Informed Trading in Regulated Industries

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Abstract

We investigate informed trading in firms in regulated industries. We categorize firms in financial services, pharmaceuticals, and utilities as regulated or supervised. Our empirical research strategy employs several different approaches to examine informed trading in supervised firms, including panel regressions, information shocks, natural experiments, private information flows, disparities in state and federal supervision, and cross-state differences in regulatory oversight. The results of these tests, across various security markets and measures of informed trading, appear inconsistent with the hypothesis that regulatory supervision reduces informed trading. Instead, this series of tests all point in one direction, namely that informed trading occurs more readily in firms with regulatory oversight.

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In this study, we explore the impact of regulatory supervision on trading based on material, non-public information. Prior research indicates that regulatory supervision improves corporate governance, which could limit informed trading. Demsetz (1983) observes that regulatory supervision, aimed at fostering financial stability, facilitates the monitoring of corporate insiders. Fidrmuc et al. (2006) indicate that the probability of trading based on private information depends on the quality of corporate monitoring. Kanagaretnam et al. (2007) document that high levels of monitoring and internal controls serve to limit informed trading activity. Implicit in much of the law and finance literature is that regulators (Federal Reserve, Food and Drug Administration, etc.) provide another basis of governance and monitoring that could act to limit informed trading.

However, an alternative hypothesis suggests that regulators themselves may serve as a source of information leakage, thereby facilitating trades based on material, non-public information. Steele (1989) formally models information leakage as the square of the number of people who have access to the information. Intuitively, regulators could provide an alternative channel of information leakage, regardless of whether this propagation occurs inadvertently or as part of a trading strategy. Moreover, regulators may represent a special type of pseudo insider due to differences in pay between corporate officers and government regulators. Bebchuk and Grinstein (2005) report that top managers routinely earn over $21 million a year, while federal civil servants in 2009 received an average pay of $123,049[1]. Given this disparity, the opportunity costs for government regulators that trade on or leak non-public information may be considerably lower than that of the officers of the firm. Moreover, government employees could have a greater sense of entitlement due to the role that seniority plays in promotions within the civil service (Gordon and Johnson, 1982), which may again influence incentives for informed trading. Beyond regulators, there could also be differences in management between supervised and non-supervised firms that contribute to informed trading

[1] For instance, a senior civil servant (grade 15) in the FDIC will often have annual compensation of around $155,000 (2008 Federal Employee Database @ www.bea.gov). Still, recent anecdotal accounts regarding the Galleon Hedge Fund demonstrate how well compensated individuals may also engage in informed trading. Roulstone (2003) finds that low compensation levels are an important factor in understanding informed trading incentives. Goel and Rich (2007) discover that substantive gaps between government and private sector compensation increases the likelihood of illegal activity by government employees.

activity. If regulators extend the circle of informed participants, have lower opportunity costs, or oversee more opportunistic managers, then it suggests that regulatory supervision could be associated with greater informed trading.

Regulatory oversight is prevalent in several industries. Using 4-digit SIC codes, we categorize firms in finance (SIC of 6000 - 6799), pharmaceuticals (SIC of 2830, 2831, 2833, and 2836), and utilities (SIC of 4812, 4813, 4911 - 4991) as supervised. Unfortunately, comparing informed trading between supervised and non-supervised firms is difficult because supervision is not randomly distributed across firms in the economy, making causal inferences a challenge (Agarwal et al. 2012). Our research strategy to examine informed trading in these supervised firms employs several different approaches to help address this problem; including panel regressions, changes in the information environment, changes in regulatory oversight, tests on information flows, disparities in bank regulator type, and cross-state differences in regulatory oversight. The strategic use of private information can occur in various types of financial markets (Acharya and Johnson, 2007), consequently we exploit measures of informed in the short sale market, the long equity market, and the options market.

We investigate the impact of regulatory supervision on informed trading at the firm level. Supervised firms comprise about 31% of the firms in the main sample, suggesting that they represent a substantial part of the US economy. Our investigation of informed trading uses several different market-based measures designed to capture trading based on material, non-public information. The first set of tests uses panel regressions to provide some baseline results. Focusing on short sales, we examine informed trading in supervised and non-supervised firms by evaluating the ability of short sales to forecast future stock returns. Diether et al. (2009) suggest that the relative ability of short sales to forecast negative abnormal stock returns provides an especially robust indicator of informed trading. We also explore informed trading in the long equity market and apply two commonly-used measures of informed trading based on trade volume and market microstructure data, namely measures by Amihud (2002) and Easley et al. (1996). Finally, we explore informed trading in the options market by examining the bid-ask spread of options and the return predictability of option skew. To best gauge the impact of regulatory supervision on informed trading, we condition our tests on the extent of liquidity in a stock (Pastor and Stambaugh, 2003) and the scope of opportunistic trading by corporate insiders (Cohen et al. 2010). Arguably, this weakens the scope of the informed trading captured in the measures but provides a more conservative test environment regarding the nature of informed trading with regulatory oversight. Still, these tests use the firm as the unit of examination and consequently we cannot ascertain the incentives or identity of the informed trader(s).

Focusing on the relative return predictability of short sales between supervised and non-supervised firms in a sample of over 2,500 firms, we find that supervised firms exhibit about 6 times more informed trading than non-supervised firms. Employing a sample of more than 5,000 firms, the long equity market tests indicate that regulatory supervision is positively associated with greater informed trading activity. Similarly, in the options market, we find that supervised firms have about 55% more informed trading than non-supervised firms. We reach the same conclusions using propensity-score matched samples to mitigate control variable extrapolation concerns. Specifically, this analysis suggest that someone trades on material, non-public information in regulated industries. However, it is difficult to make causal inferences, even after using matched samples, from this analysis.

Our next set of tests focuses on specific information events, namely unexpected changes in quarterly earnings. Specifically, using the data on short sales, we examine whether abnormal short sales increase (decrease) just before negative (positive) earnings shocks (Christophe et al. 2004). Arguably, this test method provides an ideal setting for assessing or comparing trades, based on a specific type of private information, namely quarterly financial performance data. Importantly, this method also exploits differences in regulator ability to obtain access to specific and potentially valuable financial information. Focusing on this change in the information environment, in the full sample results, we find that supervised firms have over 2 times more informed trading than non-supervised firms. Again using propensity score matching we create a sub-sample of supervised and non-supervised firms, which have more similar firm characteristics. Once more we find that short sales in supervised firms, prior to negative earnings shocks, increase substantially more than in non-supervised firms. Differentiating among the types of regulated firms, we find that larger measures of informed trading are associated with better regulatory access to material, non-public information.[2] In sum, the earnings shock tests provide evidence consistent with trades based on material, non-public information occurring more readily in supervised than non-supervised firms.

To gain further insight into the cause of informed trading in supervised firms, we consider several natural experiments. Using difference-in-difference tests around changes in regulatory supervision, we examine the hypotheses that regulatory oversight leads to higher/lower informed trading. Specifically, we compare informed trading in firms before and after changes in the degree of regulatory supervision. Next, we compare this difference in informed trading, to the difference in informed trading for non-supervised firms during the same time period. Our first natural experiment centers on the transportation industry, specifically the regulatory oversight of airlines and trucking which was substantially reduced between 1978 and 1980. In both instances of deregulation (airlines in 1978 and trucking in 1980), we find subsequent declines in informed trading with the lower regulatory supervision. Although, the sample sizes are small, the difference-in-difference tests indicate this decrease was economically and statistically significant. In particular, we find a 67% decrease in informed trading with airline deregulation and a 16% decrease in informed trading with trucking deregulation.

We also explore the impact of an increase in regulatory supervision. The regulatory environment for financial institutions changed in 1999 with the passage of the Gramm-Leach-Bliley Act, which repealed part of the Glass-Steagall Act of 1933 to allow investment banks, commercial banks, and insurance companies to merge. Coupled with the greater ability to consolidate financial services (deregulation of operations), financial holding companies became subject to greater regulatory oversight by the Federal Reserve, FDIC, and insurance regulators, serving to increase the

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[2] Industries are regulated for various reasons and therefore provide differing types of information flows to regulators. Firms that provide detailed financial data to regulators appear to have the greater informed trading relative to firms that provide more limited financial data, who in turn appear to have greater informed trading relative to firms that provide product information to regulators.

flow of private information to regulators (Krozner and Strahan, 2011). Title II of the Act extended federal regulatory scrutiny to incorporate functional regulation of bank security regulation.[3] Again, using difference-in-difference tests, we examine informed trading in financial institutions before and after the increase in regulatory supervision. The results reveal a substantive increase in informed trading in financial institutions with the increase in regulatory oversight. Specifically, we find that informed trading increased by over 50% with the increased regulatory oversight. Thus, all three natural experiments provide evidence to indicate the informed trading increases (decreases) with increases (decreases) in regulatory supervision.

Although, using information and regulatory changes as sources of variation to improve identification can provide far more powerful tests of our two hypotheses, they do not provide evidence on the channel of any potential information flows. Consequently, we develop three additional sets of tests that focus more directly on reducing unobserved heterogeneity in the comparison group and allowing inferences about the attribution of the informed trading.

Focusing on the timing of private bank disclosures to regulators offers another avenue to test the role of regulatory oversight in informed trading. Commercial banks provide quarterly call reports to bank regulators, which remain private for forty days following the disclosure. Prior empirical research documents that these reports contain valuable, private information (Cole and Gunther, 1998). We examine the magnitude of informed trading after these information flows to regulators. In contrast to the first three sets of tests, this specification compares informed trading within a given bank during periods with and without private information flows to regulators. Thus, the comparison group in these tests is comprised of the same banks in the periods where they do not provide call reports to regulators. Again, after controlling for opportunistic managerial trades and liquidity, we find that informed trading significantly intensifies for commercial banks during this event window in both stock and option markets. Specifically, informed trading spikes in the first ten days after this report is provided to regulators and then decays over the next thirty days.

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3 See the US Senate committee on Banking, Housing and Urban Affairs summary of the Gramm-Leach-Bliley Act of 1999 (http://banking.senate.gov/conf).

Our next test uses differences in regulatory oversight among commercial banks to examine the role of private information flows between firms and regulators on informed trading. The dual banking system in the US allows commercial banks to be chartered at either the federal or state level (Scott, 1977). Both sets of banks follow the rules and regulations regarding call report provisions (Sullivan and Spong, 2007). However, a unique difference between the two banks occurs in terms of regulatory oversight because state chartered banks provide their information to both state and federal regulators. Agarwal et al. (2012), using proprietary regulator data, identify the states where there appears to be the greatest/least regulatory-duplicity by evaluating the disparate ratings provided by state and federal regulators when they receive similar types of information. Using the data reported in their Figure 5, we identify the state chartered banks that are headquartered in the "duplicit" states. Our cross-sectional tests indicate that informed trading in banks chartered in states with high levels of regulatory duplicity exhibit significantly greater informed trading than other state and federally chartered banks (and relative to non-supervised firms as well). Subsequent tests indicate that informed trading also varies by federal regulator type and by Federal Reserve district. Specifically, we find greater informed trading in banks with OCC oversight relative to Federal Reserve oversight. Among banks with Federal Reserve oversight we also document informed trading heterogeneity among the different twelve districts.

Our final approach to test whether regulatory supervision leads to higher informed trading centers on cross-state variations in regulatory oversight. More specifically, we exploit differences in state-level political corruption to examine the impact of regulatory supervision on informed trading. Concentrating on insurance and utility firms, we compare supervised firms in states with high level of political corruption with those in low political corruption states. If regulatory supervision leads to informed trading, then we expect that it should be more pronounced in states with greater political corruption. We find that informed trading in state-supervised firms is increasing in political corruption. Consequently, these tests provide evidence to suggest that within the same industry, the scope of regulatory oversight is related to the observed level of informed trading.

