^-		−0.0002		−0.0004		−0.0011
		(0.47)		(1.15)		(1.49)
c_0			−0.0586			
			(5.93)			
c_1			0.0027			
			(6.38)			
c_0^+				−0.0566		
				(3.58)		
c_1^+				0.0021		
				(3.28)		
c_0^-				−0.0578		
				(3.62)		
c_1^-				0.0030		
				(4.82)		
N obs.	37,209	37,209	37,209	37,209	8,399	8,399

(The table caption provides some further detail.) The message is clear: none of these affects the main finding. The role of bank relationships in driving information flow is robust with respect to corrections for cross-sectional dependence, heteroskedasticity, extreme observations, and errors in variables.

We next ask whether the results are robust once we control for other factors that could also influence information flow. Table 8 shows panel regressions, similar to those in Table 5, that model the CDS innovation component as a function of other controls. That is,

$$(\text{stock return})_t = a_0 + [b_0 + b_1(\text{number of banks}) + b'(\text{other controls})] \times(\text{CDS innovation})_{t-1} + \sum_{k=1}^{5} c_k(\text{stock return})_{t-k} + \varepsilon_t. \quad (7)$$

Table 7
Stock return regressions – alternative inference

The table shows the results of the regression specification (B) from Table 5, using alternative methodologies. Panel A presents the OLS estimates with heteroskedasticity-consistent and bootstrapped standard errors. The former are computed by resampling cross-sections with replacement. The latter are as per White (1980). Panel B shows the OLS results when each firm's stock returns and CDS innovations have been truncated at ±2 standard deviations. Panel C standardizes each firm's stock returns and CDS innovations by scaling by their standard deviation. Panel D gives the results of estimating the CDS innovation equation and the stock return regression jointly in a just-identified GMM system so that the standard errors reflect the joint uncertainty about both sets of coefficients. All reported p values are two-sided.

			p-Values
	Coef	Bootstrap	White
Panel A: OLS			
b_0	0.0095	0.22	0.23
b_1	−0.00094	0.046	0.042
Panel B: Trimmed			
b_0	0.0078		0.24
b_1	−0.00091		0.002
Panel C: Standardized			
b_0	0.0142		0.14
b_1	−0.00122		0.008
Panel D: GMM			
b_0	0.0088		0.27
b_1	−0.00108		0.026

We limit the specification here to one lag of the CDS innovation, but, as before, include five own lags of each stock's return. Given the robustness results in the previous table, we present only OLS estimates and t-statistics here.

We have in mind several factors that could potentially lead to a role for relationships, aside from informed trading. First, the number of banks is clearly related to the scale of a firm: bigger firms have bigger loans, which always involve bigger lending syndicates. Perhaps credit markets react more quickly for all bigger firms. That is, debt markets might, as a whole, be better informed if there are more participants of every kind. If so, the role of relationship banks could have nothing to do with their differential ability to gather information.

Specifications A and B in Table 8 include controls for the scale of each firm in the cross-market reaction coefficient. Column A shows that our results are driven by neither the overall equity value of the firm nor the book value of its debt (both in logs). This is important given the obvious scaling relationship seen in Table 4. Column B also includes the notional face value of active bank facilities. This variable measures the total amount of debt that informed traders might *want* to hedge. As such, we would not be surprised if it captured some of the insider trading effect. Moreover, being strongly correlated with the number of banks, it is highly significant when used alone. When both are included, however, it turns out to be insignificant, leaving the bank effect somewhat diminished (mostly due to a larger standard error) but still significant.

