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ABSTRACT

More Insiders, More Insider Trading: Evidence from Private Equity Buyouts*

Recent takeover activity has been characterized by broader participation in acquiror financing on both debt and equity sides. We focus on private equity buyouts, and investigate whether the number of financing participants is related to the likelihood of insider trading prior to the bid announcement. Results suggest that more insiders leads to more insider trade. We study stock, option, bond, and CDS markets. Suspicious stock and options activity is associated with more equity participants, while suspicious activity in the credit markets is associated with more debt participants. The results highlight an important channel in the flow of information and may be consistent with models of limited competition among informed insiders. They are unlikely to be consistent with models of optimal regulation.

JEL Classification: D82, G14 and K42
Keywords: asymmetric information, LBO, private equity and regulation

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1 Introduction

The unprecedented buyout wave in the first part of this decade was accompanied – if press accounts are anything to go by – by an unprecedented degree of insider trading.[1] Perhaps this is merely a matter of scale: more deals mean more opportunities for insider trade. However there are other characteristics of the recent wave that are also novel. It bears asking whether any of these institutional or industry developments played a role in fostering a greater degree of information exploitation.

In particular, this paper asks whether the recent trend towards bigger financing syndicates has driven any of the insider activity. This possibility has not escaped the attention of many who have considered the question: the use of larger pools of participants on both the debt and equity sides – compared to similar deals in the past — naturally means there have been more people with advance knowledge of the deals. It almost seems like a truism to observe that more insiders leads to more insider trade.

Yet this hypothesis is both untested and, upon reflection, not actually self-evident. Is it really clear that twenty insiders will exploit the same information to a greater extent than would ten? The answer must depend upon (among other things) the nature of the enforcement regime and penalty functions that insiders face. To take a simple example, suppose regulators investigate a deal if and only if the pre-deal volume of stock trades exceeds a known and fixed threshold, V, and that, conditional on an investigation being initiated, detection and (dire) punishment are certain. Then certainly one equilibrium outcome is that N informed traders each trade up to V/N shares, so that total trade does not rise with N. In fact, it is not difficult to see that such an enforcement regime may even be *optimal*: commitment to a ceiling on illegal trade creates a negative externality that makes the ceiling to some extent self-enforcing. (Appendix A sketches a simple model that elaborates on this logic.)

Even leading aside the effect of enforcement, a totally unregulated market might also admit only a fixed amount of insider activity due to competition among insiders for limited market liquidity. If insiders' have the same information (e.g., advance knowledge of a takeover bid) and trading is continuous, any number $N > 1$ of informed traders will drive prices immediately to their full-information level.[2] The same result would obtain in a one-time

[1] Section 2.1 below summarizes some of the informal studies documenting this trend.

[2] Holden and Subrahmanyam (1992) and Back, Cao, and Willard (2000) show this in the case of homogeneously informed risk-neutral insiders in discrete-time and continuous-time settings, respectively. Holden and Subrahmanyam (1994) and Baruch (2002) show that in discrete-time and continuous-time settings, respectively, that if risk-averse insiders are considered instead, then the effect is even stronger since the risk-averse

exchange if insiders engaged in Bertrand competition.[3]

Acharya and Johnson (2007) examine this possibility, analyzing insider trade in the market for credit default swaps (CDS), in which there is, for all practical purposes, no regulatory effort to curb such activity. Since the credit derivatives market exists precisely to enable primary lenders (banks) to mitigate their exposure to default risk, and since primary lenders actively engage in the acquisition of non-public information on default risk, the obvious use of inside information arises when adverse credit developments are discovered. That paper hypothesized that the number of banks with access to private information about a borrower would contribute to the amount of suspicious activity. While the empirical evidence was supportive of this assertion, the contrary arguments above could well have applied instead.

One potential explanation for the Acharya and Johnson (2007) result is that more monitors leads to more production (or discovery) of non-public information. A second possibility is that implicit contracts *not* to exploit non-public information play a role analogous to regulation,[4] but that these contracts become increasingly weak in larger syndicates as the marginal participants have less concern for reputation. A third hypothesis is that competition among insiders is imperfect, leading to increasingly revealing trade with the number of competitors.

The present paper provides an opportunity to further investigate these issues in a setting that differs from Acharya and Johnson (2007) along a number of dimensions. We study trading activity in stock, option, bond and CDS markets in the period immediately preceding buyout announcements by private-equity acquirors of public firms. Prior to a bid announcement, there is a well-defined set of players who possess valuable short-lived non-public information. Here the number of informed parties has nothing to do with information production: the quantum of information is the same for all deals. Moreover reputation considerations are also unlikely to play a large role since information can be exploited anonymously in the stock and options markets. On the other hand, in this setting insider trading is definitely illegal and subject to severe penalty (at least for stocks and options).

informed trader is concerned about future price risk from uncertain noise trades. The aggressive nature of insider trading induced by multiplicity of insiders is weaker compared to these settings in the model of Foster and Viswanathan (1996) wherein traders have heterogeneous information and therefore continue to retain some monopoly power.

[3]This could occur, for instance, if the informed players are also dealers who compete via price for limited uninformed orderflow. This may be a reasonable depiction of the credit derivatives market.

[4]One such implicit contract may affect lending banks who are also frequent participants in the secondary market. These may suffer from a reputation for exploitative trading if counterparties and clients deny them access to orders, liquidity, or other valuable information. Another could be an implicit contract among syndicate members not to depress secondary market prices by selling debt still held by others.

Despite the different setting, our primary findings again support the contention that insider trading becomes more likely with more insiders.[5] We offer two potential explanations for this finding.

The first explanation is that, contrary to the predictions in standard imperfect competition models, trade becomes more revealing with more competitors. Competition might be limited by limited wealth of insiders and/or exposure to timing or market risks – realistic features that are generally not considered in the microstructure literature.[6] This hypothesis raises the possibility that the *quantity* of insider activity may not actually have risen so much in the period under study, but that it has just been more detectable. Insiders may have tended to trade more aggressively, making it easier for the market to deduce their presence, and resulting in quicker price reactions.

The second explanation concerns the nature of the enforcement regime. If each potential insider regards the likelihood of detection (and the probable penalty upon detection) as independent of the number N of insiders, then one would expect a rising number of informed players to result in a rising amount of illegal behavior. We argue in the appendix that such policies may be suboptimal because the harm to market liquidity from allowing more insiders to trade can be efficiently avoided by imposing an enforcement ceiling. Beyond the simple model we consider, it also seems clear that allowing the total amount of informed trade to rise with N creates dangerous incentives. To the extent that insiders can *choose* N – e.g. one can always tip off one's friends – there could be a positive net benefit to doing so. If expected individual punishment actually weakens with N, this would create an externality making it safer for more agents to trade together. Such a policy would entail a social dimension to insider trading[7] under which "crime wave" equilibiria become possible. Bond and Hagerty (2005) study such possibilities, and show how particular enforcement regimes may promote them.

In highlighting these potential explanations, our work speaks to both the literature on the dynamics of asymmetric information, and to the literature on the design and efficiency of regulation. Our results point to the need to develop further models of enforcement games

[5]We stress that we do not claim that any of the entities we count is literally guilty of prohibited activity. Each provider of finance involves dozens of associated informed parties (e.g. lawyers, clients, accountants, friends, and family). The suspicious trading that we identify may be correlated with size of equity and debt syndicates simply because the latter are good proxies for the rate of information leakage. The exact value of syndicate size should not be literally interpreted as the number of insiders, but simply as being monotonically related to it.

[6]We do find evidence that the extent of suspicious trading is lower for companies with greater stock return volatility.

[7]See Glaeser, Sacerdote, and Scheinkman (1996) and Sah (1991).

in the presence of imperfect competition among insiders. We elaborate on this point in the final section.

The primary contribution of the paper, however, is to offer a new empirical finding relating syndicate structure to insider activity. Although there is an enormous body of work documenting differences in information asymmetry across firms (and across markets), and though these differences are widely thought to have important consequences for market dynamics, there has been perhaps surprisingly little study of *why* these differences arise. Exploiting the opportunity presented by recent developments in the takeover market, we offer an initial contribution in this direction. Large firms with more bank relationships and with larger potential bidding syndicates are likely to see more leakage of non-public information. This result stands in contrast to the frequently assumed inverse relation between firm size and information asymmetry. Furthermore, we find that information leakage is segmented: Insider trading in stock and options markets is more likely if there is a larger size of equity syndicate, whereas insider trading in CDS and bond markets is increasing in the size of debt syndicates.

The outline of the paper is as follows. The next section describes the period we examine and our sample of LBO bids. Section 3 explains our construction of the main dependent and independent variables. Section 4 presents the empirical results and considers alternative interpretations and robustness. The final section summarizes the paper and concludes.

2. Background and Sample

This section describes the setting for our study. We begin with an overview of some of the industry developments that have characterized the sample period.

The past few years have seen a dramatic rise in the mergers and acquisition (M&A) activity around the world. From a low of $1.2 trillion in 2002, the pace of merger activity increased to $3.7 trillion by the end of 2006.[8] In 2005 there were a total of 200 buyouts in the United States with a value of $850 billion; the corresponding numbers for Europe being 1300 buyouts worth some 125 billion euros. Compared to the merger boom of late 1980s, which was financed primarily by public equity and junk-bonds, the current decade's merger boom has been primarily driven by availability of syndicated bank debt and the tremendous

[8]Source: Thomson Financial Services, September 5 2006, for the volume of global M&A activity from 1985 to 2006.

growth of private equity funds. Like the buyout wave in 1980s, prices paid have also escalated during the decade.[9]

All financial markets experienced an explosion in liquidity during 2003-2006. The main sources of this liquidity boom were increased investment from petrodollars, large government surpluses in Asia, as well as growth in pension, foundation, and private wealth (Altman, 2007). Particularly striking about this burst of liquidity was the increasing proportion of capital allocated to alternative investment products, most notably private equity, which became a mainstream asset class over the period. During this time, the size of the capital commitments to private equity funds by outside investors increased dramatically. In the peak years of the first wave of LBOs, 1986 through 1988, the industry was raising about $16-18 billion a year from the limited partners who provide most of the capital. In 2006, the total capital commitment exceeded $150 billion (Kaplan, 2007). In addition to the large capital commitments, volume of public-to-private transactions has also increased substantially. The peak volume of such deals in the 1980s was reached in 1989, which exceeded $50 billion in the U.S. In 2006, the volume of such deals jumped to $233 billion (Kaplan, 2007).

With this secular increase in the volume and number of LBO transactions, there have been some important developments in the nature of institutional participation in their equity and debt financing. We review these next.

2.1 Broadening of participation in debt and equity syndicates

The syndicated loan market became a major source of deal financing during the 2001-2006 M&A boom. In 2006, the $233 billion of LBO deal volume in the United States was funded in part by about $125 billion of such loans (Altman, 2007). Broader figures for overall debt issuance show that there has been a surge in syndicated debt financing relative to corporate bond issuance. In 2001, both these issuances were around $1.5 trillion, whereas in 2005, syndicated debt financing had grown to be about twice as large, a total of $3.75 trillion relative to corporate bond issuance of $1.75 trillion.[10]

The growth of the syndicated debt market was made possible in part by a deepening of the number of participating lenders, beyond the traditional large commercial banks. According to Reuters Loan Pricing Corporation, institutions other than banks, including hedge funds and other "alternative investment" vehicles, assumed more than 60% of loans issued in 2005.

[9]See, for example, Acharya, Franks, and Servaes (2007), who report that the growth in LBO transactions during 2001-2005 matches the growth from 1985 to the peak of 1988-1989, and that the EBITDA to valuation ratio for targets, relative to the market average, declined to a low of 4% in 2006, as compared to 5% in 1989.

[10]Source: Merrill Lynch Research based on Dealogic database.

As participation in initial syndicates expanded, so too did the (previously rare) practice of secondary market trading. Important to note for our study are the ramifications that the wider participation in initial and secondary markets have for the flow of information. Holders of any stake in a syndicated loan are entitled to all the non-public information gathered by the lead banks in their capacity as monitors of the borrowing firm.

A related and equally important development in the recent buyout wave was the increase in the syndication among private equity firms on individual deals. Twenty-one "club" deals – involving more than one acquiror – were announced in 2006, valued at $176.5 billion, double the amount in 2005.[11] As deals have grown larger, portfolio diversification motives of private equity pools have essentially ruled out complete equity funding by a single firm. This was especially true in 2005 and 2006 as deals started expanding to relatively large (over $1 billion value) public firms. Such "clubbing" of deals has greatly expanded the universe of people who are privy to the negotiation process leading up to the launch of a buyout bid.

2.2 An increase in insider trade?

The broadening of participation in debt and equity syndicates, and the increasing role played by hedge funds, is widely believed to have increased the incidence of insider trading in a number of different markets prior to buyout announcements. The reason for this belief seems to be well-founded. The list of insiders on deals now includes bidders, investment bankers, lawyers, lenders, as well as management of the target company. As the pool of people with inside information expands, the potential for inappropriate use of material non-public information clearly increases.[12] Also, when public companies attract interest from would-be acquirors, they often sound out other potential buyers or conduct confidential auctions in search of better prices, further swelling the circle of insiders. It has been well-recognized in the media that the increasing size of LBOs and the increase in number of participants are perhaps responsible for the recent surge in insider trading prior to LBO announcements.[13]

[11] Source: "Global Overview" by Casey Cogut, David Sorkin and Kathryn King Sudol, Simpson Thacher & Bartlett LLP, in "Getting the Deal Through", Private Equity 2007.

[12] The TXU bid of 2007, for example, involved seven investment banks and twelve law firms.

[13] "How many people can you have knowing a secret and keep it a secret?" asks John Coffee, a securities law expert at Columbia University in New York. 'Under about 10 people. I think Wall street can keep a secret. But much beyond that, I dont know'." (Quoted in "Insider Trading," Bloomberg Markets, August 2007.) In fact, Keown and Pinkerton (1981), studying the abnormal stock price reactions prior to public M&A transactions recognized this possibility quite early in the literature: "You start with a handful of people, but when you get close to doing something the circle expands pretty quickly. You have to bring in directors, two or three firms of lawyers, investment bankers, public relations people, and financial printers, and everybody's got a secretary. If the deal is a big one, you might need a syndicate of banks to finance it.