Individually, each test in this study could be interpreted along multiple dimensions. Although, our tests do not incorporate the identity of the informed trader(s), they do provide compelling evidence that regulatory supervision is associated with informed trading, even after incorporating liquidity traders and opportunistic managerial trades. Another caveat is that these tests do not provide evidence to shed light on the relative effectiveness of the type of regulatory oversight. More specifically, these results do not speak to the notion of how well regulators enrich corporate governance, achieve their mandates, or enhance social welfare (Haddock and Macey, 1987). Instead, this analysis provides a series of tests that point in one direction, namely that informed trading occurs more readily in firms with regulatory oversight. More specifically, the first three sets of tests provide evidence to suggests that informed trading is increasing in regulatory supervision. The final set of tests reports evidence consistent with the idea that informed trading in supervised firms is a function of information flows to regulators and the degree of political corruption.

The remainder of this paper is organized as follows. In Section I we develop our hypotheses. Section II describes the data and sample, variable measures, the matching process, and summary statistics. Section III discusses the cross-section tests. Section IV provides additional tests. We conclude in Section V.

I. The Role of Regulators

All publicly traded firms are regulated in the US in terms of disclosure requirements. These requirements can be viewed as market empowering and are designed to create a more level playing field with regard to the information available to investors. Firms are also regulated in terms of licensing, pollution, wages, and occupational safety. However, a subset of firms undergoes additional scrutiny that focuses on monitoring firm activity for market or public safety reasons.

A. Regulatory Pressure

Regulators provide government supervision of these key industries to improve financial stability and public safety. Williamson (1996) suggests this supervisory oversight serves as an important mechanism of corporate governance. John and Qian (2003) stress that regulatory supervision performs a monitoring role that compliments other governance structures because regulators seek competently governed firms. Joskow et al. (1993) highlight that approve/disapprove oversight provides government regulators an especially powerful tool when seeking strong internal control systems. This close monitoring of firm health provides regulators the ability and power to push for strong corporate governance.

Others indicate that regulators, while not interested in protecting shareholder interests per se, pressure supervised firms to adopt effective governance structures to promote financial stability and safety (Becher and Frye, 2011). Regulators, for instance, directly encourage directors to attend board meetings in supervised firms (Adams and Ferreira, 2008). Hadlock et al. (2002) observe that regulatory pressure also influences CEO hiring decisions and compensation packages in supervised firms. Houston and James (1995) describe how subsequent bonuses and pay raises in supervised firms are subject to regulatory oversight. Thus, regulators actively influence corporate governance in supervised firms, including compensation, board of directors, and internal control policies. Booth et al. (2002) emphasize that regulators directly monitor managers and push for effective internal control systems to limit unethical behavior. Prior empirical literature provides an array of evidence that is consistent with claims by regulators that they focus on managerial ethics and character.

Governance and internal control systems are thought to be important components of curbing informed trading. Rozanov (2008) reports that trading on private information is negatively related to good corporate governance. Jaglolinzer et al. (2011) indicate that internal control process quality is directly linked to trading based on private information. Others suggest that corporate governance influences information leakage and informed trading by finance professionals (Lowenstein, 1996). Young et al. (2008) observe that leakage of sensitive information to hedge funds or other professional managers depends on the effectiveness of internal controls and governance systems. Ferreira and Laux (2007) indicate that financial professionals appear to have more informed trades in firms with weak corporate governance. Overall, a rich body of empirical research suggests that government supervision could lead to lower informed trading.

B. Informed Regulators

Regulators have substantial access to material, non-public information. Bank regulators, for instance, receive advance information on new products, mergers and acquisitions, and quarterly profits prior to their public announcement. A particular bank may have a team of supervisors who compile information to gauge the health of the bank and the banking industry as a whole. Regulators obtain information regarding bank health through a variety of mechanisms. For instance, regulatory supervision involves banks providing quarterly reports to the Federal Reserve Board that include detailed financial data. These quarterly reports have been shown to influence subsequent market prices after public revelation. Prior research, by Federal Reserve employees using proprietary or protected data, indicate these quarterly reports may well be the most informative tool in the federal reserve's toolkit, outperforming examiner visits in predicting future bank performance (Cole and Gunther, 1998). In sum, prior research indicates that bank regulators have access to material, non-public information that can have substantive market impact[4].

Insurance companies and utilities are often supervised at the state level and typically involve detailed cost and profit data. It is common for states to have a regulatory commission that may be comprised of elected officials and/or career officials. While for a given state the number of regulators tends to be relatively small, aggregating across all of the states provides a potentially large circle of individuals with access to material, non-public information. Regulation in pharmaceuticals differs from that of financial institutions, and centers more on product safety rather than firm performance per se. However, the current regulatory structure suggests that access to material, nonpublic information in pharmaceuticals should arrive in a relatively irregular fashion compared with those industries that experience broader government oversight. Nonetheless, the ability to engage in informed trading is exemplified by the 2011 FDA case whereby a researcher traded on confidential information. On October 18, 2011, an employee of the FDA who has regulatory

[4] Periodic examiner visits occur approximately every 12 to 18 months and result in cumulative bank safety ratings on a scale of 1 to 5 (DeYoung et al. 2001). These bank ratings, frequently discussed using the acronym CAMELS, remain fairly steady over time, with large banks typically receiving high ratings (Berger et al. 2000). The Federal Reserve does not make current or historical CAMELS ratings public.

oversight of pharmaceuticals, pleaded guilty to using confidential government data on specific firms to engage in illicit trades through accounts of friends and family (FBI Press Release: Washington Field Office).

Of course, government agencies have extensive proscriptions in place that prohibit regulators from trading on this private information. Two presidential executive orders (#12677 April 12, 1989 and #12731 October 17, 1990) explicitly bar federal employees from engaging in financial transactions using non-public government information to facilitate trades. Federal and state agencies also typically have investigative offices and/or inspector generals who are given the task of monitoring illicit behavior of government employees. State level anti-corruption laws may also apply to government employees who seek to gain profits by accessing material, non-public information.

Focusing on legal outcomes, several different convictions highlight the notion that government employees who use material non-public information can be convicted for illicit trading. Hass v Henkel (1910), US v Peltz (1970), US v Bryan (1995), US v Royer (2008) represent prominent instances where government employees, at both the state and federal level, have been found to misappropriate material, non-public government information for personal gain (Nagy, 2011). Government employees may have access to private information on a particular company or government action that could affect a particular industry or markets in general. For instance, in Blyth v SEC (1969) a Federal Reserve employee provided the firm material, non-public information of upcoming government activity that constituted insider trading.

Government employee access to material, nonpublic information could manifest itself in a myriad of different ways in the market. Congresswoman Slaughter (New York), in a subcommittee hearing in 2009 (US House of Representatives Committee on Financial Services), emphasized that numerous political intelligence firms seek to provide their clients with information about pending regulatory actions. A special report by Reuters (2010) suggests that intelligence firms often hire Ex-Federal Reserve employees, who still maintain explicit privileges and access to the central bank facilities, in order to develop these information ties. This same report highlights a specific instance where a former Fed governor reportedly provided access to his consulting clients for material non-public information from the Federal Reserve. Others emphasize that consulting practices with hedge funds or other types of investors serve to monetize material, non-public information without creating a trail of trades by the regulator (Cooke et al. 2010). In the aforementioned 2009 subcommittee hearing, the Inspector General of the SEC (H. David Kotz) highlights a second avenue of concern. Mr. Kotz describes how government employees may directly or indirectly trade in those firms in which they possess confidential government information, suggesting that government agencies, including the SEC, often have limited systems or mechanisms in place to limit such informed trading.

C. Research Focus

Although our primary arguments center on the notion that supervised firms may differ in their informed trading relative to non-supervised firms, a discussion of how supervised firms possess various incentives to manipulate their reports to regulators bears considering. For instance, banks may "window dress" their reported numbers to inflate their performance (Friedman and Schwartz, 1970) and utilities may under-report in order to extract more benefits or to gain greater flexibility from authorities. If regulatory agencies are systematically fooled by supervised firms, or are unable to effectively gather information about them, then we expect to find no differences between informed trading in supervised and non-supervised firms. Ultimately, the impact of this influence by regulators on informed trading is an empirical issue that we investigate in this study. Thus, our main question centers on the relation between regulatory supervision and trading based on material, non-public information.

II. Sample Firms and Measures of Informed Trading

A. Sample

Our analysis explores informed trading in three markets, i.e., the short sale market, the long equity market, and the option market. Supervised firms are classified based on the 4-digit SIC code, including finance firms (SIC of 6000 through 6799), pharmaceutical firms (SIC of 2830, 2831, 2833, and 2836), and utility firms (SIC of 4812, 4813, 4911 through 4991).[5] The sample size changes with different measures and different markets, which we will detail below. We develop multiple measures for informed trading based on the specific type of market data available.

Short sales data is available from January 2005 till July 2007. We split our sample based on negative and positive earnings shocks, and our analysis is quarterly-based as the earnings report frequency. For the negative shock sample, we have 3,906 firm-quarter observations with 1,858 unique firms (630 supervised firms and 1,228 non-supervised firms). For the positive shock sample, we identify 5,066 firm-quarter observations with 2,086 unique firms (698 supervised firms and 1,388 non-supervised firms). Preliminary tests indicate that the distribution of negative and positive earnings shocks does not appear to differ between supervised and non-supervised firms.[6]

For the long equity market, we begin with the common stocks (Share Code = 10 or 11) in the CRSP database, excluding closed-end funds, ADRs, REITs, and foreign stocks. Our sample period ranges from 1996 to 2009, and we merge these firms with the annual financial information in CompuStat. This process yields 5,274 unique firms and 40,016 firm-year observations. We also use Thomsen Reuter's 13f database to identify blockholders for each firm and use the TAQ database for market microstructure information.

We obtain options trading data from OptionMetrics, which provides daily closing bid and ask quotes and implied volatilities for all listed equity options from 1996 to 2009. We measure informed trading in options market for firms with listed options in the OptionMetrics database.

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5 Prior to deregulation in the late 1970s and early 1980s, transportation also had extensive regulatory oversight on costs and prices. Transportation however still has some regulation today, including the use of on-board computers in both truck and airlines that collect safety data (Baker and Hubbard, 2000). Yet, this regulation is typically considered less intensive than found in financials, utilities, or pharmaceuticals. Consequently, we do not include transportation firms (SIC of 4000 through 4013, 4040 through 4049, 4100, 4210 through 4219, 4512, 4513, and 4522) in either the supervised or the non-supervised subsets. The results are robust to including them in either subset of firms.

6 More specifically, we run regressions with earnings shock on supervised firm dummy and control variables, using 1) a dummy variable indicating negative shocks; and 2) absolute value of the earnings shock as the dependent variable. We find no evidence that supervised firms exhibit differing earnings shocks than the non-supervised firms.

Next, we identify 1,623 unique companies and 311,030 firm-day observations of options trading, which constitute our sample for options trading analysis.

B. Measuring Informed Trading in Short Sales

Recent studies suggest that short sales data contain useful information in predicating future stock returns, indicating informed trading in short sales market (Diether et al. 2009). To test relative informed trading, we form supervised and non-supervised firms into equally-weighted portfolios on a daily basis and we also calculate the daily portfolio short sales. We then apply time-series regressions based on the daily portfolio returns and 2-day lagged portfolio short sales as well as Fama-French 3-factors and momentum factor. We compare the portfolio return predictability of short sales between supervised firms and non-supervised firms.

We also adopt the approach in Christophe et al. (2004) to capture the informed trading contained in short sales data, and also examine short sales spikes prior to information shocks. We focus on the abnormal short sales during the 30 calendar-days window prior to the earnings announcement. We posit that if supervised firms experience greater (lower) information leakage, then we expect to observe greater (lower) abnormal short sales compared with those of non-supervised firms prior to negative earnings shocks, other things being equal. In contrast, prior to a positive earnings shock we should not observe spikes in shorts sales with information-induced volume. We measure abnormal short sales as [(average daily short sales prior to quarterly earnings announcements (day -30 to day -1) divided by average daily short sales for the year outside of pre-announcement periods) – 1]. The short sales data spans the period from January 2005 until July 2007. To split observations into positive and negative earnings shocks, we measure unexpected quarterly earnings for each firm as the residual term from the following regression:

$$EPS_{i,q} = \quad + \; {}_1EPS_{i,q-1} + \; {}_2EPS_{i,q-4} + \; {}_3EPS_{i,q-8} + \; {}_{i,t}, \qquad (1)$$

where EPS is actual earnings per share of the announcement quarter (q), the prior quarter (q-1), one year ago (q-4), and two years ago (q-8). Our final sample covers 781 (1,811) supervised (non-supervised) firms, with 2,455 (6,517) firm-quarter observations, respectively. An alternative approach to estimate earnings surprise relies on analysts' forecasts to gauge expected earnings. We find similar results using either approach but focus our analysis on historical EPS because analysts do not appear to be randomly distributed across supervised and non-supervised firms (results available upon request).