Table 8
Stock return regressions with further controls

The table shows the results of regressing daily stock returns on one lag of CDS innovations. The lag coefficient is modeled as $b_0 + b_1$(number of bank relationships) $+ b'$(other controls). The controls are: non-leads (number of participant banks in active loan facilities); size (log of market capitalization); debt (log of Compustat book value of debt); loan amt (log notional value of active loan facilities); CDS b/a (percentage bid/ask spread of credit default swap); bonds (number of public dollar-denominated bonds of parent company); CB ind (indicator $=1$ if any of the bonds counted in the previous variable are convertible and $=0$ otherwise); volume (log daily stock market volume in millions); turnover (daily stock market turnover); ILLIQ (absolute value of stock returns divided by volume); credit spread: (mid-market CDS level); rating: (integer scale of credit rating); $|r_{t-1}|$ (lagged absolute stock return); and σ_{6mo} (standard deviation of last 6 months' stock returns). All regressions also include an intercept and five lags of the dependent variable. OLS t-statistics appear in parentheses.

	Scale		Liquidity		Risk	
	(A)	(B)	(C)	(D)	(E)	(F)
b_0	0.0003	0.0091	−0.0110	0.0729	−0.0549	−0.0556
	(0.01)	(0.21)	(0.45)	(1.68)	(1.53)	(1.53)
Banks	−0.0010	−0.0008	−0.0009	−0.0010	−0.0011	−.00011
	(3.15)	(1.89)	(2.70)	(3.10)	(4.16)	(4.26)
Non-leads			−0.0017			
			(3.73)			
Size	0.0003	0.0007				
	(0.10)	(0.22)				
Debt	0.0007	0.0013	0.0046	0.0036		
	(0.20)	(0.31)	(1.45)	(1.04)		
Loan amt		−0.0031				
		(0.64)				
CDS b/a			0.0078			
			(0.37)			
Bonds			0.0157	0.0117		
			(1.82)	(1.37)		
CB ind			−0.0004			
			(1.15)			
Volume				−0.0085		
				(2.10)		
Turnover				0.0021		
				(0.74)		
ILLIQ				−0.0045		
				(1.63)		
Credit spread					0.0019	0.0027
					(1.10)	(1.15)
Rating					0.0024	0.0024
					(1.78)	(1.79)
$\|r_{t-1}\|$						−0.4024
						(4.29)
σ_{6mo}						0.0238
						(1.46)

The next specifications attempt to control for other determinants of liquidity. Scale itself might not matter, but the amount of secondary market (informationless) trading still might. Column C includes controls for debt-market liquidity. Besides the book value of debt, we include the following: the percentage bid/ask spread on each firm's credit default swap; the number of public bond issues of each firm at each date; an indicator variable if any of these issues is a convertible bond; and the number of *non-lead* (participant) banks for outstanding loan syndicates. This last variable is included because some researchers (e.g., Sufi, 2004) view participants as uninformed players who depend on the lead banks for information. In that case, the number of non-lead banks might capture informationless hedging activity.

The results in Column C show that the role of banks is undiminished by these liquidity controls. The number of public debt issues shows up with a positive sign, meaning that there is *less* lagged information flow for firms with more non-bank debt. We interpret this as indicating that cross-market arbitrage is probably more active in these firms, i.e., that any informational advantage in debt markets is exploited faster.

Interestingly, the influence of non-lead banks is apparently larger than that of lead banks (although the p value for no difference is 0.17). It does not lessen the effect of leads, and so does not support the idea that our main effect is due to informationless activity. Instead, it appears that these banks provide an even stronger measure of *informed* activity. This is perhaps not surprising given that (a) non-leads have all the same rights and responsibilities for monitoring as leads; (b) private information is instantly shared electronically; and (c) non-leads might have less incentive *not* to exploit this information.

With firm-level controls we can also revisit the hypothesis that the lead-lag relationship is due to slower stock market reactions by including measures of stock market liquidity. Specification D includes volume and turnover, as well as Amihud's (2002) measure of market impact computed at a daily level. Supporting the findings in Table 6, these controls again fail to diminish the role of banks in explaining the lead-lag effect, and even increase its statistical significance. Stock volume alone appears to be an additional significant conditioning variable. Curiously, its negative sign implies that CDS lagged innovations matter *more* for more highly traded stocks. This could be due to unmodeled heteroskedasticity: volume is known to be positively associated with volatility. Both are driven by the quantity of news released about a given stock. The result here could simply be telling us that there is more information flow when there is more information.

