Becker Meets Kyle: Inside Insider Trading[*]

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Abstract

How do illegal insider traders act on private information? Do they internalize legal risks? We address these questions using a unique sample of illegal insider traders convicted by the Securities Exchange Commission (SEC). To shed light on the traders' investment strategies, we analyze, theoretically and empirically, the tradeoff between the risk of information becoming public (information risk) and the risk of being subject to enforcement actions (legal risk). Consistent with Kyle (1985), insiders manage their trades' size and timing according to prevailing liquidity conditions, fundamental and noise volatility, and the value of the private tips they receive. Behavioral variables, such as gender, age, and profession, play a lesser role. Using various shocks to legal risk, we find that insiders internalize such risk by moderating trade aggressiveness, providing empirical support to the regulators' actions. Consistent with Becker (1968), positive shocks to legal risk also induce insiders to concentrate on fewer private signals of higher economic value. Thus, insider trading enforcement could hamper stock price informativeness.

First Draft: March 16, 2018. ***This Version*****:** May 9, 2019

[*]For comments and helpful conversations we thank Fany Declerk, Itamar Drechsler, Ruslan Goyenko, Chris Hansman, Pete Kyle, Pascal Maenhout, Lasse Pedersen, Natasha Sarin, Michela Verardo, Luigi Zingales, and seminar participants at ASU, Imperial College London, Wharton, the Buyside Conference (London), the Dolomiti Winter Finance Conference, the World Finance Conference (Dubai), the 2018 European Financial Association conference (Warsaw), and the 2018 NBER Summer Institute on Crime. A previous version of this paper circulated under the title "Inside Insider Trading."

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1 Introduction

A large literature in economics and finance argues that private information is transmitted into asset prices through the actions of informed traders. The canonical representation of this process is given by the Kyle model (1985): Knowing the fundamental value of an asset, and internalizing the price impact of trades, an informed trader cautiously spreads trades over time. Despite its extraordinarily intuitive appeal, the empirical testing of this framework is thin. Moreover, the literature largely abstracts from *how* the private information is produced. In the Grossman and Stigliz (1980) tradition, a trader pays a fee to become informed, usually regarded as fundamental research. In real markets, however, private information is frequently obtained by an insider in breach of a fiduciary duty, generating exposure to legal risks, and converting a regular investor into a criminal. Do such *illegal* informed traders behave rationally, as in the Kyle model? Do they internalize legal risks, as in Becker (1968)? Our understanding of these questions is important, since it has implications for efficiency and welfare (Ausubel (1990), Leland (1992)), capital formation (Manove (1989), Easley and O'Hara (2004)), and could help regulators to enhance detection infrastructure (DeMarzo et al. (1998)). While important, these questions pose formidable identification challenges: neither private information nor legal risks are observable.

To address these challenges, we build a hand-collected data set on illegal trading investigations prosecuted by the SEC that documents in detail how certain individuals trade on nonpublic information and summarizes the legal outcomes. We characterize over 5,000 trades in 840 firms over the period 1995–2015, therefore representing a fairly large universe of assets and market conditions. In the first part of the paper, we examine in depth the information sets, trading strategies, and penalties of illegal insider traders, a study that to our knowledge has never been undertaken before. We provide direct evidence on their time horizons, the value distribution of their private signals, the dynamics of information transmission, and construct several metrics of strategic behavior, including the degree of order splitting and measures of informed trade size. To better understand the determinants of those strategies, in the second part of the paper, we develop and test a simple Kyle framework of informed trading activity in which we incorporate legal penalties and random deadlines. Finally, to evaluate the influence of enforcement actions on strategies, we design multiple quasi-natural experiments that exploit exogenous sources of variation in legal risk. To sum up, controlling for individual-level behavioral predictors, the evidence provides strong support both to the predictions of the Kyle-like framework and to the notion that legal risk influences trading strategies.

Sections 2 and 3 provide an end-to-end characterization of illegal insider trading, from the moment in which a private tip on the fundamentals of a given firm is received to the resolution of the legal penalties. First, we assess the value of the information motivating trades by computing hypothetical stock returns that one could realize by initiating a trade when receiving the tip and closing the trade immediately after the corresponding public announcement. The average return of 32.29% indicates that such value is economically large, especially since it accrues over a relatively short period, with a mean information horizon of 28 days. Earnings and M&A events, the two dominant categories, display significantly different averages: 17.78% and 44.26%. M&A events involve, on average, smaller firms, with more short-run upside potential. These figures do not account for embedded leverage in options, which represent 31.83% of the trades in the sample. The distribution of profits is highly skewed: The average and median profits are $757,127 and $44,318. The counterpart of such profitability is found in the value of penalties: The mean and median pecuniary penalties are $2.85m and $0.2m. Slightly more than 10% of the traders are sentenced to jail.

The empirical characterization of the trading strategies offers several novel perspectives. First, consistent with the Kyle model, most traders split trades over time, albeit to different degrees. Among these, the median trader splits trades over a period equivalent to 71% of the information horizon. At the same time, we find that about 20% of insiders do not split their trades at all, which suggests that additional frictions such as attention allocation or other fixed costs could be important. Consistent with this intuition, investors who do not split their trades trade smaller quantities, so they could be relatively less concerned about price impact. Also consistent is the finding that splitting occurs not only over time but also in quantities. Conditional on trading at multiple dates, a simple measure of volume duration indicates that quantities are fairly evenly distributed over time. Finally, we document a great degree of skewness in the distribution of total dollar volume, with an average and median trade of \$1.56m and \$0.15m. The distribution of volume is heterogeneous across assets: On days when insiders trade, they represent nearly 10% of the total volume for stocks and 30% for options.

In the second part of the paper, we aim to understand insiders' trading decisions. The simplest behavioral hypothesis posits that heterogeneity in strategies should be driven by individual characteristics. Indeed, our sample contains various types of individuals, retail traders with a small amount of available capital, wealthy individuals, and institutional investors, such as hedge funds (e.g., Galleon Group, SAC Capital). A substantial fraction of the individuals work in the finance industry or have top executive jobs. Others, have background seemingly unrelated to trading, such as medical doctors and lawyers.

A less behavioral alternative postulates that, despite appearing categorically different, traders respond rationally to the risks and economic incentives they face. To give content to the latter, Section 4 develops a simple two-period Kyle model with insiders deciding when and how much to trade. Apart from an adverse realization of the uninformed traders' order flow, we incorporate two additional sources of risk that are more specific to this environment. Traders face legal risk associated with possible enforcement action, with penalties that are proportional to the economic value of the trade, and they face information risk, that is, the possibility that information becomes public after only one period. The latter risk is likely to affect trades motivated by unscheduled announcements (e.g., Back and Baruch (2004)), but also reflects the risk of competition more broadly (e.g., Holden and Subrahmanyam (1992)). Insiders face a crucial tradeoff: To trade more aggressively when facing greater information risk, or to act more conservatively—splitting orders more evenly and reducing trade size—when facing higher expected legal costs. The equilibrium outcome is a response to the relative strengths of these two forces.

In Section 5, we construct empirical counterparts for the model parameters. We associate events with high information risk to unscheduled M&A events, and validate this intuitive approach by showing that the time between receiving the private tip and the initiation of trades is shorter for these. To proxy for legal risk at the trader level, we use predictive regressions where the dependent variable indicates the legal outcome, either pecuniary or jail penalties. We use controls that are predetermined relative to trades, representing as best as possible traders' ex-ante information sets. Interestingly, penalties are strongly related to traders' legal residence, which determines the litigation court. On the other hand, we find that penalties do not relate significantly to a host of variables that are likely to affect trading decisions.

Next, to test our hypotheses on insiders' strategies, we exploit a regression design that includes as controls the information and legal risk measures, as well as proxies for the Kyle model parameters and several individual-level characteristics (e.g; age, gender, professional background). Among many valuable insights, we find that, first, the baseline predictions from the Kyle model on strategies hold: The value of information and the volatility of the asset value and uninformed trading play, as expected, an important role. At the same time, we do not find evidence that personal characteristics, in the behavioral sense, play an equally central role: Virtually all coefficients of these controls are statistically insignificant. Second, insiders *internalize legal risk*. Everything else being constant, traders facing higher legal risk tend to split their trades more and place orders of more moderate size. Third, traders also factor in information risk: Consistent with the theory, cases with high information risk display values of trade splitting that are, on average, 18% lower, and display relatively lower volume duration. Overall, relative to the benchmark, traders display a remarkable degree of rationality.

A potential identification concern regarding the impact of legal risk is that omitted variables that influence predicted penalties could also affect trades. Such concern is alleviated by the lack of systematic relation between penalties and the various predictors of strategic decisions that we consider. Nonetheless, in the interest of robust identification, we propose multiple quasi-natural experiments that exploit plausibly exogenous sources of variation in legal risk. We consider three time-series and three cross-sectional sources of variation.[1] In the interest of space, we delay until Section 6 a thorough discussion of the institutional and implementation details. The null hypothesis, however, is common across tests: If legal risk increases (decreases), insiders should act more (less) prudently. The model gives content to the notion of prudence: The insider should trade lower quantities and exhibit relatively more early volume and order splitting.

In the first time-series test, we argue that the adoption of the *Dodd-Frank Act* strengthened legal risk. Indeed, we document that in the wake of the new regulation, related Federal penalties increased significantly. We then show that, as a result of this change, the average insider shifts trade volume to earlier periods and is less likely to submit large trades. Our second time-series shock is the 2014 Supreme Court ruling on *SEC vs. Newman*, which significantly narrowed the application of insider trading laws, and was subsequently used as a precedent to redeem many allegedly guilty subjects. We find that, following this shock, the average trader becomes *less* cautious, increasing quantities and trading duration. Finally, we investigate whether *subjective* perceptions of risk can influence strategies. With that goal, we design a test that exploits Google Trends searches associated with the phrase "illegal insider trading". Our results indicate that periods of high incidence of such searches are associated with more prudent insider behavior.