C. Measuring Informed Trading in the Equity Market

In order to capture informed trading in the equity market, we use two commonly used measures in the finance literature. Extant studies provide theoretical rationale as well as empirical evidence on these measures for information asymmetry. Our first measure is based on Amihud (2002), which suggests that the daily ratio of absolute stock return to dollar stock trading volume offers a measure for informed trading. This measure builds on the notion that market makers cannot distinguish between order flow that is generated by informed traders and that is generated by liquidity traders; they set prices that are an increasing function of the imbalance in the order flow which may indicate informed trading (Kyle, 1985). The Amihud measure does not utilize detailed order flow information but it is positively and strongly related to the microstructure estimate of Kyle's measure (Amihud, 2002; Brennan and Subrahmanym, 1996) and it has been shown to perform well comparing to measures using intraday data (Goyenko et al. 2009). Greater values of Amihud indicate higher information asymmetry and more severe informed trading. More specifically, our first measure, which we denote as Amihud, is measured as the absolute value of daily stock return divided by the corresponding daily dollar volume (in $million), averaged over the year. The full sample consists of 7,223 unique firms and 40,016 firm-year observations.

Our second measure of informed trading is PIN (Probability of Informed Trading).[7] Easley et al. (1996) propose a sequential trading model of market microstructure in which the uninformed traders can infer the probability of informed trades from the number of buy and sell orders. We first infer the number of buys (B) and sells (S) from the TAQ database following Lee and Ready (1991),

[7] We present the analysis in the equity market using the Amihud and PIN measures of informed trading. We find similar results using C2 (Llorente et al. 2002) and information asymmetry component of Bid-Ask Spread (Huang and Stoll, 1997) (available upon request).

and then estimate the PIN model by numerically maximizing the likelihood function described in Easley et al. (1996).

The intuition is that when the private information arrives, buy (sell) orders cluster according to the information and PIN is computed as expected informed trades as a fraction of expected total trades. We calculate PIN based on intraday stock trading data for each firm year from 1996 to 2008, and the larger the PIN the greater the likelihood of informed trading for this firm during the year. Our estimates are consistent with the ones presented in Easely, Hvidkjaer, and O'Hara (2002). Our full sample consists of 6,818 unique firms and 35,022 firm-year observations.

Measures of informed trading potentially capture both information asymmetry and market liquidity. For instance, the Amihud measure by construction captures both asymmetric information and illiquidity. Illiquidity is also an important component of the PIN measure (Duarte and Young, 2009). In order to isolate the asymmetric information component of our informed trading measures, and to control for the effect of (il)liquidity, we apply the procedure developed in Pastor and Stambaugh (2003) which we denote as Liquidity-PS. The Pastor-Stambaugh measure examines the extent of stock returns reversal after a high trading volume period, and therefore it is unlikely to capture private information. We include it as a control variable in our multivariate analysis using long equity and option data. Another approach is to orthogonolize our equity-based informed trading measures with the Pastor-Stambaugh measure. We obtain similar results using either approach in our equity market tests. Importantly, an advantage of the control variable approach is that we can easily implement it across our tests of informed trading in different markets.

D. Measuring Informed Trading in the Option Market

Prior literature suggests that the options market offers an appealing platform for detecting information contained in trading activities. This is due to option market's leverage effect and short-time horizons (Black, 1975), as well as a lower trading cost for investors (Easley et al. 1998). Prior research also shows that option prices incorporate specific corporate events such as earnings forecast and M&A activity (Cao et al. 2005). Pertinent to our study, Amin and Lee (1997) find that option prices reflect material non-public information contained in future earnings shocks, consistent with the notion that options trading activities can be used to detect informed trading. We adopt the the measure developed in Anderson et al. (2011) and rely on the stock return predictability component from option skew to capture the information contained in options trading activities. More specifically, we run daily stock return for each firm within each year on the lagged daily option skew and the Fama-French factors[8]. The beta coefficient measures the sensitivity of future returns to lagged option trade; the larger the coefficient, the greater the information contained in option trading. We follow Anderson et al. (2011) and use the t-statistic on the beta coefficient (i.e., beta-t) to capture the power of options trades to predict future stock returns. The option market data generates a sample of 1,623 unique firms and 3,886 firm-year observations of beta-t.[9]

An alternative measure for detecting the asymmetric information in option trading is the options bid-ask spread. More specifically, we denote our second measure based on the option market as "Option Spread", which is measured as the relative bid-ask spread of OTM options (Ask-Bid)/((Ask+Bid)/2)). We focus on OTM options, which provide informed investors with higher leverage and are more likely to be exploited by informed investors. We present the option spread of put options for the sake of brevity. We note that results based on OTM call option offer qualitatively similar inferences. We identify a sample of 1,376 unique firms and 3,386 firm-year observations with available option spread data.

E. Control Variables

In the short sale-return predictability tests we use the specifications and control variables developed in Diether et al. (2009). Consequently, these tests use the daily Fama-French 3 factors and the momentum factor. However, in using the long equity and option market measures we

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8 Skew is measured by the ratio of the implied volatility of out-of-the-money (OTM) put option over that of at-the-money (ATM) call option for each firm i on day t. Prior literature (Xing et al. 2010) suggests that the adverse selection component of option skew is associated with negative future stock return and, as such, the beta coefficient on Skew can be used to infer the inside information from option trading activities.

9 On an annual basis, the number of unique firms ranges from 139 to 788 with a mean of 338 and median of 284.

develop an alternative approach. Our empirical design for detecting informed trading is based on inference from market trading activities, which includes all potential informed traders. One common group of insiders found across all types of firms is corporate managers and directors. Prior research has found evidence that insider reported trading activities contain valuable information about the firm. Another perspective is that managerial trading may also represent the information (or shocks) a firm experiences which triggers informed trading. Any difference in informed trading activities between supervised and non-supervised firms may be simply due to these two diverse groups having different tradable information. In short, we include managerial insider trading activities to offer some control over the firms' innate information set.[10]

Following Cohen et al. (2010), we rely on the reported trades by the managers and directors on SEC form 4, and we focus on the "opportunistic" trades rather than the routine trades of the insiders. Arguably, not all corporate insider trades are informative; suggesting is necessary to focus on the trades of the "opportunistic" insiders. Using the approach described in Cohen et al. (2010) to filter out the non-informative trades, we obtain the number of trades for all the informative "buy" and "sell" trades for every firm. In our multivariate test, we include both informative buy and sell trades to control for the firms information set.

As noted above, we include the Pastor-Stambaugh measure, denoted as Liquidity-PS, to isolate informed trading from liquidity trading. In addition, we also control for the liquidity effect using stock turnover. Stock turnover is the average of daily stock turnover (trading volume divided by common shares outstanding) across the year.

In our multivariate analysis, we also include the following firm characteristics as control variables: firm size is measured as log of total assets, larger firms usually face greater media coverage and subsequent analysis, possibly resulting in greater transparency and less informed trading. The analyst following is the log of the number of analysts who give out quarterly EPS forecasts within a

[10] Focusing on the regulatory pressure hypothesis the inclusion of this control variable may result in an over controlled specification. We find similar inferences regarding the relation between regulatory supervision and informed trading with or without including this variable. Focusing on the informed regulator hypothesis, including this variable provides a robust test environment.

year. Analyst coverage also incorporates the information environment of the firm. Stock return volatility is the standard deviation of the daily stock returns within a year. Volatility is an important factor for informed trading, as greater volatility suggests greater uncertainty about the firm or more noisy traders involved in the trading. Intuitively, informed trading has more profitable opportunities in those firms. We also control for industry competitiveness, as recent studies suggest that industry structure has significant implication on corporate governance such as the market for corporate control (Giroud and Mueller, 2011; Kadyrzhanova and Rhodes-Kropf, 2011). Another perspective is that in a competitive industry, the information about a single firm can be largely inferred from the information on the peer firms, indicating a decreasing chance for informed trading. We measure the industry competitiveness by the Herfindahl index based on sales which we denote Industry HHI.

Ownership structure is measured by a dummy variable equal to 1 if the firm has at least one blockholding institutional investor with equity holding larger than 5%. Blockholders may have preferential access to inside information and thus associate with aggravated informed trading. Alternatively, blockholders may curb informed trading due to their significant interest in the firm's equity by engaging in more diligent monitoring. In Appendix A1, we list the variables in our tests and provide a brief description for each of them.

F. Matching Sample

Our purpose is to compare two types of firms: supervised and non-supervised. In addition to the full sample results, we adopt a propensity score matching procedure to mitigate concerns about extrapolation across control variables. Unfortunately, matching does not provide a particularly powerful approach to address endogeneity concerns, as supervised and non-supervised firms are segmented by industry type. Yet, there may still be an improvement relative to the full sample tests in terms of control variable effectiveness. Thus, we apply a logit regression based on a dummy variable equal to 1 if the firm belongs to a supervised industry, and we include control variables such as firm size, industry HHI, analyst following, stock return volatility, stock turnover, ownership structure, liquidity-PS, and managerial opportunistic trading.

For most of our tests, we use a one-to-one matching approach based on a caliper of 0.1 and a common support range of 0.1-0.9. We apply the matching procedure to each sample in our tests based on the measures from the short sale data, the equity data, as well as the options data. As such, the matched sample coverage is different from measure to measure. Propensity score matching process on short sales data yields a sample of 380 (376) unique supervised (non-supervised) firms with 1,071 (1,071) firm-quarter observations based on negative earnings shock sample. For positive earnings shock, we identify 378 (374) unique supervised (non-supervised) firms with 1,316 (1,316) firm-quarter observations.

In the long equity market, based on the Amihud measure for informed trading on equity data, the matching process yields 2,034 unique supervised firms, 2,240 unique non-supervised firms, with roughly equal firm-year observations of 10,281 each. Based on PIN, the matched sample consists of 4,467 unique firms and 20,112 firm-year observations. Based on beta-t, the matching process yields 1,812 firm-year observations of supervised firms and non-supervised firms, involving 419 supervised firms and 418 non-supervised firms. Finally, the matching process based on option spreads yields a similar outcome, with 1,572 firm-year observations.

Appendix A2 provides information on the quality of the matching process. For instance, using the Amihud sample, the propensity score matching process reduced the observed heterogeneity between supervised and non-supervised firms by 94%, relative to the full sample results. Reducing the caliper to 0.01 gives a reduction in observed heterogeneity of 95%, relative to the full sample results.

G. Descriptive Statistics

Table 1 presents the summary statistics based on the full sample of supervised and non-supervised firms. Our classification of supervised firms includes those classified by the conventional wisdom in academic studies: finance, utility, and pharmaceutical. More specifically, based on 4-digit SIC code, supervised industries consist of the following groups: Finance (6000-6799), Utilities (4812, 4813, 4911-4991), as well as Pharmaceuticals (2830, 2831, 2833, 2836). Our proposition centers on the concern that these supervised industries face additional information disclosure to the regulators which constitutes a potential source of information leakage to the market, or an added governance device that limits managerial opportunism. As our samples vary across trading activities in equity market, options market and short sales, we present summary statistics separately.