The last competing interpretation of the role of banks that we explore concerns its relation to risk. In the previous section, we documented that the lead-lag effect is higher when the threat of losses is larger. In addition, there is some evidence that firms with higher risk have larger lending syndicates[10] and hence more relationships. So it is worthwhile to ask whether credit risk is the driving factor behind our bank effect. Another possibility is that asset value risk drives our information flow effect, and that the association with banks is entirely coincidental. Columns E and F employ measures of debt and equity risk as additional conditioning variables in the lagged response coefficient.

There is no evidence that these have any influence on the bank term, which actually becomes stronger statistically. Credit rating, using the integer scale of Odders-White and Ready (2005) which increases with credit quality, has the hypothesized sign. Credit spread level is insignificant, as is long-term stock volatility. The one noteworthy contribution comes from very short-term risk. The degree of lagged information flow increases strongly with the absolute value of yesterday's stock return. This supports the notion that risk affects information flow, but in a way that is entirely consistent with banks responding to risk incentives.

[10] See Sufi (2004), although his finding here is at odds with Lee and Mullineaux (2004).

The evidence presented thus far supports the interpretation that the information flows we have documented stem from banks using their monitoring role to uncover relevant credit information about borrowers and then engaging in informed hedging when negative information arises. Our measure of informed activity, developed in the previous section, is singularly driven by the number of parties with access to non-public information. We have ruled out several alternative explanations for this effect, and also found supporting evidence. The effect is stronger for non-lead banks, who might have less disincentive to exploit private information, and it rises with some measures of risk, i.e., as the incentive to exploit such information increases.

4. Effects of informed trading

Does insider trading in the credit derivatives markets matter? As discussed in the introduction, there is abundant evidence that participants, regulators, and industry bodies all regard it as a serious threat to the integrity of the market. Having isolated some predictors of relative insider activity, we are now in a position to offer evidence on this topic.

To do so, we need to first consider what is actually perceived as being under threat. Our interpretation of the prevailing view is that the situation is analogous to the classic moral hazard dilemma in any other insurance market. The threat of informed purchase of insurance leads to a lemon's problem in which insurance premia are set too high and the quantity of insurance written in equilibrium is too low.

Since we have no information on the amount of credit risk insured and, anyway, cannot hope to gauge the efficient amount of such transfer, our approach is to try to detect the effect of information asymmetry on bid and ask prices in the CDS market. If the threat of informed trading drives a wedge between the reservation prices of buyers and sellers, then the effect is the same as in classic microstructure models in finance (where uninformed market-makers face potentially informed buyers *and* sellers). For the CDS markets, such a wedge is likely to arise since on average banks are buyers of these swaps from insurance companies who constitute the most important sellers of CDS protection.[11] Unlike most microstructure settings, the one-sidedness of the threat in the CDS market further implies that we could see an effect in the levels of prices, i.e., insurance could be too expensive.

Relying on our results above, we now use number of bank relationships as our measure of the prevalence of non-public information in the credit market. At this point, we need to address the endogeneity of this measure with respect to credit risk and liquidity. There are two *potential* endogeneity biases, stemming from the possible roles of information quality and *ex ante* default risk in determining the amount of a firm's borrowing and the number of banks, given that amount. For the purposes of this section, these two influences work in opposite directions. If riskier firms have more banks, then this could bias us towards inferring a positive effect of non-public information on borrowing costs or liquidity. Conversely, if more transparent firms have bigger syndicates, this could mask any such positive effect.

[11] See Allen and Gale (2005), who present a table decomposing the total buying and selling of credit derivatives among various institutional categories, such as banks, securities houses, hedge funds, corporates, insurance companies, mutual funds, pension funds, and government/export credit agencies (source: British Bankers' Association Credit Derivatives Report 2001/2002).