The first cross-sectional test exploits differences in detection sources. In particular, we contrast the trades of insiders who are detected through the SEC Whistleblower Reward Program (WRP) with those identified through different means. We argue that the WRP group is likely more sophisticated, since regulatory agencies, by design, fail to identify their trades; therefore, their sensitivity to legal shocks could be different. We find that WRP traders reduce quantities more sharply in response to the Dodd-Frank enforcement shock. Second, we exploit exogenous variation in individual courts' enforcement strength. Specifically, we investigate the impact of Preet Bharara, the U.S. Attorney of the Southern District of New York (SDNY), who earned a reputation of a "crusader" prosecutor. Given that his employment spell was ex-ante uncertain, we regard his 2009–2013 tenure as a positive shock to legal risk. We find that traders *within* the SDNY jurisdiction significantly

[1] Naturally, panel data analysis is not feasible in this setting, since prosecuted traders do not reappear in periods subsequent to legal actions.

reduced their trade aggressiveness over this period. Finally, we consider the trades of investors who, according to the SEC, traded on superior information, but, according to a judge, acted *lawfully*. We show that their strategies show *more aggressive* trading profiles, consistent with them not acting under the threat of similar legal risk.

Besides the various tests on strategies, we also assess the impact of legal risk from the perspective of the ex-ante choice of engaging in criminal activity. Following the insights from Becker (1968), a rational trader that internalizes legal risk would be less willing to act on any given private signal if either the probability of enforcement or the conditional penalty increase. Under this view, the result of a shock to expected legal costs is that the insider acts on fewer private signals with higher expected return. We test this hypothesis by comparing the average private signal value motivating trades before and after the considered time-series shocks to legal risk. Consistent with this canonical crime model, we identify a strong increase in that average at times of greater risk.

Our paper relates to several strands of literature. In addition to the theoretical work on illegal insider trading we cite above, on the empirical front, an important paper by Meulbroek (1992) documents its impact on stock returns and market efficiency. Our evidence on the importance of expected legal costs strongly suggests that the institutional framework is an important determinant of market efficiency. More recently, Del Guercio et al. (2017) study the effect of a time-varying enforcement environment on price discovery. Their evidence is consistent with our time-series characterization of expected legal risk. Kallunki et al. (2018) analyze the impact of wealth on the decision to engage in insider trading. We complement their results by providing evidence on the impact of expected legal costs regarding that decision.[2]

Second, we provide new direct evidence on what determines the use of private information in financial markets. Theoretical literature has identified links between private information and stock liquidity (e.g., Glosten and Milgrom, 1985; Kyle, 1985; Easley and Hara, 1987), option liquidity (e.g., Biais and Hillion, 1994), stock price volatility (e.g., Wang, 1993), and option price volatility (e.g., Back, 1993). Empirically, Cohen et al. (2012) and Klein et al. (2017), among others, examine

[2] Also related are the studies by Cornell and Sirri (1992) on stock liquidity, Ahern (2017) on insider traders' information networks, and Kacperczyk and Pagnotta (2019) on asymmetric information proxies.

the characteristics of legal trades by corporate insiders. Among the few studies that have carefully examined flows of private information in financial markets are those of Koudijs (2015, 2016). Our evidence in support of the Kyle model prediction on *strategies* complements that of Koudijs, which is based on stock return correlations from the 18th-century Amsterdam market. We note that the historical setting in the latter study precedes currently prevailing insider trading laws.

Also related is a large literature that empirically analyzes financial misconduct. Among others, Dyck et al. (2010) analyze the behavior of whistleblowers in the context of corporate fraud. Karpoff and Lou (2010) discuss the importance of short sellers for the detection of financial reports' misrepresentations. Egan et al. (2018) analyze the sample of financial advisors and analyze ex-post penalties imposed on such advisors. Our paper is, to the best of our knowledge, the first to focus on ex-ante implications of legal risk, both for trading behavior and private information transmission.

2 Insider Trading Background and Data

2.1 Background on Insider Trading

Insider trading is a term that includes both legal and illegal conduct. The legal variety is when corporate insiders—officers, directors, large shareholders, and employees—buy and sell shares in their own companies and report their trades to the SEC. Legal trading also includes, for example, someone trading on information that was overheard between strangers sitting on a train or when the information was obtained through a non-confidential business relationship.

The illegal variety is not defined homogeneously around the world. In the U.S., the legal framework prohibiting insider trading was established by Rule 10b-5 of the Securities Exchange Act of 1934, which specifies that illegal insider trading refers to "buying or selling a security in breach of a fiduciary duty or other relationship of trust and confidence, while in possession of material, nonpublic information about the security". Under the classical view of insider trading, a trader violates Rule 10b-5 if he trades on material, nonpublic information about a firm to which he owes a fiduciary duty. Information is deemed *material* if a reasonable investor would consider it important in deciding whether to buy or sell securities. In recent decades, the scope of what constitutes illegal insider trading has increased. In particular, the 1997 Supreme Court case of United States v. O'Hagan upheld the SEC's authority to enforce insider trading under the so-called misappropriation theory. Under this theory, it is a violation of Rule 10b-5 to intentionally misappropriate and trade on confidential information in "breach of a duty owed to the source of the information". What constitutes such a violation of duty is a controversial legal issue.[3,4]

The consequences of being found liable for insider trading can be severe. Individuals convicted of criminal insider trading can face up to 20 years of imprisonment per violation, criminal forfeiture, and fines of up to $5,000,000 or twice the gain from the offense. A successful civil action by the SEC may lead to disgorgement of profits and a penalty not to exceed the greater of $1,000,000, or three times the amount of the profit gained or loss avoided. The common rule is that the penalty be equal to the size of the profits realized in the case, in addition to the forfeiture of profits realized in the case. In addition, the court requires the insiders to pay interest on the profits amount and typically bars a convict from trading activities for a substantial period. Moreover, individuals can be barred from serving as officers or directors of a public company, or in the case of licensed professionals, such as attorneys and accountants, from serving in their professional capacity before the Commission.

2.2 A Tale of an Insider Trader

To illustrate the main elements of a typical insider trading case, we begin with the story of Matthew Martoma–one of the most prominently featured insiders over the last few decades.[5] Between 2006 and 2010, Martoma worked at CR Intrinsic, an unregistered investment adviser, serving as a portfolio manager from 2008 until his departure. Martoma perpetrated the insider trading scheme with Sidney Gilman, a professor of neurology at the University of Michigan.

[3] Battacharya (2014) provides an insightful overview of the related legal arguments.

[4] Despite the aforementioned increased scope, finding a trader guilty of insider trading is not easy. The legal practice of insider trading asserts that to find a tippee criminally liable for insider trading, federal prosecutors must prove all of the following elements: (i) the insider had a fiduciary duty; (ii) the insider breached that duty by disclosing confidential information to a tippee; (iii) the tip was made in exchange for a personal benefit, meaning a benefit of some consequence; (iv) the tippee knew of the tipper's breach (that is, the tippee knew the information was confidential and divulged for a personal benefit); and (v) the tippee nevertheless used that information to make a trade.

[5] For a more extensive and vivid description of Martoma's case and his involvement with SAC Capital, see Kolhatkar (2018).

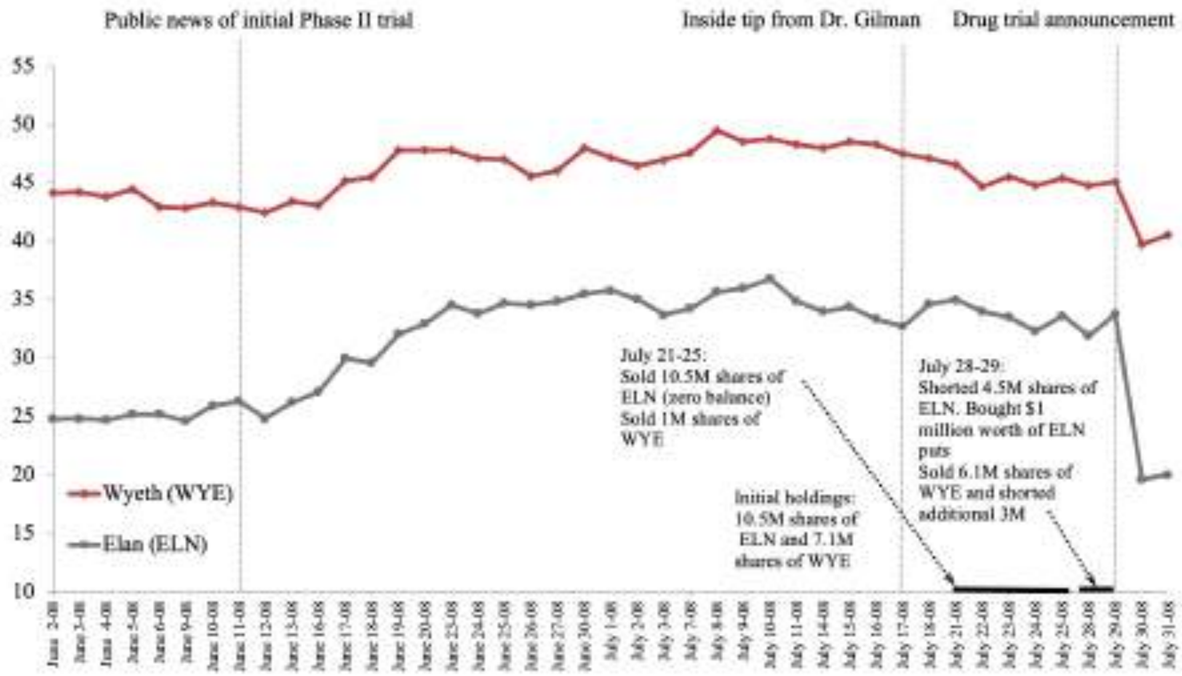
Gilman served as a consultant to Elan (ELN) and Wyeth (WYE)—two pharmaceutical companies—from 2003 until 2009. Between 2006 and 2008, Elan and Wyeth jointly conducted a Phase II clinical trial for a potential drug to treat Alzheimer's disease called bapineuzumab. As a consultant, Gilman had continuous access to material nonpublic information concerning this trial. Among many duties, Gilman agreed to present, on behalf of Elan and Wyeth, the Phase II Trial results at the International Conference on Alzheimer's Disease, a medical conference that was scheduled to be held on July 29, 2008. As a result of agreeing to serve as the presenter, Gilman was given access to the results approximately two weeks prior to the July 29 announcement. By virtue of his roles in the clinical trial, Gilman owed Elan a duty to hold in strict confidence all information he learned in connection with his participation in the clinical trial and to use such information only for Elan's benefit.