In Panel A, we present the mean, median, and standard deviation of firm size, industry HHI, analyst following, stock volatility, stock turnover, ROA, blockholder dummy, liquidity-PS, as well as managerial opportunistic trading, based on the short sale sample firms. We winsorize each variable at the 5th and 95th percentile and find similar results using 1% and 99% cut-offs. We observe that when there is a negative shock, supervised firms experience greater abnormal short sales than non-supervised firms. Furthermore, we find for positive shocks that supervised firms experience less abnormal short sales than non-supervised firms. The final 3 columns of Panel A present t-test on the mean value for each firm characteristic comparing supervised and non-supervised firms, as well as the t-statistic associated with the test. We observe that in comparison, supervised firms are much larger, perform worse, have fewer analysts, are traded much less frequently, have lower volatility, lower chance of having a blockholder, and experience less managerial opportunistic trades.

Panel B shows the statistics based on equity market sample firms. The full sample exhibits a mean value of Amihud (PIN) of 0.308 (0.236). The mean (median) total assets of the entire sample is 5,699 (448) million. On average, there are roughly 5 analysts following the firm. About 77% of the firms have at least one blockholder, and the managerial trading is 1.20. Once again, we notice that supervised firms are significantly different from their counterparts in every characteristic, as shown in the last three columns.

In Panel C, we present the statistics in a similar manner on the options based sample firms. Again, we find substantial differences between supervised and non-supervised firms. In sum, we observe pronounced differences between supervised and non-supervised firms across all three samples, highlighting the necessity for matching sample approach to mitigate variable extrapolation concerns. In terms of our central question, we note that for all three measures for informed trading, t-test shows that on average supervised firms exhibit significantly greater values than non-supervised firms. Note that non-supervised firms exhibit greater managerial opportunistic trading than supervised firms, consistent with notion of regulatory pressure. Overall, the univariate evidence based on all three markets suggests that supervised firms exhibit greater informed trading than non-supervised firms based on evidence for all three different markets.

III. Multivariate Results

A. Across Security Markets

We present multivariate results based on short sale evidence in Table 2 Panel A, examining the stock return predictability of short sales (Diether et al. 2009). More specifically, for supervised and non-supervised firm, we separately form equally-weighted portfolios using stocks that have a non-zero short interest each day. We present the time series regression results of daily portfolio returns on 2-day lagged equally-weighted portfolio short sales as well as Fama-French three factors and the momentum factor. In addition to results based on the full sample, we also show results based on a propensity score matched sample to reduce extrapolation concerns around firm characteristics. In column 1, based on the full sample, we find that coefficient of lagged short sales in the supervised firm portfolio is -0.858 and highly significant. In column 2, both the coefficient estimate and statistical significance of lagged short sales in the non-supervised firm portfolio are much smaller. The stark difference shows that short sales in supervised firms exhibit greater predicative power for future stock returns, indicating that short sales in supervised firms is almost 665% (0.858/0.129) more informative than that in the non-supervised firms. The matched sample results in column 3 & 4 lead to similar inference. The ability of short sales to predict future stock results to a greater extent in supervised firms relative to non-supervised firms, is inconsistent with the hypothesis that informed trading is lower in regulated firms than in non-regulated firms.

We use two measures for informed trading in the long equity market, Amihud and PIN, as dependent variables, in our next tests. The results are presented after controlling for opportunistic trading by corporate insiders and liquidity effect. In column 1 in Panel B, using Amihud as the dependent variable and based on the full sample, we focus on the comparison between supervised versus non-supervised firms. We find that the dummy variable for supervised firms show a significant positive coefficient of 0.128, suggesting that supervised firms experience greater informed trading in the equity market. The magnitude of the difference is also economically significant, as it represents 42% greater informed trading relative to the sample mean of 0.308. In column 2, the results show that when we split the supervised firms into three subgroups (finance, utility, and pharmaceuticals), each group exhibits a significant and positive coefficient estimate, indicating that the spectrum of supervised firms exhibit greater informed trading relative to the non-supervised firms. In column 3 and 4, we repeat the tests using PIN as the dependent variable. We find that supervised firms exhibit 12% greater informed trading compared to non-supervised firms, controlling for both the level of managerial and liquidity trading. Finally, we apply the tests on the matched sample in column 5-8, where we once again find that the coefficient estimates in the matched sample have similar magnitudes and significance as in the full sample.

In Table 2, Panel C, we present the multivariate results using the two option-based measures for informed trading as the dependent variable. In the first four columns, we show the results based on option trading measure, beta-t. The results appear similar to what we find in Table 2 Panel B, that supervised firms experience significantly higher informed option trading than non-supervised firms, and all types of supervised firms bear the same outcome. In columns 5-8, we repeat these tests with our second measure of informed option trading, option spread, and draw similar inferences. More specifically, we find that based on the full sample, supervised firms experience 20% (0.024/0.122) higher option spread than non-supervised firms. Again, we find evidence of greater informed trading across all 3 types of regulated firms[11].

B. Specific Information Events

We also develop a measure based on short sales data to gauge specific information flows of

[11] These tests incorporate opportunistic trading by managers. Yet, an alternative approach to help isolate the regulatory effect is to compare informed trading in high and low governance firms. Segregating firms into governance buckets using the GIM index (Gompers, Ishii, and Metrick, 2003) indicates greater informed trading in supervised firms, relative to non-supervised firms among both high and low governance firms.

financial data and present the results of this analysis in Table 3. The dependent variable is abnormal short sales based on a 30-day window prior to an earnings announcement date. We split the tests based on negative earnings shocks and positive earnings shocks. In column 1, we focus on negative shocks and the results show that supervised firms experience on average 0.113 greater abnormal short sales than non-supervised, which in turn suggests evidence of informed trading in short sales. The matched sample result in column 5 confirms the full sample finding. More specifically, again we find that trades before negative earnings shocks increase more in supervised firms than in non-supervised firms.

In column 2, we split supervised firms into three groups and find that finance firms exhibit significantly greater informed short sales than non-supervised firms. However, pharmaceutical and utility firms do not exhibit greater informed trading around unexpected earnings shocks than non-supervised firms. This is consistent with the notion that routine earnings information during a specific window may not be easily inferred from the required reporting to these respective regulators. Columns 3 and 4 report the tests with positive earnings shock, providing evidence to suggest that short sales potentially decrease before positive earnings shocks. In columns 5 through 8, the matched sample based tests yield very similar inferences.

An alternative interpretation of the results in columns 2 and 5 are that speculators routinely increase their short sales prior to earnings shocks in supervised firms. The results prior to positive to earnings shocks, however, provide additional evidence on this issue, suggesting that short sales decrease before positive earnings announcements. These results are inconsistent with the speculation argument and instead suggest information leakage. Overall, our short sale tests in Table 3, based on specific trades prior to information, provides evidence on the stark differences in informed trading between supervised and non-supervised firms. More specifically, these results indicate that information leakage, prior to negative earnings shocks, appears more common in supervised than in non-supervised firms.

C. Natural Experiments

Next, we examine informed trading differentials among specific samples of supervised firms that are subject to known regulatory shocks. More specifically, we identify three pseudo-natural experiments with prominent regulatory changes, and we explore whether the informed trading changes following the shocks.[12]

C1. 1978 Airline Deregulation

Beginning in 1937, the airline industry was largely supervised by the federal Civil Aeronautics Board (CAB) and served as a public utility by setting fares, routes, and even schedules (Levine, . The Airline Deregulation Act (Pub.L. 95-504), federal legislation signed into law on October 24, 1978, removed government control over fares, routes and market entry (of new airlines) from commercial aviation. This decrease in regulatory supervision provides a natural test of the impact of regulatory oversight on informed trading. In order to control for the macroeconomic condition changes that apply to all types of firms, we develop a propensity score matched sample. The process generates a matched sample of 11 airline firms and 12 non-supervised firms. In Table 4 column 1, we adopt a difference-in-difference approach using Amihud as the measure for informed trading. Specifically, we take the three-year average of Amihud for both before and after 1978 (1975-1977) and (1978-1980).[13] We then subtract the latter period Amihud from that of the former as the dependent variable. Next, we include the same control variables as in Table 2 and they are also differenced. We observe that the dummy variable for the airline industry affiliation exhibits a significantly negative coefficient estimate, consistent with the notion that deregulation curbs information leakage source. Economically, we find that the decrease (0.011) represents a 67% decrease from the matched sample mean value of Amihud.

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[12] Asker and Ljungqvist (2010) observe that several regulatory changes occurred in the US over the past few decades. We identify 3 of these regulatory changes where the scope of the regulator supervision appears to have increased or decreased.

[13] We also conduct the analysis in Table 4 using an 18 month window rather than a 36 month window and find similar results. Due to data availability, options and short sales measures are not viable. We also face data constraints in using PIN for this time period.

C2. 1980 Trucking Deregulation

The Motor Carrier Act of 1980, signed into law by President Carter on July 1, 1980, initiated deregulation for the trucking industry. This is a second natural experiment setting. Since the passage of the Interstate Commerce Act of 1887, the federal government had supervised various transportation modes, starting first with the railroad industry, and then later moving on to the trucking and airline industries. According to Jimmy Carter, the new law "… will remove 45 years of excessive and inflationary government restrictions and red tape".

Our process for this analysis is as follows: we matched trucking companies with non-supervised firms using propensity scores. In Table 4, column 2, we show the difference-in-difference results, which indicate that trucking firms experience lower informed trading. The coefficient estimate of 0.010 corresponds to a 16% decrease relative to non-supervised matched firms. Overall, our examinations on two deregulation scenarios all show that as potential regulatory supervision decreases, the firms also experience a decrease in informed trading while the non-supervised control group does not exhibit such decrease.

C3. 1999 Gramm-Leach-Bliley Act

Next, we focus on a scenario involving a regulatory requirements increase. One prominent instance is the 1999 Gramm-Leach-Bliley Act for the banking industry. The Gramm-Leach-Bliley Act (GLB), also known as the Financial Services Modernization Act of 1999, repealed part of the Glass-Steagall Act of 1933. It sought to remove barriers in the market among banking companies, securities companies, and insurance companies that prohibited any one institution from acting as any combination of investment bank, commercial bank, or insurance company. The banking industry had been seeking the repeal of the 1933 Glass-Steagall Act since the 1980s, and with the passage of the Gramm-Leach-Bliley Act, commercial banks, investment banks, securities firms, and insurance companies were allowed to consolidate.

Even though the act in general deregulated the industry by allowing mergers, in terms of information requirements and regulatory oversight, the new regulation did increase the scope of regulations; firms report more information to a greater number of regulatory bodies (e.g., The Fed, state-level insurance regulators). As such, we expect that after the legislative change, banking firms would experience greater informed trading. We show the results in columns 3-5 of Table 4 using three measures of informed trading: Amihud, PIN, and option spread. We find that banks experience on average a 48% increase in informed trading after 1999, relative to non-bank matched firms.[14]

The results of natural experiments, as in Table 4, are often interpreted to establish strong inference on the nature and direction of causality. Yet, in this particular instance, we note that our experimental tests are not of uniform power because of the fact that regulations which allow firms greater scope could increase the complexity of firm operations, thereby having an effect of increasing information asymmetry. In our tests using transportation deregulation, this aspect works against the informed regulator hypothesis. In contrast, this potential information asymmetry aspect in the GLB regulation works in the same direction as the informed regulator hypothesis. Consequently, the tests using transportation, even with additional control variables for corporate complexity, may provide a more robust platform than the test using the GLB deregulation to study the impact of regulatory supervision on informed trading.

IV. Attributing Information Leakage

Although the cross-sectional differences between supervised and non-supervised firms provide evidence on informed trading with regulatory oversight, it is difficult to infer causality. The short sale tests and the natural experiments arguably provide more robust empirical results regarding the role of supervision on informed trading. Yet, these tests suffer from small samples and provide little evidence on the specific channel of the information flows. To better gauge the potential private

[14] A potential concern is that these regulatory shocks impacted the information environment of the firm either by influencing the operations of the firm (Levine 2011) or by inducing a different level of firm disclosure. In order to evaluate this alternative explanation, we examine whether the regulatory change affected analyst forecast accuracy. We find that after GLB, banks do not experience a significant change in analyst forecast error. Furthermore, including analyst forecast error as an additional control variable in our specifications does not appear to affect our inferences about informed trading and regulatory supervision.

benefits of regulation, we examine several tests that seek to isolate the information flow to regulators and reduce concerns about unobserved heterogeneity.