Our paper does not directly address the question of whether insider trade actually *did* increase (relative to earlier periods) during 2000-2006. However our primary hypothesis is certainly motivated by the perception that it did. This perception is not purely anecdotal. In fact, it finds support in a number of non-academic studies across different markets. We briefly summarize some of these

Equities: The Financial Times[14] examined trading data for the top 100 U.S. and Canadian deals since 2003 collected by Measured-Markets, a Toronto research firm that uses a weighted average based on volume, price and number of trades to flag unusual trading patterns. The survey found suspicious trading occurred ahead of 49 per cent of all North American deals. Almost 60 per cent of the 27 big deals announced in North America in 2007 (up to August) were found to be preceded by unexplained spikes in trading in the stock of the target company, compared to 14 per cent for the seven largest deals announced in 2003.

Options: A May, 2007 study by Bloomberg[15] examined options trading for the 17 biggest U.S. takeovers in the preceding year (which partially overlaps with our sample period). Comparing volume in the three days before the bid to the average for the prior 50 days, the study found that pre-bid volume jumped 221 %. Particularly flagrant trading was mentioned in the cases of TXU Corp., HCA Inc., Sallie Mae, and First Data Corp. Interestingly the study found no unusual volume on average for acquisitions by other public companies.

CDS: As reported in the Wall Street Journal,[16] a study by a firm called Credit Derivatives Research found unusual spikes in CDS fees ahead of news or reported rumors concerning 30 LBOs in 2006. Follow up reporting by the Journal tracked several specific spikes to dates of important (secret) meetings involving the bidders and company management which were later disclosed in proxy filings.

Every time you let in another person, the chance of a leak increases geometrically." — J. William Robinson quoted in "Merger Leaks Abound Causing Many Stocks to Rise Before the Fact." Wall Street Journal (12 July 1978).

[14] See "Boom time for suspicious trades," by Victoria Kim and Brooke Masters, Financial Times, August 6, 2007.

[15] "Insider Trading Concerns Rise as Stock Options Surge" by David Scheer, Bloomberg, May 7, 2007.

[16] 'Moving the Market – Tracking the Numbers", by Serena Ng, Wall Street Journal, December 14, 2006.

2.3 Changing incentives?

While the description above (and our analysis below) suggest that insider trading may have been especially prevalent in the recent buyout wave because of broader participation in takeover activity, an alternative, not exclusive, hypothesis is that the rise in such trading was due to a laxer enforcement climate.

To the extent that insider trading takes place in new over-the-counter derivatives markets, the assertion is certainly true. As mentioned in the introduction, there are few (if any) laws against such trading in any jurisdiction. And, in the United States, there is not even a clear regulator with purview over credit derivatives.[17]

In markets that are explicitly regulated, governments have also faced other new complications. One issue that has made enforcement difficult has been the rise of cross-border trade. Notable recent prosecutions in the U.S. have included defendants in Hong Kong and Pakistan. New institutions also complicate monitoring. Hedge funds, in particular are more opaque and less subject to the responsibility to protect non-public information (via "Chinese walls").

Despite the challenges, and despite the perception among some participants that enforcement has been lenient, we know of no evidence that regulators have achieved less success during the period of our sample. In fact, since April 2006, the SEC has filed insider trading-related lawsuits against more than a dozen investment bankers, analysts and executives, a higher number of cases than during the entire decade of the 1990s.[18]

Apart from secular changes in expected penalties, insider activity would also be expected to respond to changes in rewards. As noted above, private equity firms did appear, on some measures, to pay higher and higher prices as the buyout wave progressed. However, from a historical perspective, the rewards to advance knowledge of a bid do not appear to have increased. In our sample of bids (described below), the average six-day return (from $t-5$ to t, where t represents the announcement date) to target stocks was 13.2%. By comparison, Andrade, Mitchell, and Stafford (2001) report average three-day returns of about 16% for all mergers during the 26 year period 1973 to 1998.[19] That average was virtually constant across decades, and was over 20% for cash-only deals (i.e., comparable to the buyouts we study). Thus, if anything, the rewards to advance trading seem to have been lower during

[17]Perhaps to counter this widespread perception, the Chairman of U.S. Federal Reserve Board recently asserted "U.S. securities laws against insider trading....apply broadly to ... trading in a wide range of financial instruments, including securities based on over-the-counter derivatives transactions." (Speech given by Ben Bernanke, May 15, 2007.)

[18]Source – "Insider Trading," Bloomberg Markets, August 2007.

[19]The latter number is a risk-adjusted abnormal return, the former number is a raw return.

2000-2006.

2.4 Sample

For this study, we construct a sample of buyouts of public companies from January 1, 2000 to December 31, 2006. We do not extend the sample backwards, because, as described above, merger and acquisition activity in the preceding decades was markedly different along a number of dimensions.

Our data come from Thomson Financial (formerly SDC), and consist of bid-events. We select bids by private, financial buyers of public companies for which the value of the bid exceeds 100 million dollars. We impose a few other selection criteria (described in Appendix B) whose aim is to select private equity buyouts rather than ordinary acquisitions by (possibly private) operating companies or subsidiaries.

We do not have direct information on the formal structure of the proposed acquisition, or its anticipated capital structure. So we cannot necessarily describe all our bids as "LBOs".[20] We also do not require that the bid necessarily be successful or completed. As of November 2007, only 60% of our bids had resulted in a completed deal (with about half of the rest having resulted in acquisition by a different bidder).

Table 1 presents a summary of number of bids and their size (10th percentile, median and 90th percentile), year by year for the bids that meet our initial selection criteria. The most striking feature of the table is the rise in number of transactions in 2006 (81 deals) and the substantial increase in size of deals since 2003. The median transaction size is around $200-300 million until 2003, but exceed $500 million thereafter. Note that the 10th percentile sizes also exhibit such a trend but that is less dramatic, capturing the fact that there has been a surge in very large transactions since 2003. The smallest number of transactions as well as smallest median size were in 2001, which coincides with a recession in the United States and historically high default rates. This reflects well the somewhat cyclical nature of flows into the buyout industry, a fact that has been reinforced by the virtual drying up of buyouts following the credit market squeeze in the summer of 2007.

Some other aspects of the sample deserve mention. Consistent with our sample being buyouts, the median acquiror bid for the entire 100% of the target equity. Almost all the acquirors are private equity houses or their consortia, with a few exceptions reflecting stakes

[20] There is a field in the database flagging events Thomson determines to be LBOs. The procedure for the designation is not clear. All bids so described are in our sample. But we also include several bids without this designation.

Table 1: Deal size ($ millions) by bid year

Year	# of obs.	10th %ile	Median	90th %ile
2000	28	122	257	2175
2001	5	133	256	1995
2002	15	115	314	1464
2003	10	109	244	443
2004	15	401	1208	2931
2005	41	197	605	2344
2006	64	357	1496	17074

The table presents the year by year averages of the number of bids and the 10th percentile, median and 90th percentile of proposed deal value ($mil). The overall sample consists of 178 bids over the period 2000 to 2006 from Thomson Financial (SDC) database. Sample selection criteria are as described in Appendix B.

by individuals and venture capital firms. The data spans a large number of industries, the decomposition by value being: services (SIC 70-89) 32%; manufacturing (SIC 20-39) 26%; retail trade (SIC 52-59) 14%; finance, insurance, and real estate (SIC 60-67) 13%; transportations and public utilities (SIC 40-49) 8%; wholesale trade (SIC 50-51) 4%; and mining (SIC 10-14) 1%.

Different subsets of this overall sample are used in different tests below, depending on the additional data needed and the market being investigated.

Out of our initial sample, 212 targets match with CRSP and Compustat data. Out of these 212 targets, 178 had active syndicated loan data on Loan Pricing Corporation's Dealscan database as of the bid date. These targets together had 857 loan facilities with a median maturity of 3.5 years and median facility size of $135 million. The median number of lead banks and participating banks in these loans is 5 and 6, respectively. The 10th percentile values are 0 and 1, respectively, whereas the 90th percentile values are 22 and 12, respectively. Summary characteristics of equity characteristics of these 178 firms for the 6-month pre-announcement window are provided in Table 2. The median target size is $446 million. Median stock turnover is 0.59% per day. Target firms in general tend to have low leverage (median debt to firm value ratio is 0.30 with 10th percentile leverage being zero) and are from stable sectors (median beta of 0.78). The tests below employ this 178 Thomson-CRSP-Compustat-LPC matched sample.

Table 2: Target Characteristics

	Obs	10th %ile	Median	90th %ile
Mkt cap	178	97	446	3321
M/B	170	0.87	1.64	3.39
D/V	175	0.00	0.30	0.61
β	178	0.11	0.78	1.61
σ	178	0.22	0.43	0.79
Stock volume	178	0.02	0.20	1.51
ILLIQ	178	0.0005	0.0077	0.3170
Turnover	178	0.15%	0.59%	1.53%
S&P Credit Rating	81	BBB-	BB	B

The table presents 10th percentile, median and 90th percentile of firm characteristics for the part of our buyout sample that matches with CRSP and Compustat. The measures are based the 6-month (calendar) pre-announcement period. They are calculated per firm per day, and then averaged across the 6-month period for each firm. Illiquidity, stock turnover, firm size, market beta and volatility are based on items reported in CRSP. Market to book, leverage, and S&P credit rating are based on items reported in Compustat. Mkt cap is equity market value in millions of dollars. M/B is equity value divided by book value of common equity. D/V is book value of long-term debt divided by the sum of this value and market value of equity. σ is the annualized volatility of daily stock returns. β is estimated with respect to the CRSP value-weighted index. Stock volume is in millions of shares per day. ILLIQ is measured using Amihud (2002) ratio, computed daily and averaged over the entire period and is in units of 10^{-6}. Turnover is in percent per day. S&P Credit Rating is averaged for each firm over the 6-month period.

3 Empirical Strategy

This section describes our methodology for testing for a link between the financing structure of a takeover bid and the likelihood of insider trading prior to that bid. Our first step is to construct measures of suspicious pre-bid trade for each event. This then becomes our dependent variable in the main regressions, which utilizes measures of the number of informed insiders as the primary independent variables.

3.1 Measuring Insider Activity

Insider trades can only be directly measured with detailed transactions data and knowledge of the informed status of all traders. While this information can be obtained by government investigators, even they do not have the resources to gather it systematically for large samples. Instead, typical monitoring relies initially on broader statistics that may be indicative

of suspicious activity. We take that approach here, constructing statistics that we postulate to have a monotonic relation to insider activity.[21] Meulbroek (1992) presents direct evidence that pre-bid trading by insiders results in abnormal price and volume changes. While our measures flag unusual trading activity in a number of ways, we have no way of ascertaining the degree of effectiveness of any one of them in truly identifying illegal activity. As noted by Jarrell and Poulsen (1989), unusual activity may precede takeover bids for other reasons, including acquiror building of "toeholds" and speculation based on public information. To the extent that all of our measures are noisy, the methodology is biased against being able to detect any association between the suspiciousness of trade and our explanatory variables.

It is also worthwhile to point out that our statistics could, in principle, be measuring two distinct things: (A) the *likelihood* of (some) insider activity prior to a particular bid; and (B) the *amount* of (all) such activity. Some of our measures may be more sensitive to one than the other. But, as a practical matter, we have very limited ability to distinguish which (if either) we are capturing.

3.1.1 Stock market measures

All of our target companies had publicly traded stock prior to the bid announcement date. For each, we construct measures of unusually heavy trade or unusually large positive price movement in a five-day window immediately preceding the bid. Our methodology consists of two stages. First, we design a regression specification to describe "normal" (or expected) values of each series (volume and returns). We run this regression using daily data for a three month period preceding the bid. Second, we apply a metric to the regression residuals in the pre-event window to flag the occurrence of suspicious activity on any individual day. There is no single best way to do each step. So we try a number of alternatives.

The regression specifications that we use include the following variables.

A1. Constant.

A2. Constant; lagged volume and returns.

A3. Constant; lagged volume and returns; day-of-week dummies.

A4. Constant; lagged volume and returns; day-of-week dummies; contemporaneous volume and return for market index.

[21] To be precise, we postulate that the relationship is monotone *given* that a bid did occur. There is no assumption that the measures are unconditional predictors of insider trading, or of imminent bids.

Volume and return data come from CRSP. We use the CRSP value-weighted return for the market return, and the S&P500 volume for market volume.

Notice that the last specification includes contemporaneous information. The purpose of these measures is to describe returns and volume given *all* information about the date in question, whether or not it was known prior to that date. More detailed specifications could include dummies for earnings announcements or other news events. It turns out our results are largely insensitive to the specific variables chosen.

Given these regressions, we use two functional forms to capture the presence of large positive residuals in the five trading days before the bid.

MAX. The maximum of the daily standardized residuals.

SUM. The sum of the positive standardized residuals.

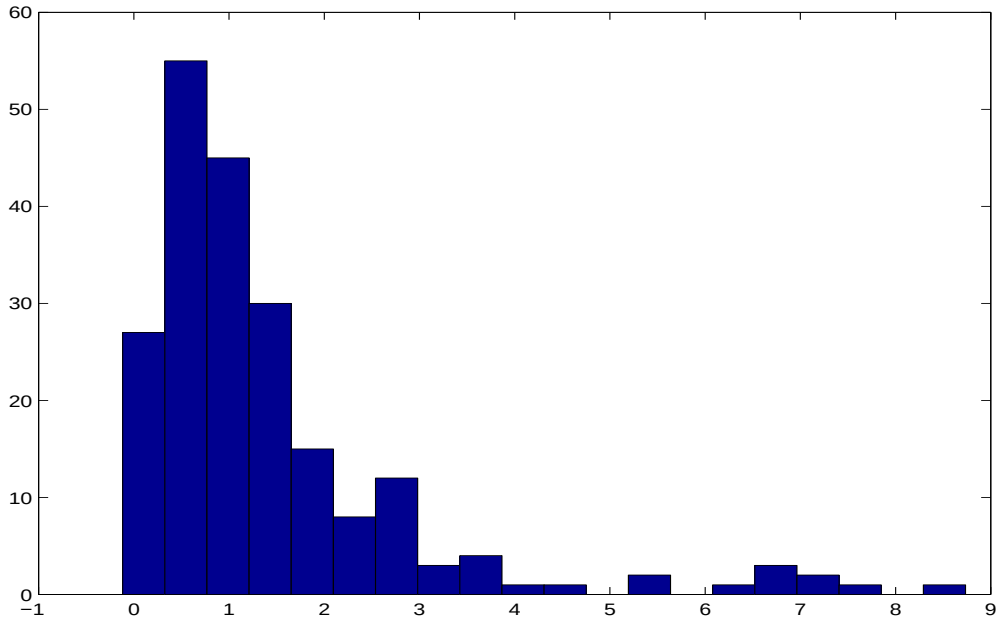
The first measure is sensitive to unusually large individual days; the second is sensitive to cumulatively large abnormal trade.[22] MAX may miss activity of a strategic insider who acts like a Kyle-type monopolist. SUM (like CAR) may miss intense bursts of activity of competitive insiders.