Gilman first met Martoma through paid consultations arranged by the expert network firm. Gilman provided Martoma with nonpublic information concerning the Phase II Trial starting in at least 2007. In the weeks leading up to the July announcement, Gilman held several calls with Martoma during which he provided information regarding the safety and efficacy results for the trial. On July 17-18, 2008, Gilman and Martoma had a lengthy phone call during which Gilman suggested that the drug had potential serious negative side effects.

On the morning of Sunday, July 20, 2008, Martoma indicated to a portfolio manager of the affiliated asset management company that he was no longer comfortable with the Elan investments held. Before the market opened on July 21, 2008, these portfolios held over 10.5 million Elan shares worth over \$365 million and over 7.1 million Wyeth shares worth over \$335 million, a combined position of over \$700 million. On the morning of July 21, 2008, the portfolio manager began selling both companies' shares. Later, the manager communicated to Martoma that he executed sales for over 10.5 million ELN at an average price of \$34.21 over a 4–day period.

Although the investment advisers' portfolios achieved a zero balance in Elan securities by July 25, 2008, they continued to sell short Elan securities on July 28 and 29, until the public announcement. By the close of the market on July 29, 2008, both companies had a combined short position of

Figure 1. Chronology of Martoma's insider trading investigation and stock prices



approximately 4.5 million securities. The gross sales proceeds of Elan shares exceeded $500 million and constituted over 20% of the reported trading volume in the seven days prior to the announcement. In addition, on July 28 and July 29, they purchased over $1 million worth of Elan put options with strike prices below the Elan share price on those 3 trading days.

Regarding Wyeth, between July 21, 2008 and July 29, 2008, both companies sold over 10.4 million shares for gross proceeds of over $460 million, including over 6.1 million Wyeth shares worth over $270 million during the announcement day. As a result of these sales, they reached a zero balance in Wyeth stock during the trading day on July 29, 2008, but continued to place short sales that day. By the close of the same day, the portfolios had a combined short position of approximately 3.3 million Wyeth shares. The trading in Wyeth securities constituted over 11% of the reported trading volume in the seven days prior to the announcement.

On July 29, 2008, after the close of the U.S. markets, Gilman presented the results of the Phase II trial at the aforementioned conference. The market reacted negatively. On July 30, 2008, Elan's shares opening price was $19.63, declining nearly 42% relative to the previous close price of $33.75.

In turn, Wyeth's stock price fell from to \$39.74 from \$45.11, a decrease of nearly 12%. Figure 1 presents the time series of Elan and Wyeth stock prices and summarizes Martoma's trades.

As a result of the trades motivated by Martoma's conversations with Gilman on July 17, 2008, the involved parties reaped profits and avoided losses for over \$276 million. At the end of 2008, Martoma received from SAC a bonus of over \$9.38 million, while Gilman received merely over \$100,000 from the expert network firm for his consultations with Martoma and other analysts.

Following the inquiry based on the whistleblower tip, the SEC launched a formal investigation. On February 6, 2014, Martoma was found guilty of insider trading. Subsequently, on September 8, 2018, the Southern District of New York sentenced him to 9 years in prison. He was also requested to forfeit his bonus. Gilman agreed to forfeit \$234,000–the amount he earned in the scheme, plus interest.

2.3 Insider Trades: Data Collection and Summary Statistics

To gain the broadest possible perspective on insider trading investigations, we retrieve a list of all SEC litigation press releases that contain the term insider trading. We use this list to obtain all the available civil complaint files available on the SEC website. In cases in which the complaint file is not available, we rely on information from the U.S. District Court where the case is filed and/or manual web searches. We collect all files starting from January 2001 until December 2015.[6] The resulting sample of 453 legal cases represents all SEC cases that were either litigated or settled out of court describing insider trading activity spanning trades over the period 1995–2015. The average number of investigations per year in our sample is 30.83, with a maximum number of cases (46) filed in 2012. Similarly to the case of Martoma, most complaint files include a detailed account of the allegations, including biographical records of defendants, individual trades, a description of the associated corporate event, and the relationships between tippers and tippees.

The information is organized by characterizing trades and information events. A *trade* is any single transaction record for which we can observe a date and a trading instrument (e.g., stocks or

[6] We track all documents that provide updates on a previously released complaint file. Whenever updated information is made available at a later date, we rely on the most recent version. For additional details on the characteristics of SEC complaint files, see Kacperczyk and Pagnotta (2019).

options). For most trades, additional information about the price, trade direction, quantity, trading profits, and the closing date of the position is also available. An *information event* is a collection of one or more trades that were motivated by a unique piece of private information, such as an earnings announcement or a merger. The key information event records include the companies involved, the nature of the leaked information, and the date at which the information was released to the public.

Firms and trades. The data collection yields a total of 5,058 unique trades involving 840 firms. The top panel of Table I displays general characteristics of the sample of trades and associated firms. The distribution of the number of firms per case is highly asymmetric. While the mean is slightly over two, approximately 80% of the cases involve a single firm, while 4% of the cases involve 10 firms or more. The sample is fairly evenly distributed over time, with over 100 trades in each year between 1999 and 2014. The observed dispersion of trades across years is an attractive feature, since it allows us to address identification issues related to time-specific macro events. The majority of cases involve single trades in a given company, but the mean and median trader in the sample executes near 20 and 10 trades, respectively, with a maximum of 97 trades. The median firm generates 13 trades.

Corporate events, industries, and traded assets. Table II describes the event types, trading instruments, and affected firms. The most frequent event categories are M&As (55.90%), followed by earnings announcements (15.06%). The business events and corporate events categories (10.71%) include, among others, items such as information about products, a firm's projects, patents, FDA medical trials, corporate restructuring, bankruptcy, or fraud. Given the importance of mergers and acquisitions in our sample, the majority of private signals are positive. Across all events, there are 4,220 buys (83.43%) and 838 sells. The vast majority of trades are executed via stocks (67.06%) and options (31.83%). The remaining few are trades in American depositary shares and bonds. The three most represented industry sectors in our sample are chemicals, business services, and electronic equipment, which account for more than 40% of all trades. However, we note that the trading involves companies spanning almost all industrial sectors.

Personal and professional background. Table III summarizes available personal background for the 1079 traders in the sample. The median age of tippers and traders is almost identical and equals 45 years and 46 years, respectively. The vast majority of tippers and traders are male. Specific corporate roles are available for 410 traders, and we observe a substantial cross-sectional dispersion among those. Low and mid-level management positions account for 25.61% and 20.48% of traders, respectively. Top corporate positions, defined as vice-president rank or higher, amount to 53.90% of jobs. An important number of traders work in the finance industry, including 59 portfolio managers, 30 brokers/dealers, and 21 analysts. Among those individuals with non-finance jobs, the top four occupations involve business owners, lawyers, medical doctors, and accountants.

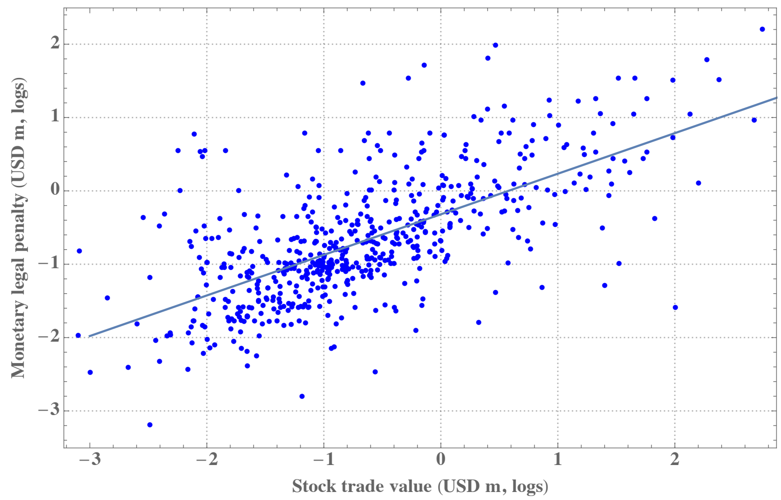
Profits. The goal of any insider trading scheme is to generate monetary profits. In most investigations, the SEC reports the profits that are generated by the traders involved. We also collect this information so as to understand its distribution. The average trade profit of $757,127 and the median is $44,318. About 49% of trades elicit at least $100,000 in profits. The most profitable trade within our sample is that of Martoma.

2.4 Legal Penalties: Data Collection and Summary Statistics

Legal risk can materialize through two types of penalties: pecuniary ones, typically determined in the process of civil court investigation, and non-pecuniary ones, determined through a criminal investigation. Typically, monetary penalties are set in proportion to the trading profits, as discussed in Section 2.1. Criminal cases usually end up with two types of resolutions: jail penalty or probation. Jail penalty varies from as little as a few months to several years. Probation does not usually take longer than 3 years. In civil courts, occasionally, a case presented by the SEC can be dismissed due to lack of strong evidence. Anecdotally, these are usually politically popular cases, or cases with a significant amount of insider trading (e.g., Steve Cohen of SAC).

We collect detailed information on each type of penalty for each defendant in the sample. Some of the information is reported in the complaint files reported by the SEC. However, a significant fraction of files misses the relevant information. We append such missing records through website

Figure 2. Insiders' trade values and monetary penalties



searches that include court reports, newspaper articles, and legal websites (e.g., Lexis Nexis). We obtain precise dollar figures for 587 traders. Panel B of Table I summarizes the data. The average monetary penalty for a given trader in our sample amounts to \$2.85 million, while the median is \$0.2 million. The largest individual penalty corresponds to Raj Rajaratnam of Galleon Fund and equals approximately \$160 million. The average total penalty per case, that is, including all involved trades, equals \$11.74 million, with the median of \$1.25 million. Penalties can vary across traders in a given case. The average standard deviation of within case penalties equals \$3.16 million, though the median is significantly smaller and equal to \$0.08 million. More than 10% of traders in our sample receive a jail penalty, with an average duration of 3.5 years. In a given case, 10% of traders are jailed. An additional 23.5% of traders receive probations. Finally, 12% of traders have their cases dropped.

The assignment of cases to courts is generally based on the geographic proximity to the trader's permanent address. We collect details on the different courts involved since, in principle, the severity of penalties could depend on the ruling court. The sample includes a total of 77 different courts. The most prominently featured courts include the Southern District of New York (30.4% of cases), the District of Columbia (6.1%), and the Central District of California (5.5%).