Table 9
Illiquidity regressions

Stock and credit market illiquidity measures are the dependent variables in daily regressions using both Fama-MacBeth (1973) regressions and panels. Stock ILLIQ is absolute returns divided by dollar volume (as per Amihud, 2002). CDS % B/A is the bid-ask spread as a percentage of the midmarket quote for our sample of credit default swaps. The controls are log market capitalization, stock volume, one-month stock return, and one-month stock standard deviation. Bank relationships are as described in the text. For the Fama-MacBeth regressions, obs is the number of cross-sections, R^2 is the arithmetic average of the R^2's from the individual regressions, and the t-statistics have been corrected for six months' autocorrelation. For the panels, the specification includes time fixed-effects, and the reported t-statistics are adjusted for clustering at the firm level.

	Stock ILLIQ		CDS % B/A	
	FM	Panel	FM	Panel
Size	−0.2365	−0.2650	0.0480	0.0499
	(10.75)	(5.32)	(8.59)	(3.55)
Volume	−0.2197	−0.2078	−0.0414	−0.0429
	(5.21)	(2.99)	(10.59)	(6.02)
r_{1mo}	−0.3098	−0.4386	−0.0144	−0.0364
	(4.10)	(3.33)	(0.48)	(1.42)
σ_{1mo}	0.6789	0.5982	0.0561	0.0780
	(5.59)	(5.54)	(1.71)	(2.42)
Banks	−0.0030	−0.0037	−0.0029	−0.0026
	(2.21)	(0.99)	(8.18)	(2.75)
obs	947	71,232	947	44,932
R^2	0.3834	0.2424	0.2646	0.1365

It turns out that, for our set of firms, the number of bank relationships passes all the tests we can think of for exogeneity. In (unreported) pooled regressions, we cannot reject the hypothesis that, controlling for firm size, the number of banks is unrelated to rating, stock volatility, recent price performance, or S&P's index of transparency. (If anything, there is a tendency for more risk to imply *fewer* banks.) Hence, without disputing the findings in the banking literature (which pertain to much broader cross-sections of firms), we proceed to employ our proxy directly – along with controls for firm size – as an independent variable.

Table 9 shows regressions of stock and CDS liquidity measures on this proxy, as well as on some standard control variables. We examine stock liquidity because the evidence of informed trading uncovered above is not necessarily evidence of asymmetric information *within* the credit markets. An alternative interpretation is that the CDS market *as a whole* is better informed, in certain circumstances, than other investors. Under this view, the threat of asymmetric information, if it exists, might be to the liquidity of other markets. Results are shown for both panel regressions with time fixed-effects, and for Fama-MacBeth (1973) regressions. In the latter case, standard errors are corrected for autocorrelations of up to six months; in the former case, the reported t-statistics are clustered at the firm level.

Both methodologies lead to the same conclusions. In the first two columns, stock liquidity is shown to be largely insensitive to the bank relationship variable. More interestingly, the second two columns indicate that these relationships do affect credit market illiquidity – but with a negative sign. Hence, to the extent that more banks implies more informed players, the evidence suggests that this leads to, or is associated with,

Table 10
Credit spread regressions

The table shows regressions of credit default swap levels in basis points on proxies for asymmetric information. The controls are lagged six-month equity return and standard deviation, log book value of debt, leverage using market value of equity, tangible asset ratio, credit rating, and estimated default frequency from the Merton (1974) model. Bank relationships are as described in the text. The CDS bid/ask spread is expressed as a percentage of the CDS level. For the Fama-MacBeth regressions, obs is the number of cross-sections, R^2 is the arithmetic average of the R^2's from the individual regressions, and the t-statistics have been corrected for six months' autocorrelation. For the panels, the specification includes time fixed-effects, and the reported t-statistics are adjusted for clustering at the firm level.