It is important to clarify that we are interested in the cross-sectional variation in our measures over our sample of events, not the time-series variation for each firm. If a given firm gets a MAX score of 5.0, for example, that certainly seems suspicious (for a standardized residual in a time-series regression). But our methodology does not require us to render a statistical verdict on each deal. Our goal is not to assess whether insider trading took place in any particular instances. Rather it is to analyze the variations in the likelihood of such trade across bids.

Figure 1 shows the histogram of MAX measure computed using the simplest regression A1 applied to returns. As a benchmark, we also show (Figure 2) the histogram of the same measure computed from a 5-day window three months before the bid. While the overall frequency distributions look similar, the histogram for 5-day window immediately before the bid shows a significantly fatter right tail. There are nine outcomes greater than five standard deviations from the mean in the first window, whereas there is only one such outcome in the second one. This provides some evidence that the cross-sectional variation in our measures during the 5-day window prior to bid announcements appears to be picking up activity related to the bid, and differs markedly from that observed in normal periods.

[22]The SUM measure is very close to the cumulative abnormal return measure (CAR) employed in much of the event study literature. Restricting the sum to positive residuals yields a number that is analogous to an F-statistic for the test of the one-sided null that none of the residuals is significantly positive.

Figure 1:



The figure shows the histogram of MAX stock return measure computed using the methodology A1 over the pre-bid window from date -5 to -1.

3.1.2 Options market measures

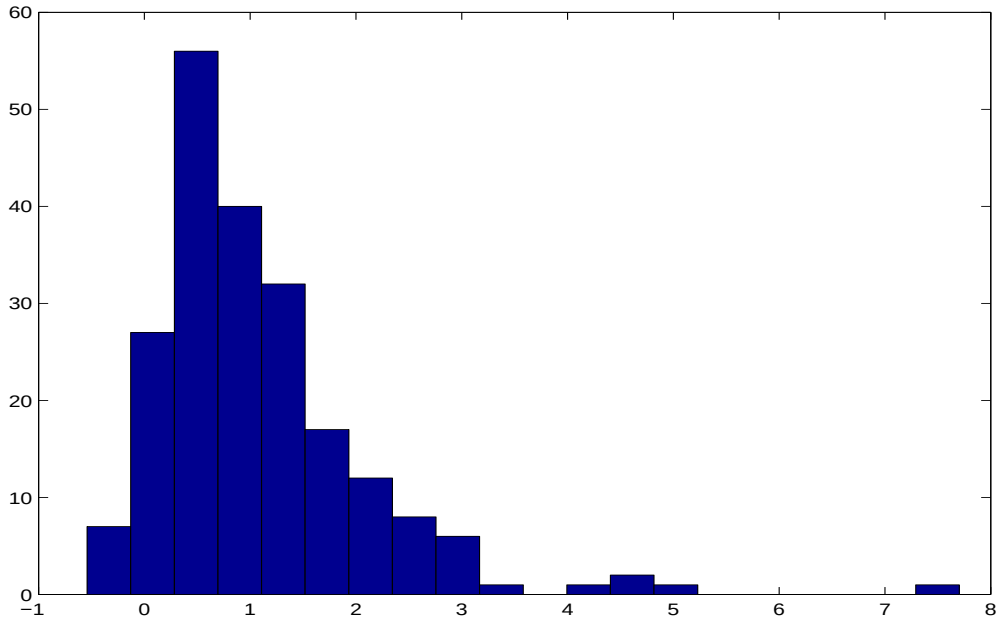
Of the 212 target firms in our sample, 84 had traded options. Options can offer an insider a cheap way to leverage private information, and options trading has featured prominently in several enforcement cases brought by the SEC. We build measures of unusual options market activity in a similar fashion to our stock market volume measures.

Options present some unique issues with aggregation. A given target company with listed options will typically have dozens of available contracts to trade on any given day (i.e., puts or calls each with several maturities and strike prices). An insider could, in principle, profit from trading in any one of these. We want a single statistic to capture activity across all of them. This adds an additional layer to our procedure.

Our information for this market comes from the OptionMetrics database, and includes daily transactions volume, and end-of-day prices for all U.S. listed options. We focus on volume measures, and define the following aggregate statistics.

- The total number of calls traded.
- The delta-weighted sum of all traded calls.

Figure 2:



The figure shows the histogram of MAX stock return measure computed using the regression specification A1 over the 5-day window which starts three months before the bid.

- The elasticity-weighted sum of all traded calls.

We use call volume because it is more efficient to speculate on the upside of a stock with calls than with puts. (We have built similar measures using call and put volume with very similar results. These are omitted for brevity). The first statistic is self-explanatory. The second statistic weighs calls by its delta, $\delta \equiv \partial C/\partial S$. This is a measure of the effective number of shares of stock exposure each commands.[23] It is thus directly comparable to stock volume. The third statistic weighs each call by the sensitivity of its returns to the returns of the underlying stock. This number, given by $S\,\delta/C$, is more sensitive to the options that one might expect speculators to prefer: those with the most "bang for the buck."

Having computed each of these for all days, we then fit regression specifications to describe the expected value of each. The independent variables in these specifications are similar to those used for the the stock regressions.

B1. Constant.

[23]Option deltas are computed by OptionMetrics using end-of-day pricing and implied volatilities based on a binomial model which accounts for the American feature of the options.

B2. Constant; contemporaneous stock market index volume and return.

B3. Constant; contemporaneous market volume and return; lagged volume and returns of underlying stock.

B4. Constant; contemporaneous market volume and return; lagged volume and returns of underlying stock; lagged dependent variable.

An additional complication in these regressions is the presence of a substantial number of zero-volume observations for some firms, that is, days for which no options traded of any strike or expiration. The presence of these days makes the data highly non-normal, and leads to potentially serious misspecification problems with OLS. To deal with this, we estimate a Heckman (1978) two-stage selection model, which fits the probability of any trade as a function of the regressors, and then estimates the volume given trade for the positive trade days. This procedure yields appropriate residuals and residual standard errors for zero and non-zero observations. As with the stock data, we then apply the metrics MAX and SUM above to these residuals.

3.1.3 Credit derivatives measures

Acharya and Johnson (2007) report evidence consistent with informed trade in credit default swap markets prior to episodes of substantial credit deterioration. Leveraged buyouts are an event of this type, since existing creditors are harmed by the increased debt taken on by the target. During the sample period covered in this study, there continued to be numerous examples, well documented in the financial press, of spikes in CDS fees in advance of takeover bids. Acharya and Johnson (2007) also find that, in general, more bank relationships for a target firm are associated with a higher tendency towards advance information revelation in CDS markets. In the present paper, we directly test for a similar association in an event-study setting and using different methodology.

Of our target firms, 22 had traded credit default swaps at the time of, and during the three months prior to, the bid. Data for CDS markets is problematic in that no actual transaction records exist. However several vendors compile indicative end-of-day quotes from market makers, making it possible to compute daily changes in quoted fees. We regress these changes (in logs) on the following explanatory variables.

C1. Constant.

C2. Constant; lagged dependent variable; lagged return on underlying company stock; day-of-week-dummies.

C3. Constant; lagged dependent variable; lagged return on underlying company stock; day-of-week-dummies; contemporaneous stock return,

C4. Constant; lagged dependent variable; lagged return and volume of firm's stock; day-of-week-dummies; contemporaneous stock return and volume; contemporaneous change in BAA-AAA yield spread;

As with the other markets, we then construct the metrics MAX and SUM to yield our measures of unusual activity in the pre-bid window.

3.1.4 Bond market measures

While default swaps may be especially well suited to informed hedging of LBO risk by exposed creditors, the same logic applies to bonds issued by the target firms. We examine unusual activity in primary debt markets as well, which may differ from that in CDS markets for two reasons. First, coverage is different. Not all firms with corporate bonds have active CDS markets. Second, the regulatory regime may differ substantially in that trading in primary debt securities is more clearly subject to U.S. insider trading regulations, and market activity is directly monitored by the SEC.

Beginning in July 2002, corporate bond trade data are available from the TRACE database. For the firms in our sample, we have transaction information for at least one debt issue during the three-month pre-bid period for 34 targets. Since some firms have several issues, we form these into portfolios weighted by issue size and study their daily returns.[24] We again employ four different specifications of expected returns for each firm's bond portfolio.

D1. Constant.

D2. Constant; lagged dependent variable; lagged return and volume of firm's stock; day-of-week-dummies.

[24]Some volume information is available on TRACE, but it is problematic in that (a) reporting requirements were not uniform over the sample period; (b) trades with non-U.S. entities and in private debt issues (144a) are not covered; and (c) reported transaction sizes are truncated, with different ceilings for differently rated bonds.

D3. Constant; lagged dependent variable; lagged return and volume of firm's stock; day-of-week-dummies; contemporaneous stock return and volume.

D4. Constant; lagged dependent variable; lagged return and volume of firm's stock; day-of-week-dummies; contemporaneous stock return and volume; contemporaneous change in BAA-AAA yield spread;

Note that, unlike our measures in other markets, here we are interested in suspiciously *negative* residuals (corresponding to increases in yields or CDS fees). To facilitate interpretation of the results, we multiply the bond residuals by minus one, so that the signs of explanatory variables have the same meaning across markets. We then apply the MAX and SUM metrics to the negative residuals.

3.1.5 Related methodologies

Measures of suspicious trading prior to takeover bids and other news events have been reported in a number of papers. Unusual pre-announcement stock trading activity was first documented by Mandelker (1974) and Keown and Pinkerton (1981). Keown and Pinkerton used daily returns and weekly volume, whereas Mandelker only used monthly returns. Similar results for options appear in Jayaraman, Frye, and Sabherwal (2001) and Arnold, Erwin, Nail, and Bos (2000). Recently, Gao and Oler (2004) and Cao, Chen, and Griffin (2005) have constructed measures of buyer-initiated and seller-initiated volume (in stock and options, respectively) prior to takeover announcements, using the former to identify presumably informed orders. Poteshman (2006) compiles distributional information for several summary statistics of options market activity, and uses these to address the unusualness of trading in airline stock options prior to September 11, 2001. Berndt and Ostrovnaya (2007) use changes in options implied volatility, as well as CDS fees and stock returns to analyze pre-event flow of information in a sample that overlaps with our own.

Relative to this literature, our paper does not claim to offer sharper evidence of insider activity and does not address the information flow across different markets. Rather, our focus is on understanding *why* insider trading occurs or when it becomes more likely. We are not aware of other work that examines cross-sectional determinants of informed trade in an event-study context.

3.2 Measuring Number of Insiders

The primary tests in the paper are regressions of the measures of unusual pre-bid market activity on characteristics of the takeover bid. In particular, we want to assess the role of the number of entities involved in financing the bid. To do this, we form separate measures of participation on the debt and equity sides.

For the equity side, our main information comes from the event descriptions provided Thomson Financial. These descriptions list the major participants in each bid, which we simply count. There is certainly some degree of irregularity in this process as the database does not purport to provide an exhaustive list of participants for each deal. Nor is it even clear that they follow a consistent procedure for deciding which entities to list. Typically LBOs involve equity stakes being taken by key officers and managers of the target entity, meaning that, technically, a large number of individuals are among the providers of equity finance. The data set appears to only list individuals in rare cases, presumably where they were key instigators or took very large stakes. We have cross-checked the counts we obtained with those obtained from another data provider for a sub-sample of our events and found good agreement. As mentioned in the introduction, we do not interpret our counts literally, but only as monotonic (not necessarily linear) transformation of the true number of informed insiders. Of course, the usual argument about noisy data applies here: to the extent that our count is corrupted by random error it is less likely that our regressions will uncover any relationships with suspicious trade.

For debt finance, we follow Acharya and Johnson (2007) in counting the number of participants in syndicated loans to the target company at the time of the deal. This definition is appropriate when, as in most LBOs, the target company is itself the borrowing entity for the debt used in the deal. It is not appropriate, for example, when the target is merged into an acquiror who itself assumes the additional debt. In our event sample, we were unable to identify instances of this. To be more accurate, we were unable to identify syndicated loans to any of the acquiring entities (e.g., Blackstone or KKR) that could be identified as having been used to finance particular bids. On the other hand, many of our targets did, in fact, take on additional debt following successful bids.

Data on syndicated borrowing comes from the Loan Pricing Corporation's Dealscan database. It provides lists of all participating entities, and identifies in particular those with lead-bank roles. We count these banks in a number of ways, reflecting various possibilities for which ones might have been informed prior to a bid.

The most narrow measure restricts to the set of syndicated loans entered into within

the six months after the bid event, and includes only the lead banks for these loans. These lead banks, who are providing takeover finance, would almost certainly have provided the bidders with prior commitments, and hence would have known a great deal about the bids. Not all our deals include records of loans specifically taken out to finance the buyout.[25] A second measure counts all lead banks in facilities active on or after the date of the bid. This adds to the previous count the target's main banks having on-going relationships at the time of the bid. Whether or not they ultimately provided deal finance, these banks are likely to have been approached as potential lenders. A third method of counting includes all bank participants in facilities that were active on or within six months after the date of the bid. This count includes non-lead banks, with whom lead banks may have been obligated to share material non-public information in advance of the bid. Non-lead participants may include hedge funds and other investment firms who may have weaker incentives to abide by confidentiality agreements.[26] Even the last count of bank relationships is clearly only a lower bound, since it ignores all non-syndicated loans and commitments. In addition, a number of our target firms had no information on bank loan relationships. One could interpret this occurrence as firms having zero banking relationships. However we instead simply exclude these bid-events from our tests involving bank counts.

Table 3 shows the distribution of our tabulation of providers of debt and equity finance for the sample bids. (The table uses the second definition of debt participants, that is, lead banks for loans outstanding at the time of the bid or within six months thereafter.) Nearly half of our deals only had a single buyer, whereas, among those having syndicated loans, the median number of banks is 5.