A. Timing of Information Flows

Our first attribution test focuses on the trading pattern of commercial banking firms during their Call Report filing window, and compares that with a sample of propensity matched non-supervised firms. Commercial banks are required to submit their Call Report to the regulator by the end of every calendar quarter, which will then be released to the public within the following 40 days. We investigate informed trading during distinct sub-periods after the call report is provided to the regulators (10 day windows) and before the public release.

In Panel A, we use the short sales data and we compare the two windows of informed trading. In column 1, we show that when there is a negative shock, banks experience significantly greater abnormal short sales than non-banks. Focusing on columns 3 and 5, again, we observe a clear pattern of informed trading that gradually decays after the information is provided to bank regulators. In addition, we observe that based positive shocks, results in column 2, 4, and 6 yield similar inference, indicating that as we move away from the call report date, informed trading on short sales exhibit a regressing pattern.

In Table 5 Panel B, we focus on the evidence provided by equity and option markets. In a similar approach as in short sale test, our dependent variable is abnormal Amihud (option spread), measured as [average Amihud (option spread) during the reporting window/average Amihud (option spread) out of the window – 1]. In column 1, we find that during the first 10 days after the call report, commercial banks experience on average 54% greater informed trading than non-supervised firms, based on abnormal Amihud. In columns 2 & 3, we focus on the subsequent windows and observe that this informed trading appears to decay over the period leading to the public release of this information. In columns 4 – 6, we shift to option market evidence, which shows a similar pattern. That is, the abnormal option spread is larger between banks and non-banks during the first 10-days window and then decays over time. Overall, results in Panel B suggest that the abnormal informed trading is decreasing as the information gradually diffuses.

Although, all three markets exhibit informed trading around private information flows to regulators, the measures used for detecting this activity are not of equal strength. Intuitively, the short sale approach, even with the shortest data set, provides a strong test of the informed trader hypothesis. In summary, the call report examination reveals an interesting and clear pattern, indicating informed trading on private information provided to regulators.

B. Federal versus State Regulation

Our next examination also centers on commercial banks. Again, by focusing on a single industry, the comparison group is comprised of more similar firms, reducing concerns about unobserved heterogeneity. Commercial banks can choose to be regulated at the federal or the state level. Agarwal et al. (2012) find evidence suggesting that state-level supervision exhibits significant cross-sectional variation, with some states exhibiting behavior suggesting regulatory duplicity. More specifically, we measure state regulator duplicity based on the analysis in Agarwal et al. (2012) who report in Figure 5, the states that exhibit greater regulatory duplicity. We denote Regulatory Duplicity, as a dummy variable equals to 1 if the state exhibits greater than median regulatory duplicity, relative to federal supervision. Thus, this dummy variable allows us to compare state charted banks in states where there appears to be greater regulator duplicity with other state chartered and national banks.

In Table 6, we apply the event study approach based on bank call report as in Table 5, focusing on this measure of regulatory duplicity across states. The informed regulator hypothesis suggests that informed trading should be higher in regulated firms headquartered in states with duplicit regulators. Columns 1 – 3 show the results based on a matched sample of state banks and national banks. We observe that the dummy variable of Regulatory Duplicity shows a significant and positive coefficient in the first two trading windows, suggesting that banks in more tainted regulatory environments exhibit greater level of informed trading. Columns 4 - 6 present the results based on the matched sample of state banks and non-regulated firms. Once again, we find that the

Regulatory Duplicity variable is significant and positive in the two windows. In contrast, we do not find that the bank dummy variable to be significant in any of the trading windows, implying that the difference in informed trading between state bank and non-bank firms stems from the incentives of state-level regulators.

Finally, in columns 7 to 9, we present the results based on all three types of firms, state and national banks and the non-regulated firms. Here we observe that the bank dummy variables is positive and significant, consistent with our main result that regulatory oversight is associated with greater informed trading. Moreover, it suggests that informed trading occurs in nationally regulated banks. In addition, we also observe that Regulatory Duplicity is positive and significant, indicating that after controlling the industry effect, the state-level supervisory quality is associated with informed trading in banks.

At the federal level bank supervision involves OCC, FDIC, and the various Federal Reserve districts (Agarwal et al. 2012). In additional tests we also investigate differences in chartered banks among these regulators. We find evidence to suggest that banks with OCC oversight exhibit greater informed trading than banks with FDIC or Federal Reserve oversight (Appendix A3 – Columns 1 and 2). Among banks with Federal Reserve oversight, we use a simple classification of Federal Reserve districts, with banks in headquartered in the Chicago and NYC districts in category 1, those in Dallas and Kansas in category 3, and the remaining banks placed in category 2 (Appendix A3 – Columns 3 and 4). We find that informed trading in banks is lower in category 1 relative to those in category 2 and that category 3 banks have higher informed trading than the category 2 banks.

C. Variation in State Regulation and Informed Trading

Our next examination on regulation and informed trading focuses on the particular regulatory environment faced by insurance and utility firms. If regulatory oversight leads to informed trading, then we expect that informed trading in supervised firms should be more prominent in states with greater political corruption, relative to those in low corruption states. Our specific empirical test centers on insurance companies and utility companies. Since they are largely governed and supervised at the state level, this presents a viable platform to test our proposition, as there is substantial variation of a regulator's behavior and discretion. We identify a matched sample of non-supervised firms based on propensity score, and we further adopt a one-to-many matched sample on top of the one-to-one matched sample thus in an attempt to mitigate the concern of sample size. The matched sample is used to address concerns about extrapolating across control variables. We present results based on both samples.

We use the inverse of the state integrity index compiled by the Better Government Association (BGA) as a measure of the state corruption level. This is denoted as Corruption. The BGA analyzes an array of laws including: freedom of information, whistleblower protection, campaign finance, open meetings, and conflict of interest. Essentially, it evaluates rules and laws and establishes the ranking based on state laws along these five dimensions.[15] The state with the highest ranking is the one that best protects against corruption and promotes integrity, while the state that ranks bottom has the weakest laws against corruption. Consequently, we use the inverse of this metric to proxy for state-wide political corruption. In these test, we include an additional control variable, Budget, measured by the difference between the state revenue and the state expense, and then scaled by revenue. The data presented is from the Census Bureau website (http://www.census.gov/govs/estimate/) and is used to capture state financial pressure.

Table 7 presents the result of how the informed trading of insurance companies and utilities varies with political corruption at the state level. In column 1 through 4, we focus on the stock market measures of informed trading, i.e., Amihud and PIN. More specifically, based on both one-to-many and one-to-one matched samples, we find that for Amihud and PIN, supervised firms have greater informed trading than the matched non-supervised firms.[16] Furthermore, we find that Corruption exhibits positive and significant in PIN regressions, suggesting market concerns about the asymmetric information of firms headquartered in states with weak laws against corruption.

[15] The BGA's complete report is available at http://www.bettergov.org/assets/1/News/BGA_Alper_Integrity_Index_2008.pdf.

[16] Because there are a small percentage of insurances and utilities in our full sample, we create this one-to-many matched sample as a balanced sample for the dummy variable. Full sample results are available upon request.

Finally, we also examine the interaction term between the supervised dummy and the corruption index, with the point estimate being 0.002 and statistically significant (t = 2.06), implying that market participants are concerned about the asymmetric information of state supervised companies in more corrupt states. Based on the results on the interaction term, we calculate the effect of corruption on informed trading, on top of regulator involvement to be 37% (28%) greater than without political corruption using the Amihud (PIN) measure.[17]

The next four columns show the results based on option market measures. Again, we find that informed trading in supervised firms is a function of state-level political corruption. More specifically, we find that supervised firms have greater informed option trading than non-supervised firms in all tests. In addition, we observe that state-level corruption exhibits significant and positive estimates, suggesting a market concern regarding misconduct. Finally, the interaction terms between supervised firm states and state corruption is positive and significant in each of the tests, suggesting that informed trading escalates to a greater extent in supervised firms in states with greater political corruption. Overall, we interpret these results to indicate that informed trading in supervised firms varies based on the degree of corruption by state officials[18].

V. Concluding Remarks

It is well accepted in the economics literature that informed trading improves price discovery and facilitates market efficiency. Informed trading based on superior insights, such as generated in fundamental analysis, is considered value adding. In contrast, informed trading that relies on preferential access to material, non-public information may harm investor confidence and market

[17] For Amihud, the sample mean is 0.153. The mean value of Corruption is 28.43. We calculate the effect of interaction term to be 0.002*28.43/0.153 = 37%.

[18] Another method to test the notion that state-level regulatory environment has an effect on informed trading focuses on variations in the regulation official generation process. Research in regulatory economics reports that states with elected officials seeks more in-depth information from companies (Beasley and Coates, 2003). In contrast, in states with appointed regulators, the regulators tend to have less information about the supervised firms (Baron and Besanko, 1984). We observe that across the entire spectrum of tests, firms in states with elected regulators exhibit greater informed trading than states with appointed regulators (available upon request).

participation.

Industries are regulated for different reasons. In the financial services industry, the regulators want to insure that the industry does not invest in risky projects because the downside is borne by taxpayers (through insurance and impact on the economy). In the pharmaceutical industry, regulators want to insure that the products that are sold are safe and effective. In the utilities industry, regulators want to guard against natural monopolies do not charge monopoly prices. In each of these cases, the nature and scope of regulation differs. Yet, a common thread among them is that regulators have access to material, non-public information. Against this backdrop, we investigate the impact of regulatory supervision on informed trading, testing hypotheses on regulatory pressure and private information.

First, we investigate the relative return predictability of short sales in supervised and non-supervised firms, finding markedly greater informed in supervised firms relative to non-supervised firms. We extend the analysis to consider and informed trading in the long equity and option markets. Controlling for both opportunistic managerial trading and liquidity traders in the long equity market, we find that supervised firms exhibit about 30% more informed trading than non-supervised firms. We also find evidence to indicate greater informed trading in supervised firms, relative to non-supervised firms, in the option market.

Although, the panel regressions (full and matched samples) across multiple security markets are inconsistent with the regulatory pressure hypotheses, it is difficult to draw causal inferences from these tests. Focusing on specific information events, negative earnings shocks, we find evidence of greater informed trading on this information prior to public release of this information. Importantly, the evidence on informed trading prior to negative earnings shocks systematically differs amongst the regulated firms in a manner consistent with the types of information flows that each regulator receives. More specifically, we find greater informed trading in regulated firms where the regulator receives financial information, but do not find such evidence when regulators only receive product information.

Next, we consider several natural experiments and analyze informed trading after various changes in the regulatory environment. Using difference-in-difference tests, we find that an increase in regulatory oversight of banks is associated with a subsequent increase in informed trading for these financial firms. In contrast, we find that deregulation in the trucking and airline industries are associated with subsequent declines in informed trading.

In order to more directly focus on the nature of information flows, we develop three additional set of tests to concentrate on attribution. We focus on the timing of information flows to regulators, finding that informed trading spikes after information is provided to regulators. To further gauge the disposition of informed trading in supervised firms, we compare informed trading in state chartered banks that are headquartered in states that exhibit regulatory duplicity, and discover these banks exhibit greater informed trading than comparable state or federal chartered banks. Additional tests indicate that informed trading differs among banks depending on the Federal Reserve District in which they are headquartered.

Our next set of tests exploits state differences in regulatory oversight in insurance and utilities. Focusing again on firms overseen by state regulators, we find that firms supervised in states with greater incidences of political corruption exhibit greater informed trading than those in states with less political corruption.

Overall, the results of this study point to trading, based on material non-public information, which seems prevalent in regulated industries. In instances where regulators have greater private information, there appears to be more informed trading in equity, short sale, and options markets. Arguably, the research design is capable of answering whether someone, other than insiders at the firm, trade on private information about firms in regulated industries. Yet, we cannot identify who is performing these informed trades. Despite this substantive limitation, this series of tests do provide evidence to indicate that informed trading is associated with regulatory supervision.

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Table 1 Summary Statistics – Full Sample

Variable definitions are given in Appendix A1.