Penalties and trades. In most situations, penalties take the form of a monetary sum determined by a court's decision or as the outcome of an out-of-court settlement with the SEC. Although penalties are frequently determined in relation to profits, a significant proportion of the profit figures reported in the investigations are joint figures involving multiple traders. To gain perspective on the relation between penalties and the economic size of the insider trading scheme, however, we can relate individual penalties to individual trades, since the latter are available in most cases. The result is displayed in Figure 2 using a log scale. Interestingly, although the relation between trade value and penalties is certainly not deterministic, one can observe a strong and positive association between these two variables. The relation documented here implies that trade values can be seen as a reasonable proxy for expected penalties. We exploit this insight in later sections.

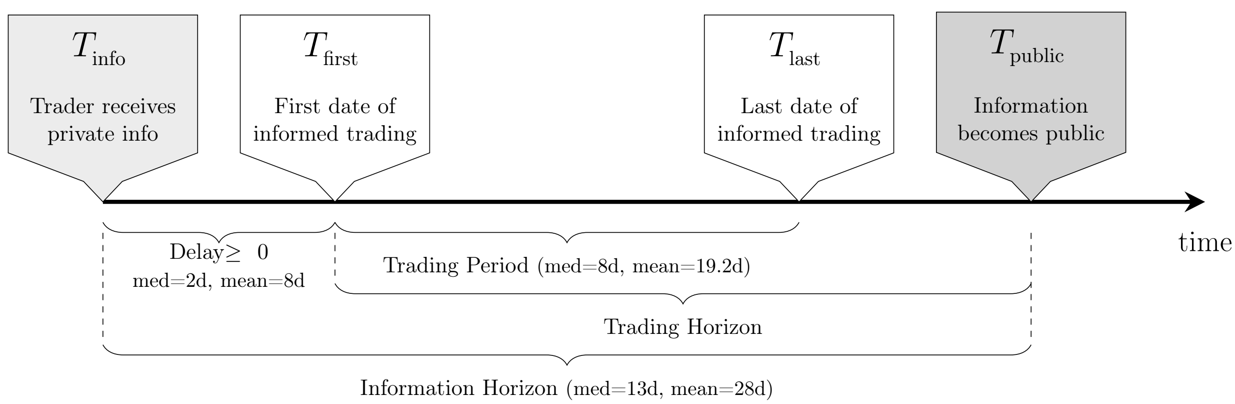
3 Private Signals and Insiders' Strategies: Direct Evidence from SEC Investigations

The case of Martoma illustrates a number of key strategic elements associated with any insider trading case. In this section, we extend the analysis to the entire sample of investigations and document novel facts about the duration of such asymmetric information episodes, the value of private signals, and the relation between information transmission and trades. Moreover, we exploit precisely identified insider trading dates and quantities to construct measures of strategic behavior that summarize the actual use of private information.

3.1 Information and Trade Horizons

We begin with characterizing the most important dates in a given investigation, which we graphically represent in Figure 3. The event begins at date T_{info} when the trader receives a private signal about a given firm's fundamentals. Such information advantage disappears at date T_{public} when that private information becomes public (e.g., a quarterly earnings release date). Given $\{T_{\text{info}}, T_{\text{public}}\}$, the trader decides upon $\{T_{\text{first}}, T_{\text{last}}\}$, the first and last dates of trading. Because trades are motivated by private information, $T_{\text{first}} \geq T_{\text{info}}$ and $T_{\text{last}} \leq T_{\text{public}}$. We take both T_{info} and T_{public} as exogenous

Figure 3. Time line of an insider trading case



parameters from the trader's perspective, while trading days can be better seen as endogenous. This allows us to benchmark individual investors' trading decisions. Accordingly, we define the *information horizon* as $T_{\text{public}} - T_{\text{info}}$ and the *trading horizon* as $T_{\text{last}} - T_{\text{first}}$, both measured in number of days. The trading horizon is trivially exogenous in the limit case where $T_{\text{info}} = T_{\text{public}}$, that is, when the trader receives the signal just before the public announcement.

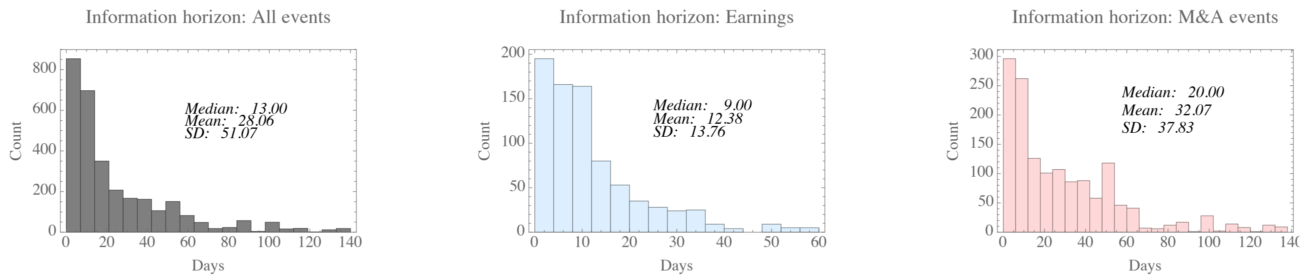
The left panel of Figure 4 displays the distribution of information horizons for the entire sample. The mean and median values are 13 and 28 days, respectively. The center and right panels display the distribution for earnings and M&A events, respectively. Private information is longer lived for M&A events: The mean value of 32 days is more than twice the value for earnings, which is 12.4 days. Given the unscheduled nature of M&A announcements, some of which are delayed for months, we observe significantly higher skewness in the right tail of the distribution. We also note that the median delay between the arrival and the use of information is two days, and that the median period from any given trade until T_{public} is seven days. The median trading horizon is eight days.

3.2 The Value of Private Signals

The SEC verifies the material and nonpublic nature of information in insider trading investigations. But how material is the information received? In other words, how strong is its information content? To shed light on this aspect, we exploit an attractive feature of our sample: the ability to observe

Figure 4. Distribution of private information horizons

This figure displays the distribution of private information horizons ($T_{\text{public}} - T_{\text{info}}$). The left panel corresponds to all events. The center and right panels correspond to earnings and M&A events, respectively.



when information is received by traders. Accordingly, for each information event, we compute the percentage change in the corresponding stock price from the opening price on T_{info} to the opening price immediately after the information becomes public, on date $T_{\text{public}} + 1$. We denote the absolute value of such return as the *private signal value* (PSV):

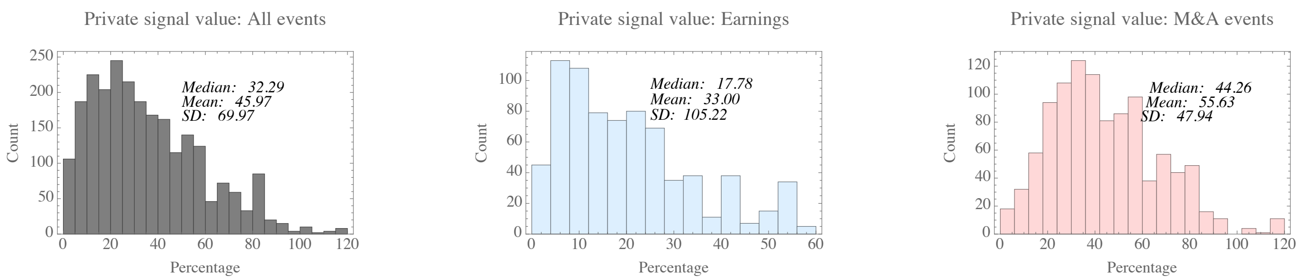
$$PSV := \left| \frac{\text{Opening Price}(T_{\text{public}} + 1) - \text{Opening Price}(T_{\text{info}})}{\text{Opening Price}(T_{\text{info}})} \right|. \tag{1}$$

The left panel of Figure 5 displays the distribution of PSV for the entire sample. The mean and median values are remarkably high at 45.97 and 32.29 percent, respectively. The center and right panels show that the distributions for earnings and M&A events are quite different: The median PSV value for earnings is only 17.78%, while the median value for M&A events is 44.36%. Indeed, for a non-negligible fraction of M&A cases, the value of PSV is greater than 100 percent.

These PSV values are remarkably large, especially in light of the median information horizon of two weeks. Moreover, one could treat these returns as a lower bound on the actual profitability, since about 30% of trades are in options, hence embedding leverage. To put the PSV figures in perspective, it is helpful to consider alternative groups of traders that likely possess private information. Kacperczyk and Pagnotta (2019) construct benchmark returns for a sample of SEC 13D form filers between 1994 and 2014. The trades of 13D filers represent significant long positions in securities and have been shown to predict positive stock returns, so they can be interpreted as

Figure 5. Distribution of private signal values

This figure displays the distribution of PSV (see equation (1)). The left panel corresponds to all events. The center and right panels correspond to earnings and M&A events, respectively.



based on positive news (e.g., Brav, Jiang, and Kim, 2015; Collin-Dufresne and Fos (2015)). The benchmark return is based on the return measured from the opening of the day when the 13D filer trades an asset until the opening of the day following the release of the trade information to the public. The mean and median returns for 13D filers are 4.9% and 2.4%, respectively.

3.3 Characterizing Insider Trading Strategies

Once a trader is in possession of private information, he must design a strategy. In principle, a strategy is a complex contingent plan involving times, quantities, and prices. It is difficult to empirically summarize all of these different dimensions using a single metric. Therefore, we construct four simple measures reflecting specific aspects, and refer to them as *strategic decisions*.

We consider two measures that reflect the timing of informed trades. First, given that strategic informed traders are expected to distribute their trades over multiple periods, we exploit precisely identified trade dates to define *Splitting* as the ratio between the trading and information horizons:

$$Splitting := \frac{T_{\text{last}} - T_{\text{first}}}{T_{\text{public}} - T_{\text{info}}} \subseteq [0,1]. \tag{2}$$

To illustrate the application of *Splitting*, consider Martoma's trade in ELN and WYE, as described in Section 2.2. The information horizon is 12 days ($T_{\text{info}} = 07/17/08$ and $T_{\text{public}} = 07/29/08$). The trading horizon is 8 days ($T_{\text{first}} = 07/21/08$ and $T_{\text{last}} = 07/29/08$). Therefore, $Splitting = 2/3$.