The table also reports characteristics of the target firms broken down by the number of participants in the bid. This allows us to assess the degree to which the number of participants is exogenous to the takeover process. As expected, the size of the target company is a key determinant of the number of participants. Companies with more than two equity participant are, on average, over twice as large as those with exactly two. Companies with more than seven lead banks are roughly seven times as large as those with fewer than four. Despite this strong size dependence, there is little noteworthy variation in target balance sheet characteristics or in the bid premium. Likewise, there is perhaps surprisingly little variation in the stock market risk measures: stocks with more participants (of either type)

[25] This could be because the borrowing entity had a separate name in Dealscan, or because the financing was not completed as of the time of this writing.

[26] Ivashina and Sun (2007) report indirect evidence of such leakage. They find that equity portfolios of institutions that hold stock and loans of the same company significantly outperform comparable investors that do not invest in the loan market.

somewhat lower volatility. Stocks with fewer lead banks are more illiquid(using the measure of Amihud (2002)).

Table 3: Target Characteristics by Number of Participants

	Equity Participants				Debt Participants		
	1	2	> 2	> 1	< 4	4-7	> 7
Obs	79	64	35	99	62	61	55
Mkt cap	351	402	1,122	515	230	319	1,605
Premium pct	24.2	28.6	21.6	26.0	26.2	27.1	21.6
M/B	1.65	1.63	1.74	1.64	1.49	1.63	1.79
D/V	0.29	0.31	0.24	0.30	0.28	0.27	0.33
β	0.81	0.81	0.67	0.78	0.69	0.78	0.82
σ	0.41	0.49	0.36	0.43	0.47	0.46	0.34
ILLIQ	0.009	0.012	0.002	0.006	0.039	0.014	0.001
Turnover	0.61%	0.59%	0.58%	0.58%	0.48%	0.60%	0.74%

The table shows characteristics (median) of target companies selected according to the number of debt and equity participants in the buyout bid. The first four columns sort targets according to equity participants; the last four use number of lead banks. Premium pct, reported by SDC, is the bid premium in excess of the stock price one week prior to announcement. Other measures are based the 6-month (calendar) pre-announcement period. They are calculated per firm per day, and then averaged across the 6-month period for each firm. Illiquidity, stock turnover, firm size, market beta and volatility are based on items reported in CRSP. Market to book and leverage are based on items reported in Compustat. Mkt cap is equity market value in millions of dollars. M/B is equity value divided by book value of common equity. D/V is book value of long-term debt divided by the sum of this value and market value of equity. σ is the annualized volatility of daily stock returns. β is estimated with respect to the CRSP value-weighted index. Stock volume is in millions of shares per day. ILLIQ is measured using Amihud (2002) ratio, computed daily and averaged over the entire period and is in units of 10^{-6}. Turnover is in percent per day.

While deal size clearly largely determines the number of providers of finance, the pairwise correlation between all lead banks and equity participants is only 0.22. Equity participants and deal size have correlation 0.36, whereas banks and size have correlation 0.51. These correlations confirm that deal size is not the only determinant of syndicate sizes, and that equity and debt syndicate sizes are driven by different considerations.

The strong correlation between number of bid participants and target size has significant implications for our empirical work, however. A common assumption in the empirical literature is that asymmetric information problems are worse for smaller firms. If so, then

controlling for size should be important in order to isolate the independent effect of number of insiders. On the other hand, size can also be viewed as an additional measure of the number of insiders. Larger companies have more officers and directors, and more investment bankers and lawyers. We have no other measure of these. Moreover, our measures of the size of the bidding syndicates are fairly crude and may also tend to undercount informed players for larger companies. For example, larger targets may be more likely to have competing bidders, each involving its own banks and advisors. We only count entities participating in a single bid. This line of reasoning suggests that target market capitalization (or deal value) should actually enter positively in our regressions. This is then another prediction of our basic hypothesis.

4 Results

We now present our primary regression results. The null hypothesis is that the number of participants in a financing syndicate is not related to the degree of suspicious pre-bid trading activity. The alternative of interest is that there is a positive relation with one or more of our measures of syndicate size (including the capitalization of the target firm). We present our results for the different markets separately. A final subsection considers some alternative specifications and robustness checks.

4.1 Stock Trading

Table 4 shows our basic tests using stock market data. The primary finding is that the number of equity participants in a deal is significantly positively associated with the degree of suspicious stock market activity using nearly every one of the 16 regressions shown. There is little association between number of the target's lead banks (the debt participants measure used in the table) and unusual activity, although the coefficient is always positive. This finding hints at the possibility, to which we return below, that different types of insiders may exploit distinct markets.

For target size, we do find a significant positive association with pre-bid volume (although not returns). As mentioned in Section 3, a positive effect of firm size is consistent with size proxying for uncounted insiders, and is the opposite of the usual finding that smaller firms have more asymmetric information.

None of the conclusions in the table is particularly sensitive to the regression specification

(corresponding to the columns) for expect volume and returns. There is also no distinct pattern separating the results for the two metrics, MAX and SUM. Section 4.6 considers the extent to which the results here may be due to other effects. But the initial evidence is solidly in favor of the view that more insiders leads to more insider trading.

4.2 Options Trading

Table 5 presents our results for unusual option activity. The table repeats the tests used in the stock market, only with slightly different regression specifications, as described in Section 3. In addition, we report results for the three methods of volume aggregation described there.

The overall conclusion from this table is that there is some evidence that the number of equity participants is linked to suspicious activity. There is no significant effect from the number of debt participants or from target size. Moreover, the positive role for equity participants is not statistically significant when options volume is weighted by elasticity. This method of aggregation give the most weight to cheap (i.e. far out-of-the-money) calls, and appears to be subject to too many false positives from uninformed retail trade. Moreover, an insider will actually not want to trade calls with a strike price higher than the imminent takeover bid price, even if their theoretical elasticity is high.

For the raw and delta-weighted measures, the effect of equity participants is stronger using the MAX metric than the SUM metric. Recall that the latter was included to account for the possible effect of stealth trading (or order splitting) by insiders, which could result in positive unexplained volume on each of several days no one of which looks unusual. Our finding here is not that such strategies do not take place, only that the number of insiders does not appear better at predicting its occurrence than at predicting unusual single days.

4.3 CDS Trading

Our primary results for credit derivatives are shown in Table 6. The table presents the basic regressions of unusual (log) changes in CDS fees, and uses three different methods of counting banks.

Neither the first method, which counts all lead and participant banks in all active syndicated loans to the targets, nor second method, which restricts attention to lead banks, shows a significant association with unusual pre-bid CDS activity using the MAX metric or the SUM metrics. However, when we only count lead banks for facilities activated *after* the bid (hoping to measure the banks that participated in the LBO financing), the association

is positive and statistically quite significant.

Our sample size is quite small, and we cannot be confident that *only* lead banks financing LBOs are associated with information leakage. But that could be the case if, in general, other lead banks of the target are not approached by the bidder as potential sources of funds, and also do not learn of the impending bid via information sharing within existing syndicates.

The bottom panel also provides the complementary result to our earlier finding that equity participants alone matter for stock and options market trading. Here debt participants in the LBO financing alone seem to matter for credit market trading. This may be evidence of a preferred habitat – or comparative advantage – for traders of different types. Banks may be better positioned to move quickly in credit derivatives. The finding also implies that cross-market arbitrage is less than perfect.

4.4 Bond Trading

We have a somewhat larger sample of targets with bond market information. The results using their measures of unusual activity are shown in Table 7. Based on the SUM metric, there is a convincing, positive association with the number of debt participants in nearly every specification. The evidence for such an association is weaker using the MAX metric, which may be indicative of slower reaction to informed trade in the bond market. As with the CDS sample, the positive association between suspicious activity and number of banks is most pronounced when only post-bid lead banks are considered. However, with the SUM metric, the relationship is just as strong when the count includes all banks. This is consistent with evidence in Acharya and Johnson (2007) that a large number of participant banks increases information leakage. This channel is widely believed to be due to increased hedge fund participation in (and purchase of) syndicated debt precisely in order to acquire nonpublic information.

4.5 Interpretation of Results

Our primary finding from above results is that more insiders indeed makes suspicious trading more likely. This is contrary to the predictions in standard informed trading models: trade becomes more revealing with more competitors. The standard models would predict that the effect of two informed traders is much the same as that of many. Hence, one explanation for our primary finding is that competition might be limited by wealth constraints of insiders and/or exposure to timing or market risks – realistic features that are generally not

considered in the microstructure literature. However, this hypothesis also raises the possibility that the *quantity* of insider activity may not actually have risen so much in the period under study, but that it has just been more detectable. Insiders may have tended to trade more aggressively, making it easier for the market to deduce their presence, and resulting in quicker price reactions. Without detailed trade and trading counterparty information, it is difficult to rule out this alternative.

The second explanation for our finding concerns the nature of the enforcement regime. If each potential insider regards the likelihood of detection (and the probable penalty upon detection) as independent of the number N of insiders, then one would expect a rising number of informed players to result in a rising amount of illegal behavior. We argue in the appendix that such enforcement policies may be suboptimal because the harm to market liquidity from allowing more insiders to trade can be efficiently avoided by imposing an enforcement ceiling of abnormal trading activity above which detection and penalties are imposed. This ceiling should be optimally declining in N to enable insiders to internalize the cost they impose on other insiders with an additional unit of trade. Beyond this model, however, it also seems clear that allowing the total amount of informed trade to rise with N creates dangerous incentives. To the extent that insiders can *choose* N – e.g. one can always tip off one's friends – there could be a positive net benefit to doing so. If expected individual punishment actually weakens with N, this would create an externality making it safer for more agents to trade together. Such a policy would entail a social dimension to insider trading under which "crime wave" equilibiria become possible (see, for example, Sah (1991), Glaeser, Sacerdote, and Scheinkman (1996) and Bond and Hagerty (2005)).

Hence, we conclude that more insiders leading to more insider trading is likely to be consistent with frictions faced by insiders due to wealth or risk considerations. The relationship between insiders and insider trading is however less likely to be consistent with the enforcement regime having optimally responded to the changing institutional structure of LBOs, which has meant larger syndicate sizes.

An additional noteworthy result is that effect of syndicate sizes seems to be segmented across equity and credit markets. Our evidence shows that equity syndicate size makes insider trading more likely in equity and options markets, whereas debt syndicate size matters for CDS and bond markets. This segmentation potentially tells us something about the nature of information flow from syndicate members to other players in financial markets. For instance, media discussions surrounding insider trading around LBOs seems to suggest that information may sometimes leak from hedge funds, who are often debt syndicate members,

to their prime brokers, who are banks and may be more naturally inclined to trade in bonds and CDS to hedge their counterparty exposure to the hedge funds. Similarly, a lead arranger of the debt financing is likely to communicate with a bond underwriter to assess whether a certain amount of debt can be placed in the market for the LBO at a desired spread. Finally, equity syndicate members may consult equity analysts to get an idea of the overall sector prospects or an assessment of valuation of the target.

Our results leave open some questions with regard to the different types of debt syndicate measures and their effect on likelihood of insider trading. For CDS markets, we found that insider trading is more likely with more lead syndicate members for LBO financing, but not with more lead syndicate members or total members in target's financing inclusive of pre-LBO financing. Althouth possibly just due to a very small sample size, this feature of the data fits well our understanding of deal timing based upon conversations with bankers involved in LBO deals. This communication suggested the following typical timeline of events: (i) Date-zero: Firm A contemplates making a bid for firm T. They approach potential lender, usually including the target's existing banks, and get a Commitment Letter from one or more, who will become Leads if a deal goes through. (ii) Date-one: Firm A actually makes a tender offer for Firm B. The Commitment Letter become public (filed with SEC). LPC news will likely have a story saying who the Leads are. Date-two: The deal is successful and Firm A will certainly need the money. The Leads then solicit other "Senior Manager" and "Bookrunner" Banks. Then the bigger group solicits general participants and institutions. (iii) Date-three: The syndicate is finalized and the loan becomes "active" as per the LPC data. Thus, as per this timeline, and assuming no leakage of information to prospective participant banks, the relevant insiders are captured by the LBO syndicate leads.

Our bond market result is, however, in contrast to that of the CDS markets and reveals that it is not just LBO syndicate size that makes insider trading more likely, but also the overall debt syndicate size inclusive of lead and participants of pre-LBO financing and participants of LBO financing. This is more in line with the result of Acharya and Johnson (2007) that information release in CDS markets prior to credit deterioration events is increasing in the total number of relationship banks of the underlying entity. The bond market result thus suggests that information leaks from LBO syndicate leads to existing bankers of the target and/or to potential participants who will be arranged in case the deal goes through.

4.6 Alternative Tests

We perform several tests to assess the robustness of our results. The first set of tests allows for additional controls in our benchmark estimations.

We consider the following set of additional control variables: the bid-premium (measured as the raw return of the stock price over the week prior to the announcement), book to market ratio, leverage, volatility of stock returns, stock beta, a measure of illiquidity (the ILLIQ ratio of Amihud (2002)) and a measure of activity (stock turnover). We expect at least some of these to be related to the intensity of insider trading. The bid premium captures the gains to be made from trading on insider information and should increase the economic motives for insiders to exploit their private information. We do not have data on the anticipated leverage of the buyout target after being acquired. But the change in leverage would be one determinant of credit spread widening, and thus be correlated with incentives to exploit private information in the CDS markets. High volatility of stock returns may deter insiders from trading aggressively since, if they have limited capital, they may be unable to diversify away risk related to their position. The systematic component of risk, measured by beta, may also capture this. On the other hand, in debt markets, where the incentive behind insider trading may be to *reduce* firm-specific risk, these measures may work in the opposite way. Finally, insiders can trade larger quantities for the same amount of private information if the underlying markets are more liquid and have greater depth (smaller price impacts). Thus, we might expect insider trading volume to be higher for liquid markets.

Tables 8, 9, 10, 11 and 12 show the results with additional controls for stock return, stock volume, option volume CDS change, and bond returns, respectively. The first observation is that, by and large, the relationship between suspicious trading and syndicate sizes is the same as in our benchmark results in terms of signs, magnitudes, and statistical significance, for both MAX as well as SUM measures: Stock return and volume and options volume measures are related to equity syndicate size, and CDS and bond return measures are related to number of LBO lead banks. The second observation is that some of the hypotheses proposed above on the coefficients of additional control variables do find support. For example, MAX and SUM for stock returns are significantly positively related to the bid-premium. Stock volatility leads to significantly lower suspicious trading for all stock market measures, but significantly *higher* unusual returns for corporate bonds. Stock liquidity is associated with greater MAX and SUM in stock volume (especially if firm size is considered a proxy for liquidity and also to some extent with turnover as the proxy, though the sign on ILLIQ is opposite of the predicted one).