Panel A – Short Sales: 8,972 Observations

	Mean	Median	Std. Dev.	Supervised	Non-supervised	t-test statistic
Abnormal Short Sales						
Negative Shock	0.017	-0.038	0.619	0.075	-0.005	4.01
Positive Shock	-0.025	-0.059	0.547	-0.031	-0.021	-2.73
Total Assets ($ mil)	5,871.18	808.35	28,346.74	12,047.35	3,545.0	13.85
ROA	-0.033	0.055	0.564	-0.089	-0.012	-6.27
Analyst (#)	9.66	8.00	7.43	8.68	10.01	-7.52
Stock Turnover	8.06	6.40	7.19	5.70	8.94	-21.05
Volatility	0.024	0.022	0.011	0.022	0.025	-13.97
Blockdummy	0.854	1.00	0.352	0.762	0.890	-16.80
Opportunistic Trade	2.08	1.00	3.67	1.61	2.26	-8.06
Industry HHI	0.133	0.075	0.160	0.018	0.176	-50.08
Liquidity-PS	-0.002	-0.000	0.048	-0.002	-0.002	0.76

Panel B – Equity Market: 40,016 Observations

	Mean	Median	Std. Dev.	Supervised	Non-supervised	t-test statistic
Amihud	0.308	0.026	0.618	0.386	0.276	18.07
PIN	0.236	0.223	0.164	0.243	0.233	5.88
Total Assets ($ mil)	5,698.94	448.16	48,131.31	14,028.80	2,293.62	24.74
ROA	-0.032	0.048	0.365	-0.006	-0.044	10.66
Analyst (#)	5.22	6.00	4.55	7.30	7.95	-8.22
Stock Turnover	7.54	4.82	9.94	4.93	8.60	-37.72
Volatility	0.034	0.029	0.020	0.028	0.037	-48.55
Blockdummy	0.77	1.00	0.42	0.65	0.82	-42.13
Opportunistic Trade	1.20	0.00	2.50	1.10	1.25	-6.15
Industry HHI	0.114	0.069	0.137	0.016	0.153	-113.93
Liquidity-PS	-0.002	-0.000	0.043	-0.004	-0.001	-7.44

Panel C – Option Market: 3,886 Observations

	Mean	Median	Std. Dev.	Supervised	Non-supervised	t-test statistic
Beta-t	0.553	0.545	0.899	0.674	0.519	4.47
Option Spread	0.122	0.106	0.078	0.127	0.120	2.12
Total Assets ($mil)	21,446.34	1,440.61	114,063.70	72,423.78	7,318.26	15.15
ROA	-0.014	0.070	0.332	-0.084	0.014	-8.25
Analyst (#)	14.67	13.00	9.02	15.00	14.58	1.21
Stock Turnover	17.10	13.81	14.96	13.60	18.06	-7.76
Volatility	0.042	0.039	0.019	0.039	0.043	-5.77
Blockdummy	0.86	1.00	0.35	0.82	0.87	-3.93
Opportunistic Trade	1.97	1.00	3.12	2.07	1.95	0.98
Industry HHI	0.114	0.072	0.136	0.026	0.139	-22.92
Liquidity-PS	-0.000	-0.000	0.001	-0.000	-0.000	1.58

Table 2 Regulatory Supervision and Informed Trading

Panel A – Short Sale Stock Return Predictability Evidence

This panel reports time series results of regressing daily equally-weighted portfolio returns on day t+2 against equ short sale interest for on day t. Portfolio Return$_{t+2}$ is the percentage return of the equally-weighted portfolio of supe firms on day t+2. Short$_t$ is the short sales volume on day t divided by total stock trading volume on day t, average stocks. Mkt, HML, SMB, and UMD are the daily Fama-French 3 factors and the momentum factor, respectively. t parentheses and are corrected for serial correlation and heteroskedasticity. Statistical significance at 10%, 5%, and 1% **, ***, respectively.

Dependent Variable:	Portfolio Return$_{t+2}$		
	Full Sample		Matched
	Supervised	Non-supervised	Supervised
Intercept	-0.290***	-0.003	-0.282**
	(-4.93)	(-0.09)	(-2.09)
Short$_t$	-0.858***	-0.129*	-0.819***
	(-4.86)	(-1.93)	(-2.79)
Mkt$_t$	0.868***	0.887***	0.863***
	(12.92)	(12.09)	(10.31)
HML$_t$	0.274***	0.164***	0.306***
	(6.68)	(6.31)	(4.89)
SMB$_t$	0.300***	0.546***	0.131**
	(10.64)	(13.35)	(1.97)
UMD$_t$	-0.170***	-0.062***	-0.020
	(-5.93)	(-3.78)	(-1.30)
Observations	676	676	676
Adjusted-R^2	0.929	0.979	0.656

Panel B - Equity Market Evidence

Variable definitions are in Appendix A1. We apply Huber-White sandwich estimator (clustered on firm-level iden
errors estimation. The t-values are reported in parentheses underneath each coefficient estimate. Statistical significanc
level is denoted by *, **, ***, respectively.

	Full Sample				Matched Sa		
Dependent Variable:	Amihud		PIN		Amihud		
Constant	0.643***	0.667***	0.347***	0.351***	0.503***	0.500***	
	(27.25)	(27.84)	(59.81)	(61.23)	(6.78)	(6.75)	
SUPERVISED (=1)	0.128***	-	0.028***	-	0.108***	-	(
	(7.09)		(9.03)		(6.00)		
FINANCE (=1)	-	0.176***	-	0.045***	-	0.097***	
		(11.52)		(13.08)		(3.69)	
PHARMA (=1)	-	0.104***	-	0.012***	-	0.139***	
		(4.92)		(3.26)		(3.11)	
UTILITY (=1)	-	0.060**	-	0.003**	-	0.104***	
		(2.26)		(2.44)		(2.85)	
Firm Size	-0.060***	-0.067***	-0.017***	-0.019***	-0.052***	-0.053***	-
	(-18.66)	(-19.82)	(-20.96)	(-22.56)	(-6.63)	(-6.71)	
Industry HHI	0.012	0.020	0.005	0.013	0.131	0.280	
	(0.39)	(0.58)	(0.43)	(1.21)	(0.17)	(0.33)	
Analyst (log)	-0.092***	-0.088***	-0.011***	-0.008***	-0.058***	-0.058***	
	(-20.81)	(-19.84)	(-7.74)	(-5.74)	(-5.84)	(-5.83)	
ROA	0.003	0.006	0.013***	0.006*	0.012	0.012	
	(0.34)	(0.69)	(3.96)	(1.80)	(1.14)	(1.13)	
Stock Volatility	4.201***	4.192***	0.097	0.067	3.307***	3.281***	
	(13.53)	(13.57)	(1.41)	(0.98)	(3.86)	(3.85)	
Stock Turnover	-0.008***	-0.008***	-0.000***	-0.000***	-0.007***	-0.007***	
	(-8.81)	(-8.81)	(-3.08)	(-2.71)	(-7.08)	(-7.29)	
Block Dummy	-0.016**	-0.014**	0.010***	0.011***	-0.007	-0.007	
	(-2.25)	(-2.08)	(4.65)	(5.13)	(-0.42)	(-0.42)	
Opportunistic Trade	0.001*	0.001*	0.001	0.001	0.001	0.001	
	(1.76)	(1.78)	(1.06)	(1.04)	(0.41)	(0.41)	
Liquidity-PS	0.110	0.112	0.019**	0.020**	0.620	0.607	
	(0.35)	(0.36)	(2.31)	(2.45)	(0.83)	(0.82)	
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	
Observations	40,016	40,016	35,022	35,022	20,563	20,563	2
Adjusted R^2	0.23	0.23	0.28	0.31	0.22	0.22	

Panel C - Option Market Evidence

Variable definitions are in Appendix A1. We apply Huber-White sandwich estimator (clustered on firm-level iden errors estimation. The t-values are reported in parentheses underneath each coefficient estimate. Statistical significanc level is denoted by *, **, ***, respectively.

Dependent Variable:	Beta-t				Option Spre		
	Full Sample		Matched Sample		Full Sample		
Constant	0.748***	0.719***	0.733***	0.805***	0.265***	0.277***	
	(5.79)	(5.38)	(3.02)	(3.08)	(24.37)	(24.29)	(1
SUPERVISED (=1)	0.152***	-	0.171***	-	0.024***	-	
	(4.04)		(3.14)		(3.67)		(
FINANCE (=1)	-	0.127***	-	0.111**	-	0.056***	
		(3.28)		(2.44)		(4.83)	
PHARMA (=1)	-	0.207***	-	0.186**	-	0.008**	
		(4.00)		(3.27)		(2.45)	
UTILITY (=1)	-	0.049**	-	0.035**	-	0.030**	
		(2.02)		(2.27)		(2.21)	
Firm Size	-0.001	0.004	-0.010	-0.007	-0.013***	-0.015***	-
	(-0.14)	(0.30)	(-0.60)	(-0.44)	(-10.06)	(-10.74)	(-
Industry HHI	0.005	-0.016	0.097	-0.043	0.023	0.033	-
	(0.05)	(-0.15)	(0.69)	(-0.17)	(1.06)	(1.51)	(-
Analyst (log)	-0.004	-0.009	-0.003	-0.009	-0.012***	-0.011***	-
	(-0.17)	(-0.36)	(-0.08)	(-0.22)	(-3.69)	(-3.27)	(-
ROA	-0.043	-0.039	-0.069	-0.072	0.000	-0.002	
	(-0.81)	(-0.70)	(-1.07)	(-1.09)	(0.01)	(-0.57)	(
Stock Volatility	1.069	1.206	-1.289	-1.330	-0.316***	-0.349***	-
	(0.86)	(0.95)	(-0.72)	(-0.74)	(-2.79)	(-3.09)	(-
Stock Turnover	-0.002**	-0.002**	0.000	0.000	-0.001***	-0.001***	-
	(-2.24)	(-2.22)	(0.12)	(0.04)	(-5.52)	(-5.65)	(-
Block Dummy	-0.016	-0.014	-0.009	-0.007	0.014***	0.014***	
	(-0.37)	(-0.30)	(-0.14)	(-0.11)	(3.99)	(3.96)	(
Opportunistic trading	0.006	0.006	0.019***	0.019***	0.000	0.000	
	(1.33)	(1.35)	(3.27)	(3.25)	(0.91)	(0.83)	(
Liquidity-PS	-3.629	-4.051	-4.250	-4.284	0.287	0.356	
	(-0.39)	(-0.43)	(-0.32)	(-0.32)	(0.28)	(0.34)	(
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Y
Observations	3,886	3,886	1,812	1,812	3,386	3,386	1,5
Adjusted R^2	0.03	0.03	0.03	0.03	0.23	0.24	

Table 3 Informed Trading and Information Shocks: Short Sale Market Evidence

Variable definitions are in Appendix A1. We apply Huber-White sandwich estimator (clustered on firm-level iden
errors estimation. The t-values are reported in parentheses underneath each coefficient estimate. Statistical significanc
level is denoted by *, **, ***, respectively.