Second, to account for the time distribution of trades *within* the trading horizon, we define *Duration* as follows:

$$Duration := \frac{1 \times |\text{Informed vol}_{\text{early}}| + 2 \times |\text{Informed vol}_{\text{late}}|}{|\text{Informed vol}_{\text{early}}| + |\text{Informed vol}_{\text{late}}|} \subseteq [1, 2], \tag{3}$$

where Informed $\text{vol}_{\text{early}}$ and Informed vol_{late} are the dollar values of informed trades during the first and second half of the trading horizon, respectively. In contrast to *Splitting*, *Duration* reflects how early trades are executed rather than whether they are spread out over time. Intuitively, values of *Duration* close to 2 indicate that a high proportion of the informed trade volume is executed near T_{public}. Because Informed vol is based on dollar figures, we restrict the computation of *Duration* to stock trades only. For options, approximating the dollar value is challenging because a significant proportion of option trades in the investigations do not contain all contract characteristics (i.e., either exact moneyness or maturity is missing).

Next, we use precisely identified trade quantities to define two volume-related measures. First, *Bet* := Informed vol, is the total dollar value that an insider trades over the entire trading horizon. Second, *Intensity,* is the ratio of informed trading relative to the normal market volume, defined as the average daily dollar volume for the same asset over the previous calendar year. Formally, for any given trader we compute:

$$Bet := \text{Informed vol (over } \{T_{\text{first}}, T_{\text{last}}\}), \tag{4}$$

$$Intensity := \max_a \left\{ \frac{\text{Informed vol}_a}{\text{Normalvol.}_a} \right\}, \tag{5}$$

where $a \in$ {stocks, calls, puts}. The max operator reflects the fact that some traders, like Martoma, use both stocks and options. For options, normal volume is computed across all contracts with the same underlying stock.

Next, we characterize the distributions of the strategic decisions. For *Splitting*, we first show that, perhaps surprisingly, the proportion of cases where insiders do not split their trades is economically significant. Indeed, the proportion of cases in which investors trade only on one day equals 20.8%

for trades motivated by earnings and 18.8% of those by M&A events. The proportion of single-day trades is higher in the case of stocks, 23.4%, than options, 14.6%.[7] *Duration* for these trades is trivially equal to one.

Second, for the majority of cases where some degree of order splitting is observed, we observe a substantial amount of cross-sectional heterogeneity, as shown in the top left panel of Figure 6. Notably, the median value is relatively high at 0.71, indicating that traders take advantage of a significant proportion of the private information horizon.

The top right panel shows that the distribution of *Duration*, for cases with more than one trade, is remarkably symmetric: The median value equals exactly 1.5. This fact suggests that the median trader splits orders *both* across times and quantities. Like for *Splitting*, we also observe a wide range of cross-sectional attitudes for this strategic dimension.

The bottom panels show the distributions of *Bet* and *Intensity*, both of which are highly skewed. The median value of *Intensity* is 7% while the mean is more than twice that amount, 19%. Moreover, we observe a significant heterogeneity across trading instruments. On average, when insiders are present, 10.76% of the corresponding daily stock volume can be attributed to their trades. For options, that proportion is 34.27%.

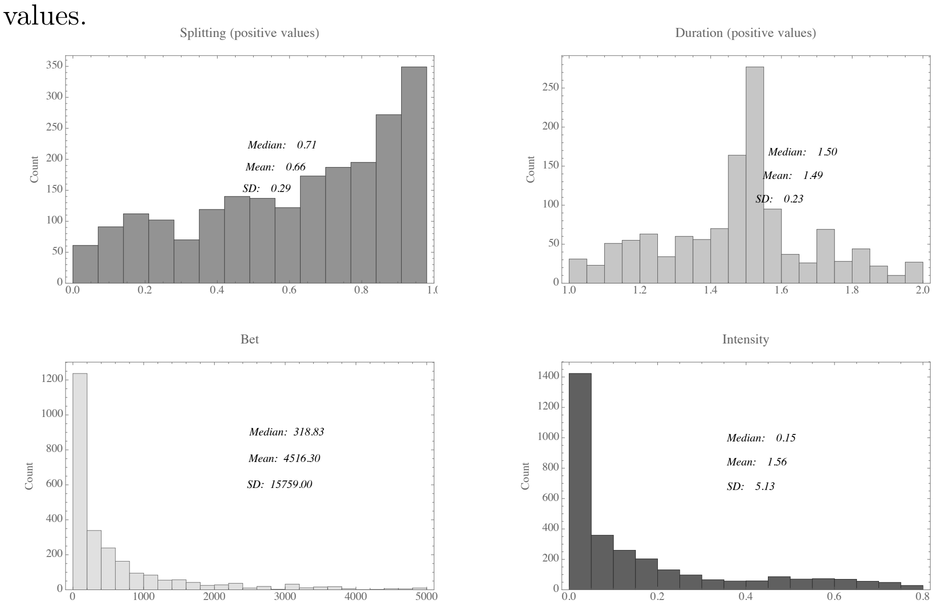
3.4 Characterizing Information Transmission

In the sections above, we characterized the value of private signals and the insider trades motivated by them. Do such trades fully reveal the information contained therein? We gain perspective on this question by studying the price adjustment process between the open on day T_{first} and the day immediately after the public release of information, $T_{\text{public}}+1$. To facilitate comparisons, we consider a nonparametric time scale by dividing the period between T_{first} and T_{public} into ten subperiods of equal length, and calculate for each subperiod the median cumulative stock return across events. The results are displayed in Figure 7. By construction, the sample of cases in the figure have trading horizons of at least ten days. Each of the first 10 bars corresponds to the trading subperiod. The

[7] We note that, albeit limited, some degree of order splitting is still possible on a single day. We face data limitations to reflect such intraday splitting, since we do not observe intraday time stamps.

Figure 6. Distributions of strategic decisions

This figure displays, from top to bottom, the empirical distribution of *Splitting*, *Duration*, *Bet*, and *Intensity* (see equations (2) to (5)). The distributions of *Splitting* and *Duration* are conditional on nonzero values.

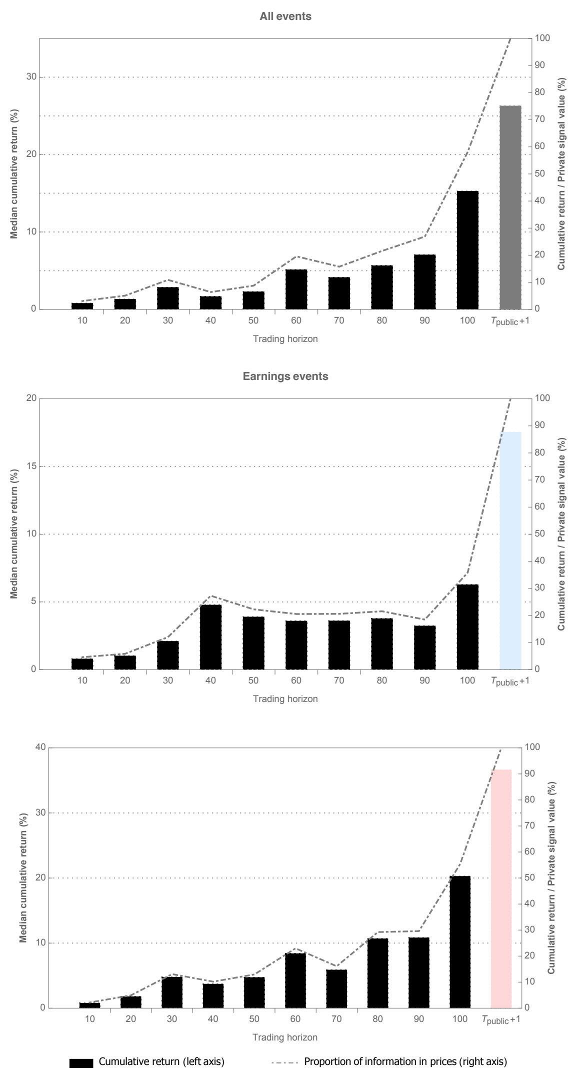


rightmost bar corresponds to the median PSV value, representing the *total* amount of information. The dotted line corresponds to the ratio of the corresponding cumulative return to the PSV, as a percentage, expressing how much private information is impounded into the price over time (100% at date $T_{\text{public}} + 1$).

The analysis delivers three insights. First, relative to counterfactual risk-neutral traders that would smooth information transmission until revealing the private signal, in the spirit of the continuous-time models of Kyle (1985) and Back (1992), insider traders here impound significantly less information into prices. The top panel of Figure 7 shows that the median cumulative return at the end of the trading period is about 58.1% of the PSV. Second, although the process of information aggregation is visible from the first period of trading, about half of the information transmission takes places in the last round of trades preceding the public announcement. Third, we observe a striking contrast among corporate event types. Consider the middle and bottom panels of Figure 7 displaying earnings announcements and M&A events, respectively. We can see that scheduled earnings events are characterized by *less* information aggregation overall. Indeed, only 30% of the

Figure 7. Trades and information transmission into prices

This figure displays the process of information aggregation into prices. Trading horizons are divided into ten subperiods. Each of the ten leftmost (black) columns represents the cumulative return from the first trade up to the corresponding decile. The rightmost column corresponds to the median private signal value. The dotted line corresponds to the percentage ratio between each decile column and the rightmost column and reflects the proportion of private information in prices.



median PSV is reflected in prices before the public announcement. Moreover, earnings display a rather flat time series of cumulative returns. The bulk of the price effect is reflected into prices during the first part of the trading period.

4 A Simple Analytical Framework

In this section, we analyze a simple theoretical framework that allows us to benchmark insiders' strategic decisions. Following the seminal contributions of Kyle (1985) and Becker (1968), we consider a profit-driven rational informed trader that internalizes both liquidity and legal risks. The insider also faces the risk of information loss, that is, the risk of losing his information advantage before the public announcement of the private signal. Such information risk stylistically captures the fact that a large proportion of the information sets documented in Section 2.3 have uncertain announcement dates, including mergers, acquisitions, and the results of medical trials or patents.

4.1 Information and Enforcement Environment

We consider a two-period strategic trading model in the tradition of Kyle (1985). The value of the asset v satisfies $v \sim N(p_0, \sigma_v^2)$. One informed trader observes v at time 0 and submits market orders x_t, $t = 1, 2$. Nonstrategic liquidity traders submit market orders of size u_t, with $u_t \sim N(0, \sigma_u^2)$. A competitive market maker observes the aggregate order flow given by $y_t = x_t + u_t$ and sets the asset price p_t accordingly.