On the one hand, these results illustrate that the relationship between suspicious trading activity and syndicate sizes is robust to additional controls. On the other hand, the fact that some of the additional controls (bid premium, volatility and liquidity, in particular) are themselves related to trading activity in a manner that is consistent with informed speculation or hedging, lends us additional confidence that our measures of suspicious trading are indeed representative of trading by informed agents.

The second alternative test is to address the concern that our bid announcement dates gathered from Thomson Financial may not in fact be 100% accurate. If the dates are late by a few days, then we might observe large trading returns and volumes prior to the recorded announcement date. We have verified for many cases by going through public records of announcements that this is not the case. We have also checked that in over 70% of our deals, the maximum standardized residual in stock returns occur on day 0 (around 50%) or day -1 (additional 20%). To account for the possibility that perhaps the bid information reaches markets a day before the actual announcement date in our data, we examine the window preceding day -1 to calculate the MAX and SUM measures. Simultaneously, we consider a 10-day window before day -1 to account for the fact that in at least some (alleged) insider trading cases discussed in media, the abnormal trading patterns were claimed to have been detected as early as two weeks prior to the bid announcement.

The results from employing this alternate pre-bid window are contained in Table 13. Overall, the link between suspicious trading and syndicate sizes is robust to this change, though the significance is weakened for the bond returns and for the SUM metric in stock return, stock volume, and option volume measures.

A final issue to consider is whether our cross-sectional result that suspicious trading indicators are linked to syndicate sizes is in fact a time-series result. We know from trends in the LBO markets that syndicate sizes have grown secularly over time. It is also plausible that the intensity of analyst following and arbitrage activities, precisely aimed at identifying LBO targets, has increased and perhaps even got better over time. If this were true, then the increase in suspicious trading we identified would simply reflect the greater information acquisition prior to bid announcements. To address this hypothesis, we re-ran the estimations of Table 4 (stock return and volume activity) with year dummies. While we do not report the entire estimations, the following points are noteworthy: First, the coefficients in the main regressions are unaffected, in size and significance. Second, the year intercepts are neither significant nor monotonically increasing. The largest year intercept for returns is 2001 and for volume 2002. Hence, it does not seem that our results are driven by an increase over

time in the extent of information generated about the likelihood of LBO deals. It is difficult to verify this for options and credit markets since we do not have observations in all years. In particular, virtually all the events in the CDS sub-sample are in 2006.

5. Conclusion

This paper uses a cross-section of buyout bids during 2000-2006 to examine what is essentially a time-series hypothesis. We link the variation across events in suspicious pre-bid trading to the variation in the size of the financing syndicate for the bid, and hence to the likely number of agents who would have had advance knowledge of it. We suggest that this relationship may have accounted for a secular increase in the amount of insider trade (across all deals) corresponding with trends towards broader participation in both debt and equity financing of takeovers.

In the introduction we suggested that either imperfect competition among insiders or inefficient enforcement could lead to the findings documented here. A natural objective for future research is to attempt to distinguish between these factors. Characterizing this distinction is important both for regulatory objectives and for the general goal of understanding the dynamics of information asymmetry.

This task raises a number of interesting theoretical challenges. Broadly speaking, what is required is to import the apparatus of legal enforcement theory (from the law and economics literature) into the framework of market microstructure. With a few exceptions, there is little work on market dynamics under conditions of both asymmetric information and legal constraints. Likewise there is considerable scope for advancement in modeling optimal regulation and enforcement of trading behavior. Specifically, this paper highlights the need for models incorporating constrained regulators (who choose enforcement and penalty policies), multiple insiders (whose competition may also be affected by limited wealth and exposure to volatility between time of trade and public release of information), and liquidity providers (who may condition on the strategies of the insiders).

On a practical note, our work illuminated the interaction of several diverse trends in recent evolution of the capital markets. The rise of private equity and the broadening of participation in syndicated lending are not isolated institutional developments. Rather they have important implications beyond corporate finance that may affect the dynamics of securities markets. We have documented effects on returns and volume in several asset markets. A further important goal is to understand the implications of our findings for the

dynamics of market liquidity.

Table 4: Stock Market Regressions

	MAX metric				SUM metric			
	A1	A2	A3	A4	A1	A2	A3	A4
Panel I : Returns								
Equity	0.3074	0.3244	0.3155	0.3423	0.2388	0.2733	0.2809	0.3067
participants	(2.83)	(3.00)	(2.98)	(3.23)	(1.66)	(1.93)	(1.96)	(2.16)
Debt	0.0450	0.0370	0.0323	0.0373	0.0799	0.0572	0.0614	0.0673
participants	(1.48)	(1.22)	(1.09)	(1.26)	(1.98)	(1.44)	(1.53)	(1.69)
Target	-0.0236	0.0016	0.0139	-0.0102	-0.0492	-0.0029	-0.0329	-0.0445
size	(0.21)	(0.01)	(0.13)	(0.09)	(0.33)	(0.02)	(0.22)	(0.30)
$F_{1,2}$	[0.002]	[0.002]	[0.002]	[0.001]	[0.016]	[0.028]	[0.021]	[0.009]
$F_{1,2,3}$	[0.001]	[0.002]	[0.002]	[0.000]	[0.008]	[0.011]	[0.012]	[0.010]
Panel II: Volume								
Equity	0.4355	0.4365	0.4190	0.3980	0.6220	0.4436	0.4363	0.4177
participants	(3.03)	(3.04)	(2.99)	(2.91)	(2.65)	(2.91)	(2.35)	(2.32)
Debt	0.0089	0.0073	0.0003	0.0128	0.0443	0.0272	0.0235	0.0359
participants	(0.22)	(0.18)	(0.01)	(0.34)	(0.67)	(0.53)	(0.45)	(0.71)
Target	0.2893	0.2779	0.2928	0.2758	0.6329	0.4329	0.4670	0.4579
size	(1.92)	(1.88)	(2.03)	(1.96)	(2.61)	(2.28)	(2.44)	(2.46)
$F_{1,2}$	[0.005]	[0.005]	[0.006]	[0.007]	[0.012]	[0.027]	[0.034]	[0.035]
$F_{1,2,3}$	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

The table presents regression results for different measures of unusual pre-bid stock market activity on bid characteristics. Equity Participants is the number of distinct bidding entities listed by Thomson Financial. Debt participants is the number of lead banks for syndicated loans to the target at the date of, or within six months after the bid. Target size is the market value of the target at the bid price. The suspicious trading measures are defined by a regression specification of expected returns (Panel I) and volume (Panel II) in three months of daily data prior to the bid; and a metric applied to the standardized residuals from these regressions within a 5-day pre-bid window to detect unusually large values. The regression specifications are labeled A1-A4. The residual metrics are labeled MAX and SUM. See Section 3 for descriptions of each. Regressions all include a constant. OLS standard errors are shown in parentheses. The table also presents results (p values) for F test that the two participant coefficients are jointly zero ($F_{1,2}$) and for the test that all three coefficients are jointly zero ($F_{1,2,3}$). There are 178 bid-events in the sample.

Table 5: Options Volume Regressions

	MAX metric				SUM metric			
	B1	B2	B3	B4	B1	B2	B3	B4
Panel I : Raw call volume.								
Equity	0.3323	0.3100	0.3657	0.3985	0.5376	0.4691	0.3445	0.3378
participants	(1.78)	(1.69)	(2.02)	(2.24)	(1.60)	(1.40)	(1.13)	(1.27)
Debt	-0.0137	-0.0184	-0.0139	-0.0049	-0.0135	-0.0207	-0.0098	0.0051
participants	(0.26)	(0.36)	(0.27)	(0.10)	(0.14)	(0.22)	(0.12)	(0.07)
Target	0.1787	0.0853	0.0219	-0.421	0.6731	0.3987	0.2266	0.1701
size	(0.71)	(0.35)	(0.09)	(0.18)	(1.49)	(0.89)	(0.56)	(0.48)
Panel II : Delta weighted call volume.								
Equity	0.4285	0.4059	0.4467	0.4470	0.6402	0.5583	0.3912	0.3739
participants	(2.32)	(2.28)	(2.43)	(2.41)	(1.90)	(1.69)	(1.25)	(1.40)
Debt	0.0042	0.0057	0.0041	-0.0042	-0.0123	-0.0166	-0.0057	-0.0093
participants	(0.08)	(0.11)	(0.08)	(0.11)	(0.13)	(0.18)	(0.07)	(0.13)
Target	0.0351	-0.0296	-0.0597	-0.0983	0.3714	0.1901	0.0713	0.0473
size	(0.14)	(0.12)	(0.24)	(0.40)	(0.82)	(0.43)	(0.17)	(0.13)
Panel III : Elasticity weighted call volume.								
Equity	0.0871	0.0517	0.1118	01121	0.2433	0.1618	0.0799	0.0527
participants	(0.49)	(0.29)	(0.63)	(0.64)	(0.73)	(0.47)	(0.25)	(0.21)
Debt	-0.0078	-0.0081	0.0005	0.0095	0.0254	0.0154	0.0188	0.0403
participants	(0.16)	(0.16)	(0.01)	(0.20)	(0.27)	(0.16)	(0.22)	(0.58)
Target	0.2750	0.2074	0.0276	0.0155	0.6752	0.5141	0.1702	0.1846
size	(1.14)	(0.87)	(0.12)	(0.07)	(1.51)	(1.12)	(0.41)	(0.55)

The table show regression results for measures of unusual pre-bid options volume on bid characteristics. Equity Participants is the number of distinct bidding entities listed by Thomson Financial. Debt participants is the number of lead banks for syndicated loans to the target active at the date of, or within six months after the bid. Target size is the market value of the target at the bid price. The top panel aggregates daily options volume by summing all call trades. The second panel weighs each transaction by the delta of the call before summing. The third panel weighs each transaction by its elasticity. The suspicious trading measures are defined by a Heckman (1978) specification of expected volume and a metric applied to the standardized residuals from this in a 5-day pre-bid window. The regression specifications are labeled B1-B4. The residual metrics are labeled MAX and SUM. See Section 3 for descriptions of each. Regressions all include a constant. OLS standard errors are shown in parentheses. There are 83 bid-events in the sample.

Table 6: CDS Change Regressions

Panel I : Counting all banks.

	MAX metric				SUM metric			
	C1	C2	C3	C4	C1	C2	C3	C4
Equity	0.3622	0.3046	0.3472	0.3287	0.4182	0.3476	0.4153	0.3605
participants	(0.80)	(0.75)	(0.85)	(0.81)	(0.69)	(0.67)	(0.82)	(0.71)
Debt	0.0096	0.0122	0.0113	0.0109	0.0321	0.0246	0.0253	0.0252
participants	(0.24)	(0.33)	(0.31)	(0.30)	(0.59)	(0.53)	(0.55)	(0.55)
Target	0.7684	0.6431	0.6060	0.6225	1.1286	0.8950	0.8417	0.8659
size	(1.44)	(1.33)	(1.23)	(1.30)	(1.57)	(1.46)	(1.40)	(1.44)

Panel II : Counting lead banks.

	MAX metric				SUM metric			
	C1	C2	C3	C4	C1	C2	C3	C4
Equity	0.3457	0.2915	0.3333	0.3153	0.3907	0.3266	0.3938	0.3392
participants	(0.77)	(0.72)	(0.83)	(0.79)	(0.65)	(0.64)	(0.79)	(0.68)
Debt	0.0826	0.0705	0.0730	0.0708	0.1556	0.1188	0.1216	0.1210
participants	(0.77)	(0.73)	(0.76)	(0.74)	(1.09)	(0.97)	(1.02)	(1.01)
Target	0.6271	0.5272	0.4845	0.5046	0.8789	0.7044	0.6468	0.6720
size	(1.12)	(1.04)	(0.96)	(1.00)	(1.17)	(1.10)	(1.03)	(1.07)

Panel III : Counting LBO leads.

	MAX metric				SUM metric			
	C1	C2	C3	C4	C1	C2	C3	C4
Equity	-0.0260	-0.0462	-0.0056	-0.0191	-0.1714	-0.1525	-0.0829	-0.1311
participants	(0.08)	(0.15)	(0.02)	(0.06)	(0.42)	(0.44)	(0.25)	(0.39)
Debt	0.5251	0.4756	0.4780	0.4712	0.8035	0.6806	0.6783	0.6691
participants	(4.31)	(4.33)	(4.42)	(4.33)	(5.57)	(5.56)	(5.76)	(5.56)
Target	0.5824	0.4788	0.4398	0.4583	0.8646	0.6683	0.6167	0.6442
size	(1.49)	(1.36)	(1.27)	(1.32)	(1.87)	(1.70)	(1.63)	(1.67)

The table show regression results for measures of unusual pre-bid CDS log changes on bid characteristics. Equity Participants is the number of distinct bidding entities listed by Thomson Financial. Debt participants is defined as follows. In Panel I, it is the number of all banks taking part in syndicated loans to the target active at the date of, or within six months after the bid. In Panel II, it is the number of lead banks for such loans. In Panel III, it is the number of lead banks for syndicated loans originated after the bid. Target size is the market value of the target at the bid price. The suspicious trading measures are defined by a regression specification of expected changes and a metric applied to the standardized residuals from these regressions in a 5-day pre-bid window. The regression specifications are labeled C1-C4. The residual metrics are labeled MAX and SUM. See Section 3 for descriptions of each. Regressions all include a constant. OLS standard errors are shown in parentheses. There are 22 bid-events in the sample.

Table 7: Bond Return Regressions

Panel I : Counting all banks.

	MAX metric				SUM metric			
	D1	D2	D3	D4	D1	D2	D3	D4
Equity	0.3131	0.2541	0.2376	0.2510	0.2120	0.1613	0.1739	0.1609
Participants	(2.08)	(1.65)	(1.64)	(1.76)	(0.98)	(0.82)	(0.91)	(0.84)
Debt	0.0208	0.0217	0.0271	0.0346	0.0482	0.0510	0.0658	0.0745
Participants	(1.39)	(1.42)	(1.87)	(2.44)	(2.24)	(2.59)	(3.46)	(3.91)
Target	0.2187	0.0710	0.0284	-0.0801	0.5207	0.1476	-0.0045	-0.1055
Size	(1.20)	(0.38)	(0.16)	(0.47)	(1.99)	(0.62)	(0.02)	(0.46)

Panel II : Counting lead banks.