	(A)		(B)	
	FM	Panel	FM	Panel
r_{6mo}	−90.43	−92.25	−71.60	−93.31
	(4.19)	(4.94)	(2.91)	(4.84)
σ_{6mo}	260.5	439.5	212.6	439.0
	(6.35)	(5.02)	(3.91)	(4.80)
Debt	15.59	10.39	12.75	13.26
	(2.79)	(1.03)	(1.87)	(1.73)
Leverage	−9.12	73.26	−20.33	65.69
	(0.22)	(1.02)	(0.39)	(0.98)
Tangible	53.26	46.23	52.95	44.65
	(2.19)	(1.23)	(2.32)	(1.28)
Rating	−20.92	−17.01	−19.57	−17.57
	(6.70)	(3.77)	(5.78)	(4.23)
EDF	0.6424	0.1325	1.3303	0.1325
	(1.73)	(2.03)	(1.30)	(1.97)
Banks	−0.2946	0.4508		
	(0.97)	(0.45)		
Bid/ask			−74.30	−8.98
			(1.70)	(0.18)
obs	891	39,964	891	39,964
R^2	0.6140	0.5283	0.6343	0.5276

narrower spreads and greater liquidity provision. In further tests, we find this result to hold during periods of overall market stress, when average credit spreads are high, and on days with negative credit news. These findings provide no support for the view that the presence of informed players threatens the stability of the CDS market.

Table 10 investigates whether the risk of informed trading shows up in the cost of credit insurance, i.e., the CDS levels themselves. In principle, the moral hazard effect could raise these prices even if there is no direct effect on liquidity. However, the first two columns establish that, controlling for known determinants of credit spreads, bank relationships play no additional role. Finally, we check whether our one direct measure of liquidity, the bid/ask spread of the default swaps, influences prices directly. This test allows for the possibility that, in using bank relationships, we have simply failed to isolate a valid proxy for asymmetric information. However, the regressions in the rightmost columns show no influence of bid-ask spreads on levels.[12] We have replicated these results using numerous

[12]These results contrast with those of Chen, Lesmond, and Wei (2005), who report a significant positive role for illiquidity in determining credit spreads on corporate bonds. The different findings may together be consistent

additional controls, including nonlinear terms, transparency ratings, and other structural indicators. It does not appear that asymmetric information or liquidity are priced in this market.

To summarize, returning to the policy question at issue, we find no evidence that the presence of informed insiders adversely affects liquidity provision or raises the price of credit insurance.

4.1. Interpretation

An important reason for our failure to detect a possible liquidity effect of insider trading risk concerns our measure of illiquidity in this market, namely the bid-ask spread. This statistic captures no information about market depth or price impact, and it impounds broker-specific effects that might not reflect true conditions in the inter-dealer market. The lack of data on trades, volume, or orders precludes us from improving on our measure. It might simply contain too much noise to detect anything.

Equally important, our failure to find liquidity or pricing effects could be due to our tests having failed to isolate enough of the actual insider trading activity. As noted earlier, the nature of data and the design of our tests consistently bias us towards *under-detecting* the incidence of insider trading. First, use of daily data precludes detecting insider trading activity when the cross-market arbitrage takes place within a day. Second, when news affects bonds and stocks in opposite directions (for example, rumors of LBOs), our regression coefficients would be diminished. Finally, since the CDS market closes prior to the stock market in our data, we are limiting the possibility of detecting predictive power of CDS price changes for stock returns.

However, as noted earlier, there are also a number of possible microstructural mechanisms that could also counteract the adverse liquidity (and price) effects of insider trading risk. We provide a few candidate explanations that are consistent with our findings and briefly discuss their relative merits.

The first candidate explanation is based on the observation that even informed players need to know the nature of the order flow (the pattern of uninformed trading) in order to strategically disguise their informed trades. CDS markets are relatively opaque. In particular, quotes posted at CreditTrade are anonymous: until a trade takes place, the counterparty information is not revealed to the two involved parties. Bloomfield and O'Hara (1999, 2000) have shown through trading experiments that in opaque markets, the informed players emerge as liquidity providers and post narrower bid-ask spreads (compared to other agents and more transparent markets). This is consistent with the informed players learning about liquidity for a strategic reason and in the process providing liquidity to the market. (See also Hong and Rady (2002) on the strategic timing of trades by informed agents when they are uncertain about the exact nature of uninformed trading.) Since privately informed banks are also intermediaries in the CDS markets, this explanation can potentially rationalize the greater information revelation for those CDS firms that have more relationship banks, who enjoy greater liquidity compared to those with fewer relationship banks.