Apart from an adverse realization of uninformed orders u, the informed trader faces two additional sources of risk. The first one is *information risk*. With probability ρ, the value v is publicly announced between periods 1 and 2 and the informed trader loses his informational advantage after one period. Everything else being equal, unscheduled corporate announcements can be linked to high values of ρ. In contrast, scheduled corporate earnings can be seen as events with relatively low ρ values.[8]

[8]We note that ρ can still be positive for earnings, for example, if quarterly figures accidentally leak to the public in advance of the announcement. Moreover, the insider can be concerned that other insiders could receive the same tip and become competitors (e.g., Holden and Subrahmanyam (1992)). To keep the analysis simple, we interpret greater risk of competition as an increase in the same parameter, ρ.

Second, the informed trader internalizes *legal risk*. With probability q the regulatory agency detects the illegal trade and, in that case, assigns a monetary penalty, C. The expected penalty, K, is thus $q \times C$. We assume that enforcement takes place after trades, that is, any legal penalty is known after period 2. Furthermore, conditional on detection, the penalty is set according to $C(x_1, x_2) = c(|x_1| + |x_2|)^2$, $c > 0$.

One can interpret insider trading detection as originating from a whistleblower or industry player such as a broker reporting to a regulator about suspicious trades, wither x_1 or x_2 or both. Regardless of the detection method, the analysis of the insider's trading account by regulators reveals the sequence $\{x_1, x_2\}$. The fact that C is an increasing function of x reflects the intuitive fact that the regulator imposes penalties that are proportional to the economic importance of the illegal trade. The quadratic functional form is primarily chosen for tractability. Although the evidence in Section 2.4 suggests that monetary penalties may not bear a convex relation with trade size, such a relation could be reasonable provided large illegal trades are more likely to lead not only to civil but to criminal prosecution as well. In other words, potential jail penalties for large trades can be seen as having large pecuniary equivalents.

We note that information risk and legal risk are likely to imply different trade paths. If information is lost after period 1, one would not anticipate $x_2 > 0$. Otherwise, regardless of the ex-post investigation outcome, the insider is likely to trade in each period. In other words, the regulator can impose ex-post penalties on insider trading but cannot stop trades in either period.

4.2 Trade Dynamics and Equilibrium

At the beginning of period 1, having observed v, the informed trader has a value function V_1 given by

$$V_1 = \max_{x_1 \in \mathbb{R}} \left\{ \mathbb{E}\left[(v - p_1) x_1 + (1 - \rho) V_2 | v \right] - \rho K(x_1) \right\}. \tag{6}$$

The third term in equation (6) corresponds to the expected penalty in the event that information is disclosed early and trading in period 2 becomes worthless, where $K(x_1) = q \times c x_1^2$.

Conditional on no early disclosure, the value function in period 2 is given by

$$V_2 = \max_{x_2 \in \mathbb{R}} \left\{ \mathbb{E}\left[(v - p_2)\, x_2 | v, p_1 \right] - K\left(x_1, x_2\right) \right\}. \tag{7}$$

Competition and informational efficiency force the market maker to set prices $p_1 = p_0 + \mathbb{E}\left[v - p_0 | y_1\right]$ and $p_2 = p_1 + \mathbb{E}\left[v - p_1 | y_1, y_2\right]$. The following proposition characterizes the resulting linear equilibrium.

Proposition 1. *There exists a unique linear equilibrium with $x_t = \alpha_t + \beta_t v$ and $p_t = p_{t-1} + \lambda_t \left(x_t + u_t\right)$, $t = 1, 2$, given by*

$$\beta_1 = \frac{\left(1 - \left(\frac{1-\rho}{2\gamma_2}\right)(\lambda_1 + 2qc)\right)}{2\left(\gamma_1 - (\lambda_1 + 2qc)^2 \left(\frac{1-\rho}{4\gamma_2}\right)\right)}, \quad \alpha_1 = -p_0 \beta_1, \tag{8}$$

$$\beta_2 = \frac{1}{2\gamma_2}\left(1 - 2qc\beta_1\right), \quad \alpha_2 = \frac{1}{2\gamma_2}\left(2qc\beta_1 p_0 - p_1\right), \tag{9}$$

$$\lambda_1 = \frac{\beta_1 \sigma_v^2}{\beta_1^2 \sigma_v^2 + \sigma_u^2}, \tag{10}$$

$$\lambda_2 = \frac{\beta_2 \sigma_v^2}{\left(\beta_2^2 + \beta_1^2\right)\sigma_v^2 + \sigma_u^2}, \tag{11}$$

$$\gamma_t = \left(\lambda_t + qc\right). \tag{12}$$

Proposition 1 allows us to investigate the connections between the information and legal variables, and the behavior of insiders and market makers, $\{\beta_t, \lambda_t : t = 1, 2\}$. These relations are illustrated in Figure 13. Next, we exploit such connections to derive empirical predictions for order timing and trade quantities.

4.3 Empirical Predictions

To illustrate the implications of the model's equilibrium, we study the average trading behavior of the informed trader using metrics that resemble the (italicized) strategic statistics in Section 3:

$$\text{Splitting} = \mathbb{E}\left(1 - \frac{|x_1 - x_2|}{|x_1| + |x_2|}\right), \tag{13}$$

$$\text{Duration} = \mathbb{E}\left(\frac{1 \times |x_1| + 2 \times |x_2|}{|x_1| + |x_2|}\right), \tag{14}$$

$$\text{Intensity} = \mathbb{E}\left(\frac{|x_1| + |x_2|}{2}\right). \tag{15}$$

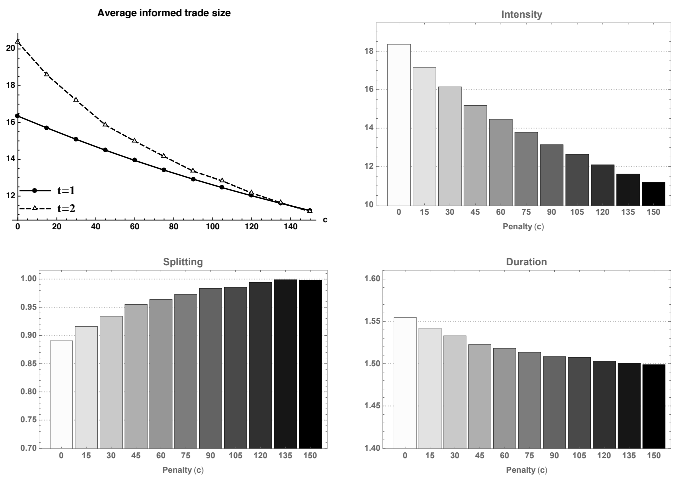
Splitting reflects how evenly distributed over time informed trades are, and takes a value equal to 0 if all trades are concentrated in a single period, and a value equal to 1 if all trades are identical. *Duration* reflects the proportion of early/late trade volume, taking a value between 1 and 2. *Intensity* captures the average informed trade volume. Because there is only one asset in the framework, the expression is simpler than the empirical counterpart in equation (5).

We simulate trading sessions to compute the moments defined by equations (15) to (14). The median information horizon in the sample equals two weeks and, therefore, in assigning parameter values, we interpret a period as representing a trading week. We set the standard deviation of noise trading equal to the within-sample standard deviation of stock volume at weekly frequencies, $\sigma_u = 67.49$. To set σ_v, we consider a representative stock price of $p_0 = 10$ and find the standard deviation value that rationalizes the mean PSV value in the sample. We do so by inverting the mean equation of the folded normal distribution,[9] obtaining $\sigma_v = 8.43$. Finally, we set the (empirically unobservable) probability of detection equal to 20%. For expositional clarity, in the simulations that follow, we condition the moments on paths for which there is no early information disclosure.

Legal risk. To develop economic intuition, consider first the case where the insider faces legal but no information risk ($c > 0$, $\rho = 0$). The top left panel of Figure 8 displays the average informed trade size per period, and the remaining panels display the strategic metrics (13) to (15). As the

[9]Recall that if $x \sim N(\mu, \sigma)$, $y = |x|$ has a mean value $\mu_Y = \sigma\sqrt{\frac{2}{\pi}}e^{\left(-\mu^2/2\sigma^2\right)} + \mu\left(1 - 2\Phi\left(\frac{-\mu}{\sigma}\right)\right)$.

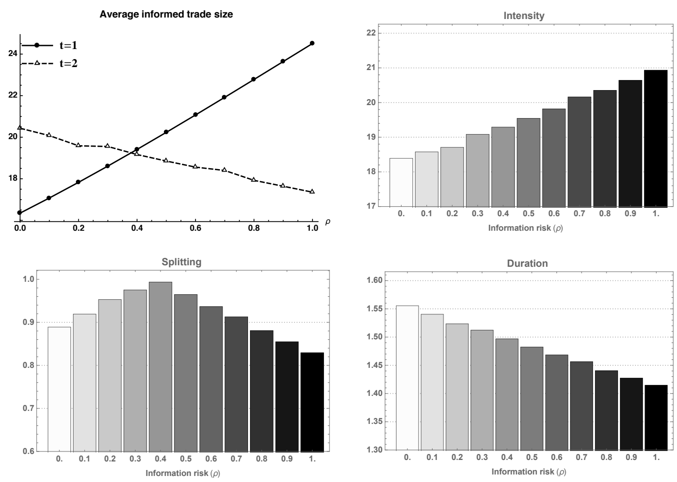
Figure 8. Empirical Predictions: Legal Risk



penalty parameter c increases, the insider internalizes expected enforcement costs by reducing the order size in each period and, in equilibrium, the price is less informative about the private signal. Note, however, that the effect on trade sizes is not identical. Indeed, penalties act as a factor that increases the effective impact of an informed trade, thereby incentivizing more even trades over time, thus increasing the value of *Splitting*. As the relative weight of trades at time $t = 1$ increases, the value of *Duration* decreases.

Information risk. Consider now the case in which the insider faces information risk but no legal penalty ($\rho > 0$, $c = 0$). The left panel of Figure 9 displays the average informed trade size, and the remaining panels display the strategic metrics (13)–(15). As the risk of losing the information advantage increases, the insider trades more aggressively in the early trading round and less aggressively in the late one. These trading patterns imply that the value of *Splitting* increases for relatively low values of ρ, and decreases for relatively high values. The effect on *Duration*, on the other hand, is monotonic: The greater the value of ρ, the greater the importance of informed trading in the first period. In the aggregate, the informed trade volume increases and *Intensity* displays higher values.