	MAX metric				SUM metric			
	D1	D2	D3	D4	D1	D2	D3	D4
Equity	0.3027	0.2466	0.2305	0.2419	0.1932	0.1500	0.1613	0.1459
Participants	(2.04)	(1.60)	(1.56)	(1.65)	(0.90)	(0.73)	(0.77)	(0.68)
Debt	0.0744	0.0592	0.0623	0.0800	0.1444	0.1064	0.1264	0.1468
Participants	(1.78)	(1.36)	(1.49)	(1.94)	(2.39)	(1.82)	(2.15)	(2.44)
Target	0.1251	0.0228	-0.0005	-0.1184	0.3787	0.1225	-0.0078	-0.1193
Size	(0.63)	(0.11)	(0.00)	(0.61)	(1.33)	(0.45)	(0.03)	(0.42)

Panel III : Counting LBO leads.

	MAX metric				SUM metric			
	D1	D2	D3	D4	D1	D2	D3	D4
Equity	0.1838	0.1482	0.1410	0.1544	-0.0471	-0.0619	-0.0408	-0.0415
Participants	(1.20)	(0.92)	(0.90)	(0.98)	(0.22)	(0.30)	(0.19)	(0.18)
Debt	0.1445	0.1191	0.1099	0.1114	0.2907	0.2521	0.2456	0.2336
Participants	(2.40)	(1.87)	(1.79)	(1.79)	(3.48)	(3.15)	(2.94)	(2.64)
Target	0.2871	0.1508	0.1381	0.0674	0.6907	0.3422	0.2675	0.2142
Size	(1.82)	(0.91)	(0.86)	(0.42)	(3.16)	(1.64)	(1.23)	(0.93)

The table show regression results for measures of unusual pre-bid target firm bond returns on bid characteristics. Target firm bonds are formed into an issue-size weighted portfolio and the portfolio returns are multiplied by minus one. Equity Participants is the number of distinct bidding entities listed by Thomson Financial. Debt participants is defined in each panel as described in the caption to Table 6. Target size is the market value of the target at the bid price. The suspicious trading measures are defined by a regression specification (labeled D1-D4) of expected changes and a metric (MAX and SUM) applied to the standardized residuals from these regressions in a 5-day pre-bid window. Regressions all include a constant. OLS standard errors are shown in parentheses. There are 34 bid-events in the sample.

Table 8: Stock Return Regressions with Further Controls

	MAX metric				SUM metric			
	A1	A2	A3	A4	A1	A2	A3	A4
Equity	0.3340	0.3477	0.3362	0.3629	0.2639	0.2977	0.3007	0.3362
participants	(3.03)	(3.18)	(3.14)	(3.37)	(1.82)	(2.09)	(2.09)	(2.35)
Debt	0.0494	0.0401	0.0359	0.0402	0.0816	0.0581	0.0620	0.0683
participants	(1.55)	(1.27)	(1.16)	(1.29)	(1.94)	(1.41)	(1.49)	(1.65)
Target	-0.0153	0.0597	0.0682	0.1005	0.0560	0.1591	0.1231	0.1123
size	(0.07)	(0.27)	(0.31)	(0.46)	(0.19)	(0.55)	(0.42)	(0.39)
Bid	0.0122	0.0129	0.0125	0.0108	0.0192	0.0206	0.0202	0.0178
premium	(1.95)	(2.08)	(2.05)	(1.77)	(2.32)	(2.55)	(2.47)	(2.19)
Book/	0.3757	0.4188	0.3823	0.1964	0.4642	0.4389	0.4258	0.2553
Market	(1.01)	(1.11)	(1.05)	(0.54)	(0.94)	(0.91)	(0.87)	(0.53)
Leverage	0.0564	0.0698	0.0537	0.0628	0.1062	0.1249	0.1097	0.1276
	(0.42)	(0.57)	(0.41)	(0.48)	(0.62)	(0.72)	(0.62)	(0.73)
σ	-1.2540	-1.2908	-1.2605	-1.3292	-1.9502	-1.9618	-1.8359	-2.2905
	(1.69)	(1.75)	(1.75)	(1.83)	(1.99)	(2.04)	(1.89)	(2.38)
β	0.1939	0.1531	0.1298	0.1196	0.1554	0.1410	0.0932	0.1476
	(0.87)	(0.69)	(0.60)	(0.55)	(0.53)	(0.49)	(0.32)	(0.51)
ILLIQ	0.0021	0.0032	0.0031	0.0053	0.0047	0.0061	0.0056	0.0075
	(0.37)	(0.56)	(0.56)	(0.94)	(0.62)	(0.81)	(0.74)	(1.01)
Turnover	0.0523	0.0732	0.0759	0.1134	0.0746	0.0952	0.0969	0.1428
	(0.45)	(0.69)	(0.67)	(0.99)	(0.48)	(0.63)	(0.64)	(0.94)
$F_{1,2}$	[0.001]	[0.001]	[0.002]	[0.000]	[0.014]	[0.022]	[0.020]	[0.014]
$F_{1,2,3}$	[0.002]	[0.002]	[0.002]	[0.001]	[0.020]	[0.021]	[0.021]	[0.017]

The table presents regression results for different measures of unusual pre-bid stock returns on bid characteristics. The dependent variables are as described in the caption to Table 4. The independent variables here are defined as follows. Bid premium is the bid premium in percent excess of the stock price one week prior to announcement. Book/Market is the book value of target equity divided by bid value. Leverage is the target enterprise value divided by bid value of equity. σ is the annualized volatility of the target in the three months prior to the bid. β is its beta with respect to the CRSP value-weighted index in the same period. ILLIQ is the cross-sectional rank of the illiquidity measure of Amihud (2002). Turnover is the annualized volume in shares divided by shares outstanding. OLS standard errors are shown in parentheses. The table also presents results (p values) for F test that the two participant coefficients are jointly zero ($F_{1,2}$) and for the test that all three coefficients are jointly zero ($F_{1,2,3}$). There are 177 bid-events in the sample.

Table 9: Stock Volume Regressions with Further Controls

	MAX metric				SUM metric			
	A1	A2	A3	A4	A1	A2	A3	A4
Equity	0.4477	0.4553	0.4417	0.4271	0.6254	0.4483	0.4460	0.4347
participants	(3.08)	(3.14)	(3.11)	(3.07)	(2.65)	(2.41)	(2.38)	(2.39)
Debt	0.0005	-0.0014	-0.0085	0.0023	0.0303	0.0174	0.0156	0.0257
participants	(0.01)	(0.03)	(0.21)	(0.06)	(0.44)	(0.32)	(0.29)	(0.49)
Target	0.6290	0.5697	0.5612	0.4926	1.5042	0.9993	1.1052	0.8841
size	(2.14)	(1.94)	(1.95)	(1.76)	(3.15)	(2.66)	(2.67)	(2.40)
Bid	0.0105	0.0117	0.0118	0.0102	0.0172	0.0154	0.0159	0.0149
premium	(1.27)	(1.42)	(1.46)	(1.30)	(1.28)	(1.46)	(1.49)	(1.44)
Book/	0.0329	0.0282	-0.0140	-0.1587	0.4546	0.1052	0.0823	-0.1191
Market	(0.07)	(0.06)	(0.03)	(0.34)	(0.57)	(0.17)	(0.13)	(0.19)
Leverage	0.2033	0.2125	0.2222	0.2253	0.3756	0.2573	0.2481	0.2524
	(1.14)	(1.20)	(1.28)	(1.33)	(1.32)	(1.13)	(1.08)	(1.13)
σ	-2.1030	-1.9663	-1.9291	-2.0202	-3.3534	-2.3840	-2.4128	-2.7070
	(2.15)	(2.01)	(2.02)	(2.17)	(2.11)	(1.90)	(1.91)	(2.21)
β	-0.0346	-0.0002	0.0371	-0.0037	-0.0693	-0.0305	0.0219	-0.0216
	(0.12)	(0.00)	(0.13)	(0.01)	(0.14)	(0.08)	(0.06)	(0.06)
ILLIQ	0.0119	0.0103	0.0097	0.0089	0.0264	0.0173	0.0173	0.0149
	(1.57)	(1.36)	(1.30)	(1.23)	(2.14)	(1.78)	(1.76)	(1.57)
Turnover	0.2118	0.1950	0.1761	0.1895	0.4046	0.2562	0.2556	0.2453
	(1.38)	(1.27)	(1.17)	(1.29)	(1.62)	(1.30)	(1.29)	(1.27)
$F_{1,2}$	[0.005]	[0.004]	[0.005]	[0.006]	[0.016]	[0.034]	[0.038]	[0.040]
$F_{1,2,3}$	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]

The table presents regression results for different measures of unusual pre-bid stock volume on bid characteristics. The dependent variables are as described in the caption to Table 4. The control variables are as described in the caption to Table 8 OLS standard errors are shown in parentheses. The table also presents results (p values) for F test that the two participant coefficients are jointly zero ($F_{1,2}$) and for the test that all three coefficients are jointly zero ($F_{1,2,3}$). There are 177 bid-events in the sample.

Table 10: Options Volume Regressions with Further Controls

	MAX metric				SUM metric			
	B1	B2	B3	B4	B1	B2	B3	B4
Equity	0.4090	0.3787	0.4179	0.4281	0.6798	0.5817	0.3662	0.3351
participants	(2.11)	(2.03)	(2.14)	(2.18)	(1.94)	(1.70)	(1.12)	(1.20)
Debt	-0.0210	-0.0168	-0.0136	-0.0222	-0.0441	-0.0569	-0.0283	-0.0374
participants	(0.33)	(0.28)	(0.22)	(0.35)	(0.39)	(0.51)	(0.27)	(0.41)
Target	0.3958	0.3316	0.2929	0.2818	1.7109	1.4361	1.1593	0.7160
size	(0.65)	(0.57)	(0.48)	(0.45)	(1.55)	(1.33)	(1.12)	(0.81)
Bid	-0.0115	-0.0109	-0.0091	-0.0068	-0.0091	-0.0118	-0.0134	-0.0141
premium	(0.78)	(0.77)	(0.61)	(0.46)	(0.34)	(0.46)	(0.54)	(0.66)
Book/	0.9513	0.9886	0.4946	0.6910	1.7316	1.8312	0.8250	1.5295
Market	(1.05)	(1.13)	(0.54)	(0.75)	(1.06)	(1.14)	(0.54)	(1.17)
Leverage	0.5973	0.5198	0.4036	0.4143	1.0429	1.1488	0.6424	0.6747
	(0.73)	(0.66)	(0.49)	(0.50)	(0.70)	(0.79)	(0.46)	(0.57)
σ	-1.0117	-1.0934	-0.4599	-0.3032	-5.5573	-5.7025	-4.5878	-2.2833
	(0.50)	(0.56)	(0.23)	(0.15)	(1.53)	(1.60)	(1.35)	(0.79)
β	-0.1599	-0.1902	-0.1141	-0.1865	-0.0075	-0.1162	-0.0302	-0.2784
	(0.38)	(0.47)	(0.27)	(0.43)	(0.01)	(0.15)	(0.04)	(0.45)
ILLIQ	0.0195	0.0199	0.0184	0.0191	0.0888	0.0834	0.0737	0.0398
	(0.55)	(0.58)	(0.51)	(0.53)	(1.38)	(1.33)	(1.22)	(0.77)
Turnover	0.1219	0.1057	0.0686	0.1094	0.7355	0.6934	0.5092	0.2446
	(0.37)	(0.33)	(0.21)	(0.32)	(1.22)	(1.18)	(0.91)	(0.51)
$F_{1,2}$	[0.147]	[0.168]	[0.138]	[0.130]	[0.195]	[0.273]	[0.573]	[0.516]
$F_{1,2,3}$	[0.201]	[0.234]	[0.211]	[0.203]	[0.106]	[0.196]	[0.464]	[0.542]

The table presents regression results for different measures of unusual pre-bid delta-weighted options volume on bid characteristics. The dependent variables are as described in the caption to Table 5. The control variables are as described in the caption to Table 8 OLS standard errors are shown in parentheses. The table also presents results (p values) for F test that the two participant coefficients are jointly zero ($F_{1,2}$) and for the test that all three coefficients are jointly zero ($F_{1,2,3}$). There are 83 bid-events in the sample.

Table 11: CDS Change Regressions with Further Controls

	MAX metric				SUM metric			
	C1	C2	C3	C4	C1	C2	C3	C4
Equity	-0.0314	-0.0875	-0.0446	-0.0507	-0.1986	-0.1638	-0.1120	-0.1399
participants	(0.09)	(0.31)	(0.16)	(0.18)	(0.48)	(0.49)	(0.35)	(0.42)
Debt	0.5356	0.4927	0.4933	0.4865	0.8010	0.6799	0.6795	0.6692
participants	(4.82)	(5.38)	(5.42)	(5.28)	(5.92)	(6.29)	(6.56)	(6.18)
Target	2.0147	2.2255	2.0619	2.0975	1.3132	1.6244	1.3843	1.4790
size	(1.88)	(2.52)	(2.35)	(2.35)	(1.01)	(1.56)	(1.39)	(1.42)
Bid	-0.0099	-0.0024	-0.0026	-0.0034	0.0080	0.0128	0.0181	0.0161
premium	(0.25)	(0.07)	(0.08)	(0.10)	(0.16)	(0.33)	(0.49)	(0.41)
Book/	1.1872	1.7292	1.5059	1.4507	2.2029	2.2803	2.0569	1.8767
Market	(0.71)	(1.25)	(1.10)	(1.04)	(1.08)	(1.40)	(1.32)	(1.15)
Leverage	-0.3720	-0.2080	-0.2835	-0.2823	-0.5478	-0.4928	-0.5443	-0.5622
	(0.61)	(0.41)	(0.56)	(0.55)	(0.73)	(0.82)	(0.95)	(0.94)
σ	-7.6141	-8.3140	-7.9649	-7.9478	-7.9919	-7.4555	-7.4544	-7.2540
	(1.37)	(1.81)	(1.75)	(1.72)	(1.18)	(1.38)	(1.44)	(1.34)
β	1.1477	1.3381	1.3310	1.2714	2.0486	1.8206	1.9661	1.7537
	(0.95)	(1.34)	(1.34)	(1.26)	(1.39)	(1.54)	(1.74)	(1.48)
ILLIQ	0.3199	0.3639	0.3458	0.3503	0.1349	0.2227	0.1931	0.2090
	(1.67)	(2.30)	(2.20)	(2.20)	(0.57)	(1.19)	(1.08)	(1.12)
Turnover	0.5724	0.7102	0.6759	0.6758	0.0522	0.2053	0.1814	0.1963
	(1.13)	(1.71)	(1.64)	(1.61)	(0.09)	(0.42)	(0.39)	(0.40)
$F_{1,2}$	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$F_{1,2,3}$	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

The table presents regression results for different measures of unusual pre-bid CDS changes on bid characteristics. The dependent variables are as described in the caption to Table 6. Debt participants is the number of lead banks for syndicated loans originated after the bid. The control variables are as described in the caption to Table 8 OLS standard errors are shown in parentheses. The table also presents results (p values) for F test that the two participant coefficients are jointly zero ($F_{1,2}$) and for the test that all three coefficients are jointly zero ($F_{1,2,3}$). There are 22 bid-events in the sample.