(*footnote continued*)
with the liquidity impact being absorbed in the "basis" between CDS fees and bond yields. The arbitrage relation between these two quantities breaks down primarily when the bonds themselves are less liquid.

The second candidate explanation views the informed agents not as liquidity providers but simply as responding to exogenous fluctuations in volume to time their trades so as to minimize their price impact and trading costs. Firms with more relationship banks might naturally have more uninformed trading due to the portfolio rebalancing of those banks, or due to hedging of residual CDO tranches and regulatory-arbitrage activities. This would increase the attractiveness of these credits to informed players. If an increase in banking relationships sufficiently increases the relative intensity of uninformed trading to informed trading, then there would be greater liquidity for CDS firms with more bank relationships, and, simultaneously, greater information discovery.

The final explanation we propose is based on the idea of competition among informed agents. Holden and Subrahmanyam (1992) show that if a large number of informed agents receive the same piece of information about an asset's value, then they trade aggressively, instantly revealing most of this information. The depth of the market in the limiting case becomes infinite as the informed agents compete and erode each other's profits. It is possible that all relationship banks receive the same quantum of credit information about the underlying CDS firm (e.g., in a meeting arranged by the firm for its syndicate banks), and, in an attempt to capitalize on this information, transmit all of this information into prices. This would also simultaneously generate a greater information release and greater liquidity for CDS firms that have more bank relationships. Note, however, that in our specific setting, we would expect the competing informed banks to also trade in the stock markets, an outcome of which would be a coincident release of information in the CDS and stock markets. Since our CDS innovations are orthogonal to contemporaneous stock market innovations, the information flow from CDS innovations to future stock market changes is necessarily due to information revealed *only* in the CDS markets.[13]

The data and tests we have employed cannot shed conclusive light on the relative merit of these candidate explanations. The general finding of liquidity rising with information asymmetry runs counter to much of accepted wisdom in market microstructure. Future work employing better proxies of insider trading risk, perhaps using intraday data on actual transactions in the CDS market, would be valuable in shedding further light on these issues.

5. Conclusion

In this paper, we provide empirical evidence that there is an information flow from the credit default swap markets to equity markets and that this flow is permanent and more significant for entities with a greater number of bank relationships. The information flow is concentrated on days with negative credit news, and for entities that experience or are more likely to experience adverse credit events. These findings are consistent with the existence of hedging by banks with lending exposure and access to privileged information.

However, we do not find evidence that the degree of insider trading risk adversely affects prices or liquidity provision in the credit markets. This could be because our proxies are too noisy, or because informed players simultaneously play offsetting roles in the process of price determination. Our work constitutes a first step towards understanding whether

[13]This last point makes it clear that the first two explanations implicitly rely on imperfect competition between informed players in the CDS markets.

there is a case for the current regulatory response to concerns about the threat posed by insider trading in these markets.

Appendix A. Corporate entities with CDS and stock market data in our sample from January 2001 till October 2004