Figure 9. Empirical Predictions: Information Risk

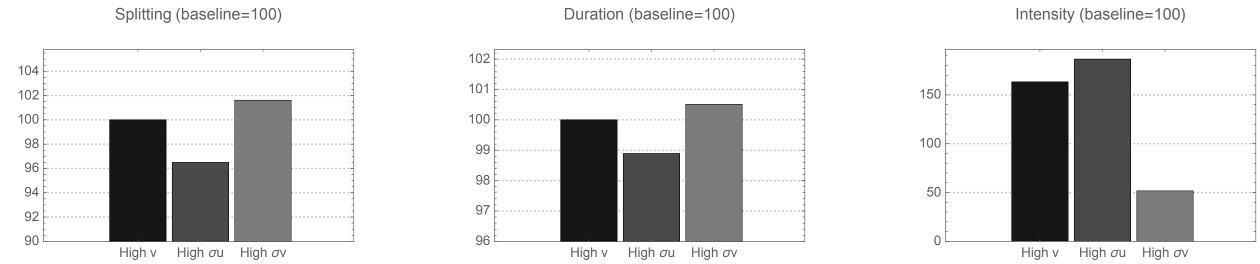


Kyle model parameters. Besides legal and information risk, the economic environment is defined by three primitives that are also present in the traditional Kyle model: the value of the private signal realization, $(v - p_0)$, the volatility of noise trading, σ_u, and the ex-ante volatility of asset value, σ_v. We briefly comment on the impact of parameter changes, as illustrated in Figure 10. As one would expect, an increase in the value of the private signal increases the average trade size in each period and, therefore, increases *Intensity*. On the other hand, *Splitting* and *Duration* are unaffected, since the relation between β_1 and β_2 is not driven by the realization of v. Also familiar is the effect of an increase in σ_u and σ_v, which have a positive and a negative effect on *Intensity*, respectively. The effect on *Splitting* is also of opposite sign: An increase in σ_u decreases its value while an increase in σ_v induces the informed trader to split trades more evenly.

Next, based on the insider trading and legal penalties samples in Section 2, we construct empirical proxies of the various parameters and design empirical tests to evaluate the model's predictions.

Figure 10. Comparative Statics: Kyle Model Parameters

Baseline parameter values are as in Section 4.3, $\rho = 1/2$ and $c = 1/60$. High v, σ_u and σ_v correspond to 15, 16.86, and 135, respectively.



5 Empirical Strategy and Baseline Results

We are interested in understanding the determination of insider traders' strategic trading decisions in light of the economic fundamentals discussed in previous sections. For that, we estimate the following regression model:

$$StrategicDecision_i = a + b \times Kyle_i + c \times Indiv_i + d \times Inforisk_i + e \times Legalrisk + \text{error}_i, \quad (16)$$

where *StrategicDecision* refers to either *Splitting*, *Duration*, *Bet,* or *Intensity*, as defined in Section 3.3. The vector of variables *Kyle,* in equation (16), corresponds to a set of controls that act as proxies for the parameters of the Section 5's model. To proxy for the asset value uncertainty (σ_v), we use *Realized Volatility,* based on 30-minute stock returns and averaged over the previous calendar year. We measure the amount of noise trading (σ_u) using the average volatility of daily trading volume over the previous calendar year, *Volume Vol.* To account for the value of the private signal, we compute *Strength* by replacing T_{info} by T_{first} in equation (1). This is because movements in the market price can cause the value of the private signal at the time of trading to differ from the corresponding PSV. We also include the natural logarithm of market capitalization, *Ln (mkt. cap),* to account for the ex-ante heterogeneity in liquidity levels that can affect informed traders' decisions. Table IV provides descriptive statistics for the dependent variables and regressors.

Next, we elaborate on the specification of additional control variables related to individual characteristics and the measures of information risk and legal risk.

5.1 Individual Characteristics

Prior behavioral research shows that trading behavior could be affected by individual characteristics, such as age, gender, or occupation. For example, age could proxy for individual risk aversion. Holding everything else constant, one could expect older traders to behave more conservatively. On the other hand, age could be a proxy for career concerns, implying that older insider traders may exhibit greater risk tolerance. Likewise, various psychological studies argue that males are, on average, more overconfident than females. As such, they should be less sensitive to penalties and other risks. Finally, trading expertise could affect the propensity to place trades carefully, for example, by splitting trades more extensively.

To account for the above characteristics, we add the following additional controls. *Age,* corresponding to traders' age (in years). *Gender,* an indicator variable equal to one if a trader is a male, and zero if a trader is a female. We note that traders in our sample are predominantly male and, therefore, we may have limited statistical power to identify gender effects. *Executive,* is an indicator variable that equals one when the trader is a top executive in any industry (defined as vice president or higher rank). *Finance* is an indicator variable that equals one when the trader works in the financial services industry. The latter two variables can be seen as proxies for trading experience or familiarity with the trading process of stocks and options; each one encompasses about a fourth of the individuals in the sample.

An additional individual-specific factor we consider relates to the information source, as follows. We define *Tipper Insider* as an indicator variable that equals one if the trader or the tipper works for the affected company. The intuition we rely on is that traders could deem information as being more reliable when its source comes directly from the affected firm (first-hand information). High information precision could reduce the incentive to wait for subsequent signals, decreasing *Duration*, and/or could induce larger trade sizes.

5.2 Information Risk

To proxy for information risk, that is, the risk that private information is lost before T_{public}, we primarily rely on the content of information sets. Specifically, we define an indicator variable *Inforisk* equal to one for trades associated with M&A activity, and zero for all other trades. The intuition is that, relative to alternative corporate events such as earnings, M&A events expose the insider trader to higher risk of an early public announcement.

Second, as an alternative way to measure information risk, we consider the number of traders involved in a given SEC investigation, *NumberTraders*. Economic intuition suggests that the speed of information use should increase when there is a threat of losing it to a competitor (e.g., Holden and Subrahmanyam, 1992). In this context, however, the connection between the number of informed traders and information risk is more nuanced, because those traders could be part of an insider trading ring. Nonetheless, we hypothesize that, the larger the number of individuals that have access to the private signal, the larger the risk that such signal is lost to a potential competitor. Hence, traders acting on information that has also been disseminated to others, could be less willing to delay action.

To assess whether our empirical proxies are related to actual information risk, we explore whether they affect the opportunity cost of delaying informed trading, measured as the interval between receiving the private signal, T_{info}, and T_{first}. Formally, we define *ActionDelay* as follows:

$$ActionDelay := \frac{T_{\text{first}} - T_{\text{info}}}{T_{\text{public}} - T_{\text{info}}} \subseteq [0, 1].$$

If the type of corporate announcement or the number of traders are related to information risk, one would expect to see a negative relation with *ActionDelay*. To assess such hypothesis, we estimate the following regression model:

$$ActionDelay_i = a + b \times Inforisk_i + c \times Traders_i + d \times Controls_i + error_i,$$

where *Controls* is a vector of control variables including those in *Kyle* and *Indiv* as in equation

(16). Table V presents the estimation results. Column (1) corresponds to a univariate regression model without controls. Columns (2) and (3) extend the empirical specification by adding *Kyle* and *Indiv* as controls, respectively. We obtain very similar results in all specifications: There is a strong and inverse relation between *ActionDelay* and *Inforisk*, consistent with the above intuition. The coefficient is both statistically and economically significant. In the most comprehensive model, moving from scheduled events to unscheduled events reduces *ActionDelay* by 33% of the variable's cross-sectional standard deviation. At the same time, *NumberTraders* does not display a significant statistical association. Therefore, in the subsequent section, we rely on *Inforisk* as a primary empirical proxy for information risk.

It is also noteworthy to discuss the direction of the two additional estimated coefficients. We observe a negative and statistically significant coefficient for *Strength,* indicating that traders use their private signals more quickly when they are more valuable. Such an effect is consistent with the notion of heterogeneous opportunity cost of delaying trades in the context of an uncertain information horizon. On the other hand, insiders delay the use of private signals relatively more when trading stocks with high *Realized Volatility.* The latter finding is consistent with traders relying on timing options for highly volatile assets.

5.3 Legal Risk

In the analysis of Section 4, the informed trader internalizes the effect of the expected penalty cost as given by the product between the probability of detection and the conditional penalty. Ideally, one would like to account for each variable separately in the cross-sectional analysis. Theoretically, say, the probability of detection could vary from one trader or financial institution to another. However, such an approach is clearly unfeasible.

To proxy for legal risks, therefore, we rely on the data on pecuniary and jail penalties, described in Section 2.4. Because legal risk is an ex-ante construct we use predicted penalties as proxies therefor. Specifically, we first take the perspective of an insider with information set observed at the time of receiving the private tip and use available information to predict the value of each type of penalty. For that, we specify the following model:

$$Penalties_i = a + b \times CourtFE_i + c \times Indiv_i + d \times TipperInsider_i + e \times Controls_i + error_i, \quad (17)$$

where $Penalties$ is either a pecuniary or a jail penalty, denoted *Penalty* and $Jail$, respectively. We include a vector of court fixed effects as a natural predictor of the severity of penalties, as well as the individual characteristics contained in the vector $Indiv$, as described above. We also include $TipperInsider$, since receiving the private tip first hand could be regarded as a legal risk driver. Finally, we include a set of controls that include $Kyle$ and $Inforisk$.

The estimation results in Table VI yield two interesting insights. First, legal jurisdiction is a strong predictor of penalties. For example, the top three courts (the SDNY, District of Columbia, and California) display positive and statistically significant coefficients. While the SDNY displays the largest fixed effect on pecuniary penalties, California displays the largest value for jail penalties. Second, *Penalty* and *Jail* are not significantly related to predictors of insider trading activity included in *Kyle* and $Inforisk$. Individual characteristics estimates are not statistically significant, but for the most part display signs that are intuitive. For example, pecuniary penalties are positively related to age, being male, and working in the financial industry. At the same time, they are negatively related to $Executive$.

Next, for each insider trader, we use the predicted values from regression (17) to construct two measures of legal risk that to be used in model (16): *PredJail* for jail and *PredPenalty* for monetary penalties. Again, because all regressors in (17) are predetermined relative to strategic trading decisions, these legal risk measures capture ex-ante information sets. At the same time, one could be concerned that omitted variables driving the variation in trading decisions could also affect the value of penalties. The analysis in this section lessens such concerns, since we find that virtually all determinants of strategic trading decisions are unrelated to these predicted regressors. Nonetheless, we explore several alternative identification strategies in Section 6.