Table 12: Bond Return Regressions with Further Controls

	MAX metric				SUM metric			
	D1	D2	D3	D4	D1	D2	D3	D4
Equity	0.0023	-0.0471	-0.0160	-0.0092	-0.3505	-0.3072	-0.2239	-0.2317
participants	(0.02)	(0.37)	(0.13)	(0.07)	(1.98)	(1.79)	(1.24)	(1.22)
Debt	0.1996	0.1606	0.1552	0.1623	0.3771	0.2990	0.3076	0.3001
participants	(4.15)	(3.24)	(3.25)	(3.37)	(5.48)	(4.47)	(4.36)	(4.08)
Target	0.8388	0.6800	0.7596	0.2448	1.1086	0.3025	0.3808	-0.1460
size	(1.67)	(1.32)	(1.52)	(0.49)	(1.54)	(0.43)	(0.52)	(0.19)
Bid	0.0144	0.0328	0.0349	0.0366	0.0087	0.0320	0.0386	0.0397
premium	(1.07)	(2.38)	(2.62)	(2.72)	(0.46)	(1.72)	(1.96)	(1.93)
Book/	-1.8469	-1.0461	-0.7482	-0.9955	-2.7245	-1.3900	-0.7566	-0.9401
Market	(2.56)	(1.41)	(1.04)	(1.38)	(2.64)	(1.39)	(0.72)	(0.85)
Leverage	-0.0554	-0.1246	0.1465	0.3590	0.0081	0.1082	0.7099	0.9214
	(0.22)	(0.48)	(0.58)	(1.41)	(0.02)	(0.31)	(1.91)	(2.37)
σ	5.6964	5.6208	4.2454	4.5615	10.3336	8.4232	5.7249	6.0964
	(2.93)	(2.81)	(2.20)	(2.34)	(3.72)	(3.12)	(2.01)	(2.05)
β	-0.5689	-0.3229	-0.1231	-0.2498	-1.3981	-0.4095	-0.2746	-0.4198
	(1.42)	(0.79)	(0.31)	(0.62)	(2.45)	(0.74)	(0.47)	(0.69)
ILLIQ	0.0659	0.0520	0.0667	0.0051	0.0366	-0.0446	-0.0162	-0.0827
	(0.92)	(0.71)	(0.94)	(0.07)	(0.36)	(0.45)	(0.15)	(0.76)
Turnover	-0.2577	-0.2794	-0.2057	-0.3682	-0.4624	-0.4400	-0.3630	-0.5319
	(1.11)	(1.17)	(0.90)	(1.59)	(1.40)	(1.37)	(1.07)	(1.50)
$F_{1,2}$	[0.000]	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]	[0.000]
$F_{1,2,3}$	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

The table presents regression results for different measures of unusual pre-bid bond returns on bid characteristics. Target firm bonds are formed into an issue-size weighted portfolio and the portfolio returns are multiplied by minus one. The dependent variables are as described in the caption to Table 6. Debt participants is the number of lead banks for syndicated loans originated after the bid. The control variables are as described in the caption to Table 8 OLS standard errors are shown in parentheses. The table also presents results (p values) for F test that the two participant coefficients are jointly zero ($F_{1,2}$) and for the test that all three coefficients are jointly zero ($F_{1,2,3}$). There are 34 bid-events in the sample.

Table 13: Alternate Pre-Bid Window

	MAX metric				SUM metric			
	1	2	3	4	1	2	3	4
Panel I : Stock Returns								
Equity	0.2801	0.2934	0.2914	0.2969	0.1987	0.2348	0.2688	0.2802
participants	(2.71)	(2.89)	(2.99)	(3.02)	(1.20)	(1.44)	(1.65)	(1.71)
Debt	0.0127	0.0081	0.0059	0.0020	0.0474	0.0371	0.0349	0.0350
participants	(0.44)	(0.28)	(0.22)	(0.07)	(1.02)	(0.81)	(0.76)	(0.76)
Target	0.0069	0.0213	0.0275	0.0117	-0.0333	0.0082	-0.0114	-0.0542
size	(0.06)	(0.20)	(0.28)	(0.18)	(0.19)	(0.05)	(0.07)	(0.32)
Panel II : Stock Volume.								
Equity	0.3545	0.3411	0.3351	0.3319	0.2638	0.2351	0.2627	0.2263
participants	(2.40)	(2.33)	(2.35)	(2.40)	(0.90)	(0.99)	(1.10)	(0.97)
Debt	-0.0479	-0.0585	-0.0594	-0.0561	-0.0337	-0.0417	-0.0459	-0.0271
participants	(1.16)	(1.43)	(1.49)	(1.45)	(0.41)	(0.63)	(0.69)	(0.41)
Target	0.3183	0.3532	0.3447	0.3334	0.8033	0.6536	0.6799	0.6092
size	(2.09)	(2.34)	(2.35)	(2.34)	(2.65)	(2.66)	(2.76)	(2.53)
Panel III : Option Volume								
Equity	0.5044	0.4684	0.5265	0.4847	0.5977	0.6048	0.3585	0.4179
participants	(2.96)	(2.90)	(3.08)	(2.92)	(1.88)	(1.92)	(1.16)	(1.58)
Debt	-0.0372	-0.0377	-0.0257	-0.0350	-0.1063	-0.1399	-0.0667	-0.0771
participants	(0.76)	(0.81)	(0.52)	(0.73)	(1.16)	(1.55)	(0.75)	(1.01)
Target	0.0779	0.0361	0.0233	0.0522	0.3693	0.0445	0.1167	-0.0004
size	(0.33)	(0.16)	(0.10)	(0.23)	(0.84)	(0.10)	(0.27)	(0.00)

Table 13 – continued

	MAX metric				SUM metric			
	1	2	3	4	1	2	3	4
Panel IV : CDS Changes								
Equity	0.3793	0.3113	0.2682	0.2746	0.6916	0.6871	0.6733	0.6727
participants	(1.50)	(1.38)	(1.21)	(1.24)	(1.72)	(2.02)	(2.01)	(1.98)
Debt	0.3019	0.2696	0.2752	0.2694	0.5690	0.4774	0.4859	0.4780
participants	(3.35)	(3.37)	(3.49)	(3.41)	(3.96)	(3.94)	(4.08)	(3.95)
Target	0.2379	0.1874	0.1920	0.2041	0.2104	0.0614	0.0379	0.0299
size	(0.82)	(0.73)	(0.76)	(0.80)	(0.46)	(0.16)	(0.10)	(0.08)
Panel V : Bond Returns								
Equity	0.1831	0.1957	0.1574	0.1622	0.0770	0.1300	0.1429	0.1194
participants	(1.11)	(1.21)	(1.01)	(1.08)	(0.32)	(0.55)	(0.61)	(0.50)
Debt	0.0700	0.0590	0.0654	0.0620	0.1740	0.1599	0.1628	0.1280
participants	(1.08)	(0.93)	(1.07)	(1.05)	(1.82)	(1.71)	(1.76)	(1.35)
Target	0.2685	0.0827	0.0544	0.0351	0.4815	0.0525	0.0191	-0.0125
size	(1.59)	(0.50)	(0.34)	(0.23)	(1.93)	(0.22)	(0.08)	(0.05)

The table presents regression results corresponding to Tables 4 (stock returns and volume), 5 (option volume),6 (CDS changes), and7 (bond returns), respectively, but with the MAX and SUM measures computed over the 10-day window from date -11 to date -2. Note that results are reported only for delta-weighted call option volume, and for CDS and bond returns, Debt Participants is measured by the number of LBO lead banks (as described in Table 6). The number of observations in each panel is 178, 178, 83, 22, and 34, respectively.

Appendix

A A Model of Optimal Regulation of Insider Trading

This section describes a simple framework for analyzing the optimal design of insider trading regulation. The model is essentially a stripped-down version of that of DeMarzo, Fishman, and Hagerty (1998) who analyze the problem when there is a single insider. Here our interest is in the case of N insiders. The objective is to illustrate why one should expect optimal regulation to enforce a similar degree of tolerance of insider trading whatever the value of N.

The model involves a single risky asset (the stock) traded in a single period. There are four sets of players. First, there are uninformed liquidity traders who will have to randomly buy or sell the stock for unmodeled reasons. Second, there are the N insiders who are risk neutral, and who know the terminal value of the stock with certainty. Third, there is a risk-neutral market maker who must set bid and ask prices for the stock, b and a subject to a zero profit condition, and without being able to condition on the incoming orders.

The fourth actor is the regulator whose objective is taken to be that of maximizing the welfare of the uninformed, which is equivalent to minimizing the bid-ask spread (or maximizing liquidity). Following the realization of the stock's terminal value, the regulator can choose to investigate trade for a fixed price c_0. If any insider has traded, the regulator can prosecute each for a cost c_1 and recover a penalty assumed to be three times the insider's profit (as in U.S. law).[27]

The regulator's problem is to decide when to undertake an investigation. In doing so, the regulator is subject to the resource constraint that the policy must cost no more in expectation than some fixed budget K. The background assumption is that the regulator oversees many repetitions of the game, so that the constraint need not hold *ex post* for every stock.

A related assumption is that the regulator can and does commit *ex ante* to its enforcement policy. Undertaking a potentially costly investigation may not be worthwhile *ex post*. But

[27] It is important for us to focus on the nature optimal regulation as the number of insiders varies. A related literature exists which takes the regulation as given, specifically that insiders report their trades to the SEC as per the Section 16(a) of the Securities Exchange Act of 1934 (disclosure is required at the end of each trading round in the model). This literature focuses instead on the exact nature of induced insider trading within the trading round and documents that insiders may optimally add a random component to their order flow to reduce inference by the market makers. Cao and Ma (1999) and Huddart, Hughes, and Levine (2001) analyze cases of homogeneously informed multiple and monopolistic risk-neutral insiders, respectively, whereas Buffa (2007) examines a monopolistic risk-averse insider.

commitment is necessary for the threat to be credible.[28]

For simplicity, we assume there are only two possible terminal stock prices, θ. With probability p there is a takeover bid of value $H > 100$; with probability $1-p$ the asset has a liquidation value of $(100 - pH)/(1-p) < 100$, so the expected payoff is 100.

If there is no takeover bid, then there are no insiders, so $N = 0$. If there is a bid, then N takes on some value $N \geq 1$. The regulator and the insiders observe this value. If there is a bid, insiders may decide to (illegally) buy at the ask price. Clearly the bid price will never exceed H, so insiders are never sellers. (They are not paid negative fines for selling.)

The buying and selling demands of the uninformed traders are independent of one another. Since there are never any insider sellers, the zero expected profit condition applied to market maker purchases ensures that $b = 100$. So the regulator's problem is to minimize a. We assume the uninformed buying demand is Y and that it is independent of a. If the total informed buying demand is X, then the zero profit condition applied to market maker sales requires $\mathrm{E}(X+Y)(a-\theta) = 0$, which implies

$$a = \frac{100 + H\frac{\mathrm{E}X}{\mathrm{E}Y}}{1 + \frac{\mathrm{E}X}{\mathrm{E}Y}}.$$

This expression is increasing in $\mathrm{E}X$ meaning that the regulator's objective is equivalent to minimizing informed trade.

In choosing its enforcement policy, the regulator can only base policy on the observed variables N and $Z = X + Y$. In a similar setting, DeMarzo, Fishman, and Hagerty (1998) establish that, if the distribution of Y satisfies the monotone likelihood ratio property (MLRP), then it suffices to restrict attention to nonrandom policies which specify investigation if and only if total volume (of buy orders), Z, exceeds some threshold V. So we take $Y \sim \mathcal{N}(EY, VY)$ (which satisfies MLRP) and analyze policies of that form.

Given such a policy, the insiders choose their individual demands, x_n, to maximize expected profit net of expected punishment taking the policies of the market maker and the other insiders as given. Since the insiders are identical, we consider only symmetric equilibria in which their demands are identical.

As a special case, if the distribution of uninformed demand, Y, is degenerate, then clearly all trade in excess of Y is informed. Since detection is certain to the insiders, it is never optimal for them to trade above V. Given that, there is nothing stopping regulators from

[28] Moreover, the commitment itself is valuable. If the government could renege on the enforcement budget in high-N outcomes, this would induce a positive externality to insiders. See Bond and Hagerty (2005) for an analysis of how this scenario can generate "crime wave" equilibria.

imposing a ceiling of $V = Y$ (or $Y + \epsilon$) and achieving perfect enforcement at zero expected cost, regardless of N. Hence, imperfect enforcement only arises if punishment is not certain *ex ante*, which here means that uninformed demand is random.

As another special case, it is easy to show that, with sufficient resources, regulators will still impose a uniform ceiling (i.e. independent of N) which achieves perfect enforcement. Then the Nth insider's first-order condition given V is

$$3\left[\Phi_Y(V - Y - \sum_n x_n) - x_N \varphi_Y(V - Y - \sum_n x_n)\right] = 2.$$

(Here Φ_Y and φ_Y denote the normal distribution and density functions, respectively, for Y.) This has solution $x_N = 0$ if and only if $V = V_L = \Phi_Y^{-1}(2/3)$.

Suppose, however, that this policy is unaffordable. In that case, the regulator's problem is to raise the enforcement ceilings to be applied under different values of N such that the combined policy satisfies the budget in expectation (which requires some probability measure q_N over the likely number of insiders conditional on a bid).