Dependent Variable:	Abnormal Short Sales						
	Full Sample				Matched Samp		
Shock type=	Negative		Positive		Negative		
Constant	0.483***	0.500***	0.621***	0.636***	0.420***	0.381***	0.
	(4.84)	(5.08)	(4.76)	(4.87)	(3.00)	(2.62)	(3.
SUPERVISED (=1)	0.113***	-	-0.145***	-	0.051**	-	-0.
	(3.52)		(-4.00)		(2.39)		(-1.
FINANCE (=1)	-	0.221***	-	-0.230***	-	0.176**	-
		(4.22)		(-4.10)		(2.38)	
PHARMA (=1)	-	0.021	-	-0.030	-	0.015	-
		(0.44)		(-0.75)		(0.40)	
UTILITY (=1)	-	0.013	-	-0.049	-	0.016	-
		(1.35)		(-1.31)		(1.25)	
Earnings Shock	0.044**	0.053*	-0.008	-0.006	0.011**	0.013**	-0.
	(1.97)	(1.80)	(-1.19)	(-1.15)	(2.00)	(2.13)	(-0.
Firm Size	-0.058***	-0.065***	-0.072***	-0.078***	-0.046***	-0.052***	-0.
	(-6.24)	(-6.58)	(-6.03)	(-6.26)	(-4.04)	(-4.32)	(-3.
Industry HHI	-0.044	-0.010	-0.047	-0.027	-1.342*	-0.205	-1.
	(-0.52)	(-0.11)	(-0.66)	(-0.37)	(-1.76)	(-0.20)	(-1.
Analyst (log)	-0.037**	-0.047***	-0.047***	-0.055***	-0.029	-0.036*	-0.
	(-2.33)	(-2.75)	(-2.77)	(-3.13)	(-1.61)	(-1.91)	(-1.
ROA	-0.009	-0.031	0.023	0.008	0.004	-0.006	0.
	(-0.45)	(-1.39)	(1.26)	(0.39)	(0.22)	(-0.39)	(2.
Stock Volatility	-2.577	-3.242*	0.456	0.149	-1.870	-3.031	2.
	(-1.36)	(-1.73)	(0.26)	(0.08)	(-0.89)	(-1.44)	(1.
Stock Turnover	-0.002	-0.001	-0.002	-0.001	-0.003	-0.002	-0.
	(-0.89)	(-0.45)	(-1.11)	(-0.86)	(-1.16)	(-0.87)	(-0.
Block Dummy	0.007	0.002	0.010	0.014	0.018	0.029	0.
	(0.25)	(0.08)	(0.33)	(0.45)	(0.43)	(0.68)	(1.
Bid-ask Spread	1.650	1.940	0.777	0.643	1.498	1.907	2.
	(0.92)	(1.08)	(0.31)	(0.26)	(0.65)	(0.81)	(0.
Opportunistic trading	0.001	0.001	0.006	0.006	0.003	0.003	0.
	(0.65)	(0.64)	(1.45)	(1.42)	(1.29)	(1.16)	(0.
Liquidity-PS	0.401	0.453	1.180	1.213	-0.587	-0.524	-0.
	(0.69)	(0.77)	(0.48)	(0.50)	(-1.16)	(-1.08)	(-0.
Quarter dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,906	3,906	5,066	5,066	2,142	2,142	2,63
Adjusted R^2	0.18	0.22	0.29	0.32	0.12	0.16	0.

Table 4 Natural Experiments with Difference-in-Difference Test

Variable definitions are in Appendix A1. The dependent variables and controls are differenced between pre and post- regulatory change. We apply Huber-White sandwich estimator (clustered on firm-level identifier) for the standard errors estimation. The t-values (adjusted for small sample size) are reported in parentheses underneath each coefficient estimate. Statistical significance at 10%, 5%, and 1% level is denoted by *, **, ***, respectively.

Event	Airline Deregulation	Trucking Deregulation	Banking Regulation		
Dependent Variable	Amihud	Amihud	Amihud	PIN	Option Spread
Constant	-0.009	-0.008	0.377*	-0.021***	0.031***
	(-0.19)	(-1.03)	(1.92)	(-5.69)	(4.30)
AIRLINES(=1)	-0.011*	-	-	-	-
	(-1.95)				
TRUCKING(=1)	-	-0.010**	-	-	-
		(-2.11)			
BANK (=1)	-	-	0.081**	0.012**	0.025**
			(2.42)	(2.08)	(2.17)
Firm Size	-1.586**	-1.199*	-0.999**	-0.183**	-0.011**
	(-2.27)	(-1.90)	(-2.48)	(-2.02)	(-2.38)
Industry HHI	0.088	0.069	0.112	2.540	-0.119
	(1.11)	(1.30)	(1.40)	(0.79)	(-0.90)
Analyst (log)	-	-	-0.123**	-0.002	-0.027**
			(-2.51)	(0.63)	(-2.20)
ROA	0.228	0.337*	0.193**	0.021	0.004
	(0.82)	(1.67)	(1.97)	(1.60)	(0.33)
Stock Volatility	8.140**	6.825**	3.382***	0.155	-0.555
	(2.29)	(2.30)	(2.87)	(0.88)	(-0.99)
Stock Turnover	-0.328**	-0.492**	-0.238**	-0.001*	-0.001*
	(-2.09)	(-2.17)	(-2.40)	(-1.83)	(-1.70)
Block Dummy	-	-	-0.072	0.033*	0.017*
			(-1.12)	(1.80)	(1.81)
Opportunistic trading	-	-	0.000	0.003	0.011
			(0.44)	(1.60)	(1.60)
Liquidity-PS	0.290	0.118	0.225	0.033*	-0.722
	(1.10)	(1.47)	(1.28)	(1.70)	(-1.11)
Observations	23	16	2,155	1,970	320
Adjusted R^2	0.15	0.65	0.12	0.05	0.09

Table 5 Information Flows and Informed Trading: Evidence from Call Reports

Variable definitions are in Appendix A1. We apply Huber-White sandwich estimator (clustered on firm-level identifier) for the standard errors estimation. The t-values are reported in parentheses underneath each coefficient estimate. Statistical significance at 10%, 5%, and 1% level is denoted by *, **, ***, respectively.

Panel A – Short Sales Evidence

Dependent Variable:	Abnormal Short Sales					
Shock type=	Negative	Positive	Negative	Positive	Negative	Positive
Window:	t1-10		t11-20		t21-40	
Constant	0.351**	0.202**	0.333**	0.222**	0.211**	0.333*
	(2.25)	(2.00)	(2.30)	(2.11)	(2.22)	(1.90)
Commercial Bank	0.047**	-0.050*	0.044*	-0.041*	0.024	-0.033
	(2.17)	(-1.70)	(1.90)	(-1.89)	(1.32)	(-1.28)
Earnings Shock	0.029**	-0.012	0.030**	-0.011*	0.031*	-0.015*
	(2.22)	(-1.60)	(2.01)	(-1.77)	(1.95)	(-1.90)
Firm Size	-0.108***	-0.081**	-0.122***	-0.080**	-0.092**	-0.083**
	(-5.52)	(-2.30)	(-4.47)	(-1.99)	(-2.22)	(-2.15)
Industry HHI	-0.201*	0.010	-0.222	0.015	-0.259	0.018
	(-1.91)	(1.04)	(-1.50)	(1.11)	(-0.37)	(1.18)
Analyst (log)	-0.035*	-0.066*	-0.033*	-0.077*	-0.020	-0.057*
	(-1.81)	(-1.79)	(-1.92)	(-1.67)	(-1.32)	(-1.67)
ROA	-0.066	0.050	-0.089	0.022	-0.129	-0.023
	(-0.12)	(1.00)	(-0.49)	(0.69)	(-0.60)	(-1.10)
Stock Volatility	2.016	0.692	3.246	0.883	5.393	1.066
	(0.79)	(0.58)	(1.00)	(0.68)	(0.56)	(0.88)
Stock Turnover	-0.010	-0.001	-0.002	0.000	0.002	0.003
	(-0.96)	(-0.20)	(-0.62)	(0.03)	(0.11)	(0.30)
Block Dummy	-0.147**	-0.092	-0.288*	-0.129	-0.502**	-0.111
	(-2.48)	(-1.27)	(-1.90)	(-1.52)	(-2.11)	(-1.38)
Bid-ask Spread	3.248*	3.710	3.334	3.552	3.393	3.475
	(1.93)	(1.33)	(1.38)	(1.30)	(1.32)	(1.11)
Opportunistic trading	0.016***	0.008*	0.018***	0.010	0.021***	0.020*
	(4.67)	(1.73)	(4.22)	(1.60)	(2.76)	(1.85)
Liquidity-PS	-0.669	3.992	-0.827	4.322	-0.700	4.998
	(-0.70)	(1.12)	(-1.20)	(1.30)	(-0.72)	(1.13)
Quarter dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	52	68	52	68	52	68
Adjusted R^2	0.45	0.43	0.45	0.43	0.42	0.40

Panel B – Equity Market and Option Market Evidence

Dependent Variable:	Abnormal Amihud			Abnormal Option Spread		
Window:	t1-10	t11-20	t21-40	t1-10	t11-20	t21-40
Constant	0.496***	0.203**	-0.113**	1.333**	1.110**	0.888*
	(3.36)	(2.53)	(-2.11)	(1.97)	(2.10)	(1.83)
Commercial Bank	0.115**	0.088**	0.002	0.293**	0.222*	0.104
	(2.39)	(2.19)	(1.37)	(1.99)	(1.73)	(1.52)
Firm Size	-0.037*	-0.018	-0.004	-0.064	-0.055	-0.020
	(-1.82)	(-1.25)	(-1.22)	(-0.97)	(-1.20)	(-0.48)
Industry HHI	-0.061	-0.117	-0.066	-0.635	-0.553	-0.332
	(-0.27)	(-0.72)	(-0.52)	(-1.63)	(-1.21)	(-1.12)
Analyst (log)	-0.139*	-0.061	-0.020	-0.066	-0.020*	0.002
	(-1.94)	(-1.17)	(-1.02)	(-0.96)	(-1.70)	(0.58)
ROA	1.013*	0.098	-0.021	-2.123	-1.772	-1.003
	(1.70)	(1.33)	(-0.68)	(-1.60)	(-1.29)	(-0.89)
Stock Volatility	2.909	-7.737***	-5.002**	33.198**	27.220*	15.337
	(1.53)	(-2.92)	(-2.03)	(2.09)	(1.80)	(1.11)
Stock Turnover	-0.004	0.010	0.002	0.052**	0.040*	0.010
	(-1.24)	(0.60)	(0.77)	(2.26)	(1.89)	(0.42)
Block Dummy	0.057	-0.022	-0.072	0.111	0.138	0.173
	(0.58)	(-0.33)	(-1.20)	(1.10)	(1.49)	(1.33)
Opportunistic trading	0.030	0.037	0.019	0.071	0.046	0.050
	(0.97)	(1.52)	(1.22)	(1.28)	(1.10)	(0.47)
Liquidity-PS	0.992	-0.701	-1.252*	-4.239	-5.229	-5.119
	(0.56)	(-1.13)	(-1.88)	(-0.55)	(-0.48)	(-0.62)
Quarter dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	709	709	709	110	110	110
Adjusted R^2	0.28	0.28	0.27	0.68	0.68	0.68

Table 6 Federal versus State Bank Regulatory Oversight

Variable definitions are in Appendix A1. Regulatory Duplicity is a dummy variable equals to 1 if the state exhibit
regulatory duplicity, relative to federal supervision. We apply Huber-White sandwich estimator (clustered on firm-l
standard errors estimation. The t-values are reported in parentheses underneath each coefficient estimate. Statistic
5%, and 1% level is denoted by *, **, ***, respectively.