Albertsons Inc
AMR Corp
American International Group
AOL Time Warner Inc
AT&T Corp
AT&T Wireless Services Inc
Bellsouth Corporation
Boeing Co
Burlington Northern Santa Fe Corp
Campbell Soup Co
Carnival Corp
Caterpillar Inc
Cendant Corp
Centex Corp
Citizens Communications Co.
Coca-Cola Enterprises Inc
Comcast Cable Communications Inc
Compaq Computer Corp
Cooper Tire & Rubber
COX Communications Inc
CSX Corp
CVS Corp
Dana Corp
Deere and Co
Dell Inc
Delphi Corp
Delta Airlines Inc
DOW Chemical Co
Eastman Kodak Co
Electronic Data Systems Corp
ENRON Corp
Federated Department Stores Inc
Federal Express Corp
Ford Motor Credit Co
General Electric Capital Corp
General Motors Acceptance Corp
Georgia-Pacific Corp
Goodyear Tire and Rubber Co
Harrahs Operating Co Inc
Hewlett-Packard Co
Hilton Hotels Corp
International Business Machines Corp
International Paper Co
Interpublic Group Cos. Inc
Liberty Media Corp
Lockheed Martin Corp
Lucent Technologies Inc
Marriott International Inc
May Department Stores Co
Maytag Corp
Mgm Mirage Inc
Motorola Inc
Neiman Marcus Group Inc
News America Inc
Nordstrom Inc
Norfolk Southern Corp
Northrop Grumman Corp
Omnicom Group
Park Place Entertainment Corp
Philip Morris Cos Inc
Qwest Capital Funding Inc
Raytheon Co
RJ Reynolds Tobacco Holdings Inc
Safeway Inc
SBC Communications Inc
Sears Roebuck Acceptance
Southwest Airlines Co
Sprint Corp
Sun Microsystems Inc
Target Corp
Toys R US Inc
TRW Inc
TYCO International Ltd
Verizon Global Funding Corp
Viacom Inc
Visteon Corp
Wal-Mart Stores Inc
Walt Disney Co
Worldcom Inc

Appendix B. Syndicated loan originating/participating banks

ABN AMRO Bank
Allfirst Bank
ANZ Banking Group
Banca Commerciale Italiana
Banca di Roma
Banca Nazionale del Lavoro
Banca Popolare di Milano
Banco Bilbao Vizcaya Argentaria
Bank Brussels Lambert
Bank of America
Bank of Boston
Bank of Hawaii
Bank of Montreal
Bank of New York
Bank of Nova Scotia
Bank of Tokyo-Mitsubishi
BANK ONE Corp.
Bankers Trust Co.
Barclays Bank
Bayerische Hypo-und Vereinsbank
Bayerische Landesbank
BNP Paribas
CIBC
CIC Banques
Citicorp
Comerica Bank
Commerzbank
CoreStates Bank
Credit Agricole
Credit Lyonnais
Credit Suisse
Crestar Bank
Dai-Ichi Kangyo Bank
Danske Bank
Deutsche Bank
DG Bank
Dresdner Bank
Fifth Third Bank
First Chicago Corp.
First Hawaiian Bank
First Tennessee Bank
First Union Corp.
Firstar Bank
Fleet Bank
Fortis Bank
Fuji Bank
Goldman Sachs & Co
Hibernia National Bank
HSBC
HypoVereinsbank
Industrial Bank of Japan
ING Bank
IntesaBci
J.P. Morgan
JP Morgan-Chase
KBC Bank
KeyCorp
Kredietbank International
Lehman Brothers
Lloyds Bank
Long Term Credit Bank
Mellon Bank
Merrill Lynch & Co
Mitsubishi Trust & Banking
Mizuho Bank
Morgan Stanley
National Australia Bank
National City Corp.
NationsBank
NatWest Bank
Norddeutsche Landesbank
Northern Trust Corp.
PNC Bank
Rabobank
Regions Bank
Royal Bank of Canada
Royal Bank of Scotland
Sakura Bank
Salomon Smith Barney
San Paolo IMI
Santander Central Hispano
Sanwa Bank
Societe Generale
Standard Chartered Bank
State Street Bank & Trust
Sumitomo Bank
Suntrust
Swiss Bank Corp.
Tokai Bank
Toronto Dominion Bank
U.S. Bancorp
UFJ Bank
Union Bancorp
Union Bank of Switzerland
Wachovia Bank
Wells Fargo Bank
Westdeutsche Landesbank
WestLB
Westpac Banking Corp.
William Street

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