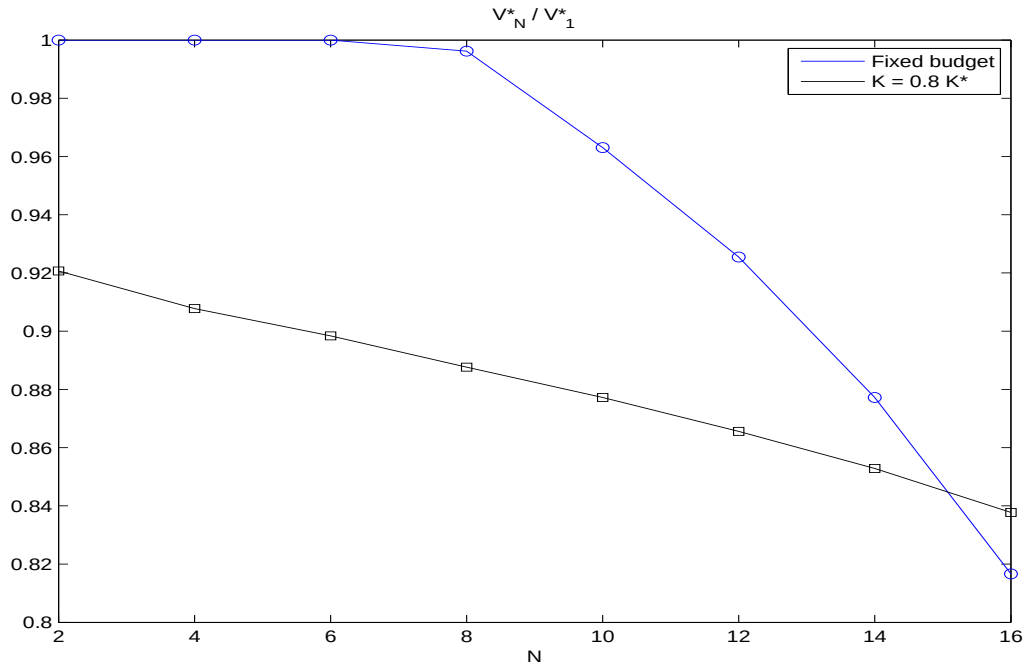
The point we wish to illustrate is that the solution to this problem is unlikely to involve enforcing a more lenient ceiling for larger values of N. We show this by computing some numerical cases below. More important is to understand why.

As we observed in the introduction, imposing an enforcement ceiling creates a negative externality to increased trade by the insiders, which is helpful to the regulator. The externality can also be expressed by the observation (noted by DeMarzo, Fishman, and Hagerty (1998)) that insiders internalize less than the full cost (in terms of expected punishments) of their own decision to increase trade. The larger N is, the smaller the fraction of the cost borne by the individual. Returning to the regulators problem, a consequence of this dynamic is that raising the enforcement ceiling when N is large results in a larger increase in insider trade than the same increase in the ceiling when N is small. This means the regulator's objective function (the liquidity of the market) is harmed more in the latter case. This favors solving his budget problem by being more lax (lowering expected costs) for fewer insiders.

To give an example, assume that, conditional on a bid occurring, with equal probability there is either one insider or $N > 1$. Also assume that $EY = 100, VY = 100, c_0 = 5$, and $c_1 = 0.5$. We solve for the optimal ceilings for various values of N and plot the ratio V_N/V_1 in Figure 3. We consider both the case that the regulator's budget is the same for each pair $(1, N)$ of outcomes and the (perhaps more reasonable) case that the budget is higher for economies with more insiders. (Specifically, the latter case fixes K at 80% of the cost of the

perfect enforcement policy.) Under either assumption, the optimal solution actually involves the regulator enforcing a *lower* ceiling when the higher outcome $N > 1$ is observed.

Figure 3:

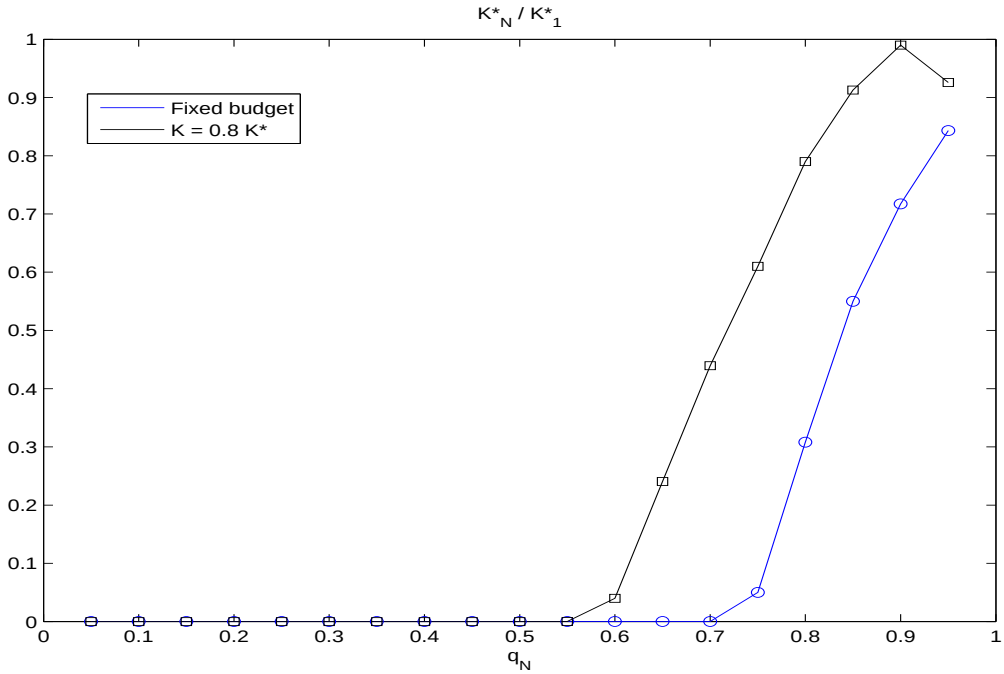


The figure shows the optimal enforcement ceiling with N insiders as a fraction of the ceiling that is optimal for one insider as N varies. Two cases are plotted, corresponding to a fixed budget for the regulator ($K = 2.4$) and a budget that is a constant fraction of the budget necessary to achieve perfect enforcement ($K = 0.8 * K_L$). The other parameters are $EY = 100, VY = 100, c_0 = 5, c_1 = 0.5$, and $q_1 = q_N = 0.5$.

A lower enforcement ceiling with higher N need not translate into less total insider trading. As the regulator's power weakens, and both ceilings rise, trade will rise faster in the high-N outcome. However, continuing the numerical example, Figure 4 shows that equilibrium insider trade in the high scenario (here $N = 8$) is still below that for the low scenario ($N = 1$), even as the probability of the former outcome rises (and expected enforcement costs increase).

We do not claim that the results here are general. One could find parameter values that would entail marginal enforcement costs falling faster with V for higher N. As discussed in the text, however, one could also greatly strengthen the case for our conclusion if one allowed N to be endogenous. If insiders think they can get away with more trade with greater numbers, they might simply fragment their own demand (e.g. with multiple trading accounts or by tipping off their friends and family) thus swamping the regulator and allowing still more trade.

Figure 4:



The figure shows the equilibrium amount of insider trade with $N = 8$ insiders as a fraction of the amount for $N = 1$ when the probability, q_N, of the former outcome varies. Two cases are plotted, corresponding to a fixed budget for the regulator ($K = 2.4$) and a budget that is a constant fraction of the budget necessary to achieve perfect enforcement ($K = 0.8{*}K_L$). The other parameters are $EY = 100, VY = 100, c_0 = 5, c_1 = 0.5$.

B Data sources and details

This appendix elaborates on some aspects of our use of the primary databases employed in the empirical work.

Event sample

In selecting events from the Thomson Financial database, we specify acquisition bids for public U. S. companies and impose the following criteria.

- Value of the bid must exceed 100 million dollars.
- Acquiror must be seeking a controlling stake.
- Bid must be an offer for publicly held securities (not a private holding).
- Bidder must be private entity or group (perhaps including individuals).
- Bidder's "type" must be given as "Financial" or its business description must make clear that it is an investment vehicle.
- Buyer may not be a bank, insurance company, or real estate investment trust.

In instances where a target is subject to more than one bid in our sample, we select only one event.[29] For multiple-bid targets, we follow these rules:

- Restrict attention to initial bids by each entity, i.e., not sweetened or subsequent bids.
- If there is more than one bid by private acquirors, take the successful one unless (a) it cannot be determined which bid was successful, or (b) another private bid occurred less than 14 days before the successful one. In these cases, take the earliest bid.
- If a non-private bid bid occurred less than 14 days before a private one, discard this target.

Our rule favors successful bids only because these deals are more likely to enable us to identify providers of debt finance (as described in Section 3.1).

Counting bank relationships

We count bank relationships by selecting active tranches of syndicated loans from the LPC Dealscan database. Loan participants are then assigned a unique code in accordance with the rules below.

- All subsidiaries/branches/Operations of one company are grouped together, e.g., Bank of Nova Scotia , Scotia Capital, BNS international bank and Scotiabanc Inc are treated as a single entity.
- Any joint entity involving two or more firms (which themselves appear separately) are treated as the subsidiary of the firm listed first: KZH-Cypress, KZH-Soleil, etc. are all treated as subsidiaries of KZH.
- Firms before and after a merger/acquisition are treated as different companies, e.g., Ag First merged with Farm Credit in 1992 to form AgFirst Farm Credit Bank. The three of them are considered separate lenders.

Corporate bond returns

We identify all corporate bonds of a firm matched by ticker symbol to the TRACE database. To obtain the firm-level bond return, individual bond returns are weighted each day in proportion to their respective issued par value (obtained from the Mergent

[29]There is one exception: Petco Animal Supplies Inc. was actually taken private twice in our sample, having been re-floated in between.

fixed-income database). Individual bond returns are computed every day as percentage change from the most recent available closing price for the bond to the given day's closing (that is, last trade) price. Note that this may result in the use of stale prices for some issues which do not trade at (or near) the close of each day. However, if a bond has no trade on a given date, then its return is taken to be zero.

References

Acharya, V. V., J. Franks, and H. Servaes, 2007, "Private Equity: Boom and Bust?," *Journal of Applied Corporate Finance*, forthcoming.

Acharya, V. V., and T. C. Johnson, 2007, "Insider Trading in Credit Derivatives," *Journal of Financial Economics*, 84, 110–141.

Altman, E., 2007, "Global Debt Markets in 2007: New Paradigm or the Great Credit Bubble?," *Journal of Applied Corporate Finance*, 19, 1731.

Amihud, Y., 2002, "Illiquidity and Stock Returns: Cross-section and Time-series Effects," *Journal of Financial Markets*, 5, 31–56.

Andrade, G., M. Mitchell, and E. Stafford, 2001, "New Evidence and Perspectives on Mergers," *Journal of Economic Perspectives*, 15, 103–120.

Arnold, T. M., G. R. Erwin, L. A. Nail, and T. Bos, 2000, "Speculation or Insider Trading: Informed Trading in Options Markets Preceding Tender Offer Announcements," University of Alabama at Birmingham working paper.

Back, K., H. H. Cao, and G. A. Willard, 2000, "Imperfect Competition among Informed Traders," *Journal of Finance*, 55, 21172155.

Baruch, S., 2002, "Insider Trading and Risk Aversion," *Journal of Financial Markets*, 5, 451–464.

Berndt, A., and A. Ostrovnaya, 2007, "Information Flow between Credit Default Swap, Option and Equity Markets," Carnegie-Mellon working paper.

Bond, P., and K. Hagerty, 2005, "Preventing Crime Waves," Northwestern University working paper.

Buffa, A., 2007, "Public Disclosure with Risk Averse Insider Trading," London Business School working paper.

Cao, C., Z. Chen, and J. M. Griffin, 2005, "Information of Option Volume Prior to Takeovers," *Journal of Business*, 78, 1073–1109.

Cao, H. H., and Y. Ma, 1999, "Trade Disclosure and Imperfect Competition Among Insiders," University of California - Berkeley working paper.

DeMarzo, P. M., M. J. Fishman, and K. Hagerty, 1998, "The Optimal Enforcement of Insider Trading Regulations," *Journal of Political Economy*, 106, 602–632.

Foster, F. D., and S. Viswanathan, 1996, "Strategic Trading when Agents Forecast the Forecasts of Others," *Journal of Finance*, 51, 1437–1478.

Gao, Y., and D. Oler, 2004, "Trading in Target Stocks Before Takeover Announcements," Cornell University working paper.

Glaeser, E., B. Sacerdote, and J. Scheinkman, 1996, "Crime and Social Interactions," *Quarterly Journal of Economics*, 111, 507–548.

Heckman, J. J., 1978, "Sample Selection Bias as a Specification Error," *Econometrica*, 47, 153–161.

Holden, C. W., and A. Subrahmanyam, 1992, "Long-lived Private Information and Imperfect Competition," *Journal of Finance*, 47, 247–270.

Holden, C. W., and A. Subrahmanyam, 1994, "Risk Aversion, Imperfect Competition and Long-lived Information," *Economics Letters*, 44, 181–190.

Huddart, S., J. S. Hughes, and C. B. Levine, 2001, "Public Disclosure and Dissimulation of Insider Trades," *Econometrica*, 69, 665–681.

Ivashina, V., and Z. Sun, 2007, "Institutional Stock Trading on Loan Market Information," Harvard Business School working paper.

Jarrell, G. A., and A. B. Poulsen, 1989, "Stock Trading before the Announcement of Tender Offers: Insider Trading or Market Anticipation?," *Journal of Law, Economics, & Organization*, 5, 225–248.

Jayaraman, N., M. B. Frye, and S. Sabherwal, 2001, "Informed Trading around Merger Announcements: An Empirical Test Using Transaction Volume and Open Interest in Options Markets," *The Financial Review*, 36, 4574.

Kaplan, S., 2007, "Private Equity: Past, Present, and Future," *Journal of Applied Corporate Finance*, 19, 8–16.

Keown, A. J., and J. M. Pinkerton, 1981, "Merger Announcements and Insider Trading Activity: An Empirical Investigation," *Journal of Finance*, 22, 855–869.

Mandelker, G., 1974, "Risk and Return: The Case of Merging Firms," *Journal of Financial Economics*, 1, 303–336.

Meulbroek, L. K., 1992, "An Empirical Analysis of Illegal Insider Trading," *Journal of Finance*, 47, 1661–1699.

Poteshman, A. M., 2006, "Unusual Options Market Activity and the Terrorist Attacks of September 11, 2001," *Journal of Business*, 79, 1703–1726.

Sah, R. K., 1991, "Social Osmosis and Patterns of Crime," *Journal of Political Economy*, 99, 12721295.