Dependent Variable:	Abnormal Amihud						
Matched Sample:	State Banks & National Banks			State Banks & Non-Regulated Firms			State & N Non-re
Window:	t1-10	t11-20	t21-40	t1-10	t11-20	t21-40	t1-10
Constant	1.041	1.235	2.418	0.197	0.338	0.061	0.078
	(0.87)	(0.72)	(1.54)	(0.44)	(0.66)	(0.16)	(0.21)
Bank (=1)	-	-	-	0.087	0.084	0.067	0.124**
				(1.15)	(0.94)	(0.81)	(2.33)
Regulatory Duplicity	0.099*	0.098*	0.076	0.105**	0.079**	0.028	0.048*
	(1.93)	(1.74)	(1.16)	(2.47)	(1.98)	(1.45)	(1.93)
Firm Size	-0.008	-0.010	-0.041	-0.022	-0.011	-0.025	-0.032
	(-0.25)	(-0.31)	(-1.36)	(-0.72)	(-0.38)	(-1.23)	(-1.03)
Industry HHI	-0.236*	-0.105	-0.146	0.054	0.286	0.249	0.272
	(-1.79)	(-1.03)	(-0.99)	(1.36)	(1.43)	(1.28)	(0.94)
Analyst (log)	-0.068	-0.026	-0.078	-0.081	-0.029	-0.041	-0.086*
	(-1.02)	(-0.47)	(-1.25)	(-1.59)	(-0.61)	(-0.71)	(-1.92)
ROA	0.386*	0.318	-0.215	0.265*	0.185	-0.149	0.156
	(1.91)	(1.30)	(-0.85)	(1.73)	(0.90)	(-1.01)	(1.49)
Stock Volatility	2.115	-1.802	-4.709	0.577	-2.997	-4.088	-0.634
	(0.59)	(-0.57)	(-1.32)	(0.43)	(-1.10)	(-1.42)	(-0.25)
Stock Turnover	-0.006	-0.010	0.001	-0.005	-0.011	-0.000	-0.004
	(-0.62)	(-0.79)	(0.08)	(-0.56)	(-0.98)	(-0.11)	(-0.49)
Block Dummy	-0.100	-0.070	-0.005	-0.087	-0.038	-0.024	-0.072
	(-1.37)	(-0.85)	(-0.05)	(-1.40)	(-0.50)	(-0.39)	(-1.34)
Opportunistic trading	0.027	0.037**	0.044*	0.019	0.028	0.034*	0.012
	(1.50)	(2.27)	(1.69)	(1.03)	(1.48)	(1.68)	(0.61)
Liquidity-PS	-	-0.430	-0.227	-0.484	-0.560	-0.136	-0.639
	(-2.12)	(-0.42)	(-0.15)	(-1.49)	(-0.60)	(-0.10)	(-0.92)
Quarter Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	543	543	543	540	540	540	812
Adjusted R^2	0.262	0.177	0.166	0.262	0.227	0.177	0.224

Table 7 Political Corruption and Informed Trading: Evidence from Insurance and Utility F
Variable definitions are in Appendix A1. We apply Huber-White sandwich estimator (clustered on firm-level iden
errors estimation. The t-values are reported in parentheses underneath each coefficient estimate. Statistical significanc
level is denoted by *, **, ***, respectively.

	One-to-many Match		One-to-one Match		One-to-many Match	
Dependent Variable:	Amihud	PIN	Amihud	PIN	Beta-t	Option Spread
Constant	0.877***	0.331***	0.939***	0.329***	0.741*	0.332***
	(4.03)	(3.70)	(4.18)	(3.37)	(1.94)	(7.33)
Supervised (=1)	0.139***	0.015**	0.123***	0.016**	0.090**	0.063**
	(2.57)	(2.05)	(2.72)	(2.01)	(2.42)	(2.32)
Corruption	0.001	0.001*	0.001	0.001*	0.001*	0.000*
	(1.25)	(1.82)	(1.24)	(1.77)	(1.86)	(1.81)
Supervised * Corruption	0.002**	0.001*	0.002**	0.001*	0.003*	0.002*
	(2.06)	(1.69)	(2.15)	(1.89)	(1.92)	(1.76)
Budget	-0.163	-0.019	-0.175	-0.024	-0.630	-0.005
	(-0.47)	(-0.64)	(-0.48)	(-0.82)	(-1.44)	(-0.16)
Firm Size	-0.082***	-0.015***	-0.082***	-0.016***	-0.023***	-0.017***
	(-4.19)	(-12.41)	(-4.25)	(-12.58)	(-2.69)	(-4.27)
Industry HHI	-0.415**	-0.021*	-0.540**	-0.012	0.056	0.006
	(-2.01)	(-1.67)	(-2.13)	(-0.98)	(0.21)	(0.21)
Analyst (log)	-0.058*	-0.015***	-0.058*	-0.012***	-0.001**	-0.002***
	(-1.69)	(-6.79)	(-1.76)	(-6.11)	(-2.24)	(-3.39)
ROA	-0.185***	0.002	-0.207***	0.003	0.031	0.016
	(-2.66)	(0.27)	(-3.32)	(0.39)	(0.28)	(1.30)
Stock Volatility	5.565***	0.718***	4.808***	0.774***	2.321	0.026
	(3.11)	(5.91)	(3.10)	(6.67)	(0.57)	(0.06)
Stock Turnover	-0.019***	-0.001***	-0.019***	-0.001***	-0.003**	-0.004***
	(-2.83)	(-2.78)	(-2.79)	(-3.03)	(-2.41)	(-3.83)
Block Dummy	0.035	0.004	0.032	0.003	-0.232**	0.004
	(0.88)	(1.24)	(0.86)	(0.96)	(-2.08)	(0.43)
Opportunistic trading	0.006	0.000	0.006	0.000	0.001	0.002
	(1.29)	(1.17)	(1.40)	(1.16)	(1.06)	(0.98)
Liquidity-PS	0.293	-0.042	0.270	-0.039	-0.333	-1.154
	(0.49)	(-0.72)	(0.53)	(-0.77)	(-0.52)	(-0.80)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,311	2,653	3,960	2,436	501	411
Adjusted R^2	0.17	0.30	0.17	0.31	0.06	0.36

Appendix A1 Variable Definition

Amihud: daily ratio of absolute stock return to dollar trading volume (in $millions) averaged over the year;

PIN: probability of informed trading following Easley et al (1996);

Beta-t: the t-statistic of the beta coefficient estimate on the lag option skew in an augmented Fama-French model for every firm;

Option Spread: out-of-the-money put option daily bid-ask spread averaged over the year. Bid-ask spread is (bid - ask)/ ((bid + ask)/ 2);

Abnormal Short Sales: [(average daily short sales prior to quarterly earnings announcements (day -30 to day -1) divided by average daily short sales for the year outside of pre-announcement periods) – 1];

Supervised: a dummy variable equals 1 if the firm belongs to the supervised industry (SIC code 6000 through 6799, 2830, 2831, 2833, 2836, 4812, 4813, and 4911 through 4991).

Firm Size: log of total assets;

Industry HHI: a Herfindahl index based on annual sales for the firms in the same industry;

Analyst: number of analysts following;

Analyst (log): log number of analysts following;

ROA: income before extraordinary items divided by total assets;

Volatility: standard deviation of daily stock returns for the year;

Stock Turnover: daily stock trading volume scaled by common shares outstanding, averaged over the year;

Blockdummy: a dummy variable equals to 1 if the firm has at least one blockholder with 5% or more equity ownership;

Liquidity-PS: annual average of Pastor-Stambaugh (2003) stock liquidity measure;

Opportunistic Trade: the opportunistic reported stock trades by the firm insiders during the year as in Cohen et al (2010);

Bid-ask Spread: daily stock bid-ask spread averaged over the year;

Earnings Shock: residual from OLS regression of quarterly earnings per share on the EPS of prior quarter, one year ago, and two years ago;

Regulatory Duplicity: a dummy variable equals 1 if the state exhibits a CAMELS test differential greater than the median value of the sample of 45 states. The test differential data is based on Figure 5 in Agarwal et al. (2011).

Corruption: inverse of the state integrity index compiled by Better Government Association;

Budget: (State budget revenue – state budget expense)/ state budget revenue;

Appendix A2 Matched Sample Firm Characteristics

Panel A Matched Sample for Short Sale Test

	Matched Sample with 0.1 Caliper			Matched Sample with 0.01		
	Supervised	Non-	t-test	Supervised	Non-	t-test
Abnormal Short Sale	0.034	-0.055	2.85	-0.016	-0.042	1.83
Earnings Shock	0.026	0.018	1.41	0.014	0.014	0.01
Total Assets ($	8,530.72	2,930.90	4.84	6,081.09	3,199.60	3.63
ROA	-0.109	-0.038	-2.10	-0.032	-0.039	0.28
Analyst	11.542	12.356	1.48	12.543	11.920	0.91
Stock Turnover	10.773	9.654	2.28	11.278	9.621	2.49
Volatility	0.026	0.024	2.17	0.026	0.025	2.01
Blockdummy	0.883	0.918	-1.57	0.919	0.914	0.35
Opportunistic Trade	1.972	2.159	-0.82	2.385	2.445	-0.18
Industry HHI	0.036	0.044	-3.04	0.048	0.047	1.01
Liquidity-PS	-0.001	-0.001	-0.28	-0.001	-0.001	-0.26
Observations	4,774			2,988		

Panel B Matched Sample for Amihud Test

	Matched Sample with 0.1 Caliper			Matched Sample with 0.01 Caliper		
	Supervised	Non-	t-test	Supervised	Non-	t-test
Amihud	0.130	0.100	2.40	0.150	0.094	3.68
Total Assets ($	4,054.13	2,982.60	1.85	3,259.38	2,692.48	0.95
ROA	0.042	0.048	-1.11	0.034	0.036	-0.22
Analyst	9.979	8.520	4.34	9.987	8.480	4.49
Stock Turnover	9.864	8.999	2.44	9.729	8.978	2.17
Volatility	0.037	0.034	2.81	0.035	0.034	1.29
Blockdummy	0.853	0.813	3.00	0.816	0.848	-2.06
Opportunistic Trade	1.723	1.712	0.08	1.726	1.703	0.18
Industry HHI	0.051	0.051	0.42	0.051	0.051	0.07
Liquidity-PS	-0.000	-0.000	-0.08	-0.000	-0.000	-0.10
Observations	20,563			16,628		

Appendix A3 National Level Supervision

Variable definitions are in Appendix A1. The first two columns differentiate among Federal Reserve, FDIC, and OCC oversight. Fed is a dummy variable equals 1 if the commercial bank is regulated by the Federal Reserve, and 0 other wise. FDIC is a dummy variable equals to 1 if the commercial bank is regulated by FDIC, and 0 otherwise. The missing variable is OCC-regulated commercial banks. Columns 3 and 4 differentiate among the 3 categories of Federal Reserved Districts. Category 1 banks are under supervision of New York or Chicago Fed. Category 3 banks are under supervision of Dallas or Kansas Fed. This subsample only includes financial firms with Federal Reserve supervision, not the joint Fed-state supervision. Thus, the banks that are headquartered in the remaining 8 Federal Reserve Districts form the comparison group. We apply Huber-White sandwich estimator (clustered on firm-level identifier) for the standard errors estimation. The t-values (adjusted for small sample size) are reported in parentheses underneath each coefficient estimate. Statistical significance at 10%, 5%, and 1% level is denoted by *, **, ***, respectively.

	Relative to OCC Oversight		Differentiating Among Federal Reserve Districts	
Dependent Variable:	Amihud	PIN	Amihud	PIN
Constant	0.550***	0.512***	0.269***	0.468***
	(4.45)	(2.74)	(19.16)	(23.53)
Fed (=1)	-0.021*	-0.071**	-	-
	(-1.77)	(-2.17)		
FDIC (=1)	-0.011*	-0.050***	-	-
	(-1.69)	(-3.63)		
Banks HQ in Category 1 Districts	-	-	-0.007*	-0.012*
			(-1.89)	(-1.90)
Banks HQ in Category 3 Districts	-	-	0.013**	0.025**
			(2.20)	(2.13)
Firm Size	-0.501***	0.010	-0.094***	-0.018***
	(-4.36)	(0.73)	(-12.92)	(-9.91)
Industry HHI	-0.893	-0.250	0.720*	0.495
	(-0.82)	(-0.97)	(1.76)	(1.06)
Analyst (log)	-0.204*	-0.018	-0.141***	-0.013***
	(-1.87)	(-1.06)	(-8.20)	(-4.51)
ROA	0.546	0.084	0.113*	0.000
	(1.08)	(1.32)	(1.87)	(0.04)
Stock Volatility	1.972**	0.372	1.418***	0.138
	(2.21)	(0.59)	(6.38)	(1.00)
Stock Turnover	-0.052**	-0.000	-0.024***	-0.001*
	(-2.44)	(-1.10)	(-9.30)	(-1.91)
Block Dummy	-0.181	0.013	-0.054*	0.004
	(-1.06)	(0.64)	(-1.78)	(1.20)
Opportunistic trading	0.024	0.006	0.002	0.002*
	(0.93)	(1.02)	(0.43)	(1.72)
Liquidity-PS	-0.049	-0.006	-0.787**	-0.012
	(-1.05)	(-0.20)	(-1.98)	(-1.35)
Year dummy	Yes	Yes	Yes	Yes
Observations	215	188	9,237	7,475
Adjusted R^2	0.498	0.116	0.443	0.141