5.4 Baseline Empirical Results

This section presents the baseline estimation results from equation (16) that characterize the relation between insider traders' strategic behavior and economic fundamentals and risks. Table VII displays OLS estimation coefficients for the timing-related decisions*, Splitting* and *Duration,* and the volume-related decisions, *Bet* and *Intensity.* All specifications include *Inforisk* and the two measures of predicted penalties as the leading independent variables. All reported standard errors are clustered at the trader level.[10] For *Splitting,* we include an indicator variable for cases with zero values to explore the intensive margin of the variable. To facilitate the proper interpretation of the results, we normalize the value of *Intensity* using its mean and standard deviation.

Columns (1) reports the results for *Splitting.* Consistent with the theoretical prediction, we find that the coefficient of *Inforisk* is negative and statistically significant. The effect is also economically substantial: Cases with $Inforisk$=1 display values of *Splitting* that are, on average, lower by about 18% of the cross-sectional standard deviation of the variable. Also in line with the theoretical prediction is the positive and statistically significant coefficient of *PredPenalty*, indicating that traders facing higher legal risk tend to split their trades more fully. Economically, a one-standard-deviation increase in *PredPenalty* increases *Splitting* by almost 15% of its cross-sectional standard deviation. The effect of *PredJail* is also positive, but statistically insignificant, and economically four times smaller. Perhaps surprisingly, traders reduce the degree of order splitting when *Realized Volatility* is high. Although this finding is contrary to the theoretical prediction, we note that the model could lack generality in this regard, since it only considers risk-neutral traders. We also note that the variables in *Indiv* that control for individual characteristics are not statistically significant predictors of *Splitting.*

Column (2) reports the results for *Duration.* Consistent with the theoretical prediction, we find that the effect of *Inforisk* is negative and statistically significant. It is also economically large as cases with $Inforisk$=1 exhibit the levels that are lower by 33% of the cross-sectional standard

[10] Clustering at the trader level allows us to capture the within trader dependence of error terms. In unreported results, we also consider clustering at the firm level to account for within firm dependence. The results from this alternative estimation produce slightly lower standard errors. Hence, we proceed with the more conservative findings.

deviation. The relation between *Duration* and legal risk is also negative, but it is only statistically significant for $PredJail$. A one-standard-deviation movement in the latter variable reduces *Duration* by about 10% of its standard deviation. The fact that higher legal risk induces earlier trades is consistent with the model analysis, but perhaps not surprising in light of the results for *Splitting*, since these two measures are of course related. However, for the case of *Duration* more specifically, a negative coefficient is also consistent with a simple legal risk intuition: If detection of trades occurred, the insider trader would be in a better defensive position if trades were more distant in time from the official corporate event. Turning to other determinants, similar to $Splitting$, $Duration$ is not systematically related to individual characteristics. On the other hand, somewhat contrary to the model prediction, $Duration$ is higher for trades associated with high values of $Strength$ and $VolumeVol$, and negatively related to $RealizedVolatility$.

We now turn to *Bet* and *Intensity*, in columns (3) and (4). As expected, the coefficient of $PredPenalty$ is negative and statistically and economically significant for both metrics. On the other hand, we observe no statistically significant relation between *Inforisk* and informed volume. Somewhat contrary to the model intuition, insiders trade less aggressively when the private signal is more powerful. Such behavior is consistent with insiders targeting a given *nominal* monetary gain: Ceteris paribus, if a given dollar amount is targeted, signals of higher value require lower trade volume. The estimated coefficients of *Ln*(*mktcap*) for *Bet* and $Intensity$ illustrate the fact that dollar informed volume is positively related to firm size, while the opposite is true for the *proportion* of informed volume. The negative sign of $Intensity$ is consistent with traders facing some form of capital constraint. Finally, traders in the financial industry trade more aggressive quantities. All other individual coefficients are statistically insignificant.

The estimates of the coefficients defined here are broadly consistent with our theoretical predictions. In particular, for both measures of risk, we observe a positive relation with *Splitting* and a negative relation with *Duration.* The relation between *PredPenalty* and *Intensity* is negative, as predicted. The same is positive for *PredJail*, but statistically insignificant. We also note that the measure based on jail penalties is a stronger predictor of *Duration,* suggesting that expected jail penalties can also be informative about strategic trading decisions.

Taken together, the results in this section yield three important insights. First, insiders consider legal risk in the timing of their trades, and they trade off such risk against information risk in a way that is broadly consistent with the model's predictions. Second, the decision about trading quantities is less influenced by information risk. Third, perhaps surprisingly in light of previous behavioral finance results, the variables that control for individual characteristics, such as age and gender, are not statistically significant predictors of strategic decisions. Decisions seem to be influenced to a much higher degree by the canonical determinants of profit-maximizing (rational) trading considered in Kyle models, such as the amount of noise trading, the fundamental uncertainty in the asset value, and the realization of the private signal value. That said, even controlling for information and legal risk, our results also suggest that a simple Kyle model is unlikely to provide a full description of strategic decisions. Our findings suggest, that features, such as risk aversion and capital constraints that are absent in the classic Kyle model are likely to play a role as well.

The fact that strategic decisions are affected by legal penalties should be of interest not only to academics but to regulatory agencies and law makers alike. Given the importance of this finding, we end this section by noting that a potential concern with our identification scheme is that, unlike for trading strategies, exact measures of detection probabilities and ex-ante conditional penalties are not available. Given that we cannot entirely rule out measurement error in our proxies, or formally test the unlikely but problematic possibility that probabilities and penalties are negatively related, we exploit in Section 6 a comprehensive set of plausibly exogenous shocks to the components of legal risk.

6 Do Insiders Respond to Changes in Legal Risk?

To strengthen the identification of insiders' legal risk impact, we introduce and evaluate various plausibly exogenous shocks to the detection of insider trades or the corresponding penalties. The underlying null hypothesis in all tests is that, if legal risk increases, the insider should act more prudently. The model in Section 4 provides specificity to the notion of prudent behavior: The insider trader trades lower quantities, increases *Splitting,* and reduces *Duration.* We also conjecture that *Duration* should decrease if (i) the defense case of the insider is stronger, when trades do not occur immediately before an announcement, or (ii) if the regulator screens trades that occur close to that announcement.

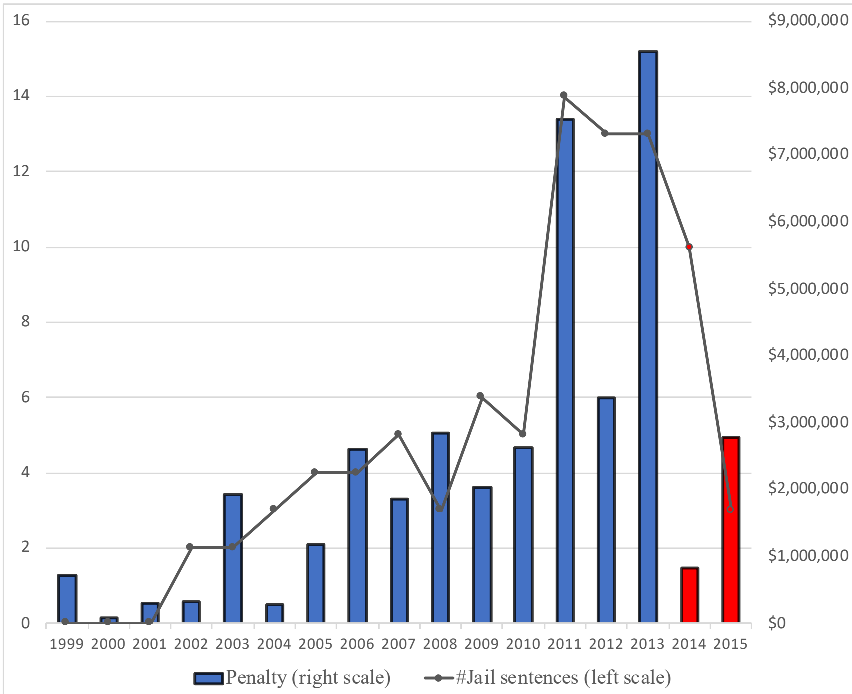
6.1 Evidence from the Dodd-Frank Act

As a reaction to the financial crisis and the negative public sentiment on the status quo of the financial industry, on July 21, 2010, President Obama signed into law the Dodd-Frank Wall Street Reform and Consumer Protection Act (the Dodd-Frank Act). This landmark legislation strengthened and expanded the regulatory oversight and enforcement authority of the SEC over securities markets. Furthermore, in the same period, the Obama administration increased the SEC budget and that of related government agencies (Del Guercio, Odders-White, and Ready (2017)). Perhaps equally important, as a component of this changing regulatory atmosphere, the SEC strengthened the investigation focus on more prominent and economically substantial insider trading investigations, imposing larger penalties. For example, besides the case of SAC capital discussed above, the SEC brought Raj Rajaratnam of the Galleon fund to court, who at the time managed over $7 billion in assets, and Rajat Gupta, head of McKinsey & Co, generating strong attention in the media and Wall Street (e.g., Raghavan (2015)).

To validate the economic importance of these developments, Figure 11 displays the time series of the annual numbers of insider trading jail sentences and the total monetary values of insider trading penalties. Starting in 2011 and up to 2013, we observe an economically significant upward shift across both series.[11] In light of these factors, therefore, we treat this period as one in which expectations regarding insider trading legal risk receive a positive shock. To test the effect of the

[11] As an example, record-breaking criminal and civil penalties were handed out to insider trading defendants in 2011. On the criminal side, federal courts sentenced a record number of insider trading defendants and sentenced a higher proportion to prison than in any prior year. The vast majority of sentences, however, remained below the Sentencing Guidelines (the "Guidelines") range and the recommendations of prosecutors. On the civil side, the SEC settled or secured judgment in almost twice the number of insider trading cases it had brought to final judgment the year before.

Figure 11. Insider Trading Penalties and Jail Sentences 1999–2015



shock, we set 2008–2010 as a natural control period. Such symmetric time window reduces the possibility that we capture additional regulatory changes over more extended periods that could affect the results. Next, we estimate the following regression model:

$$StrategicDecision_i = a + b \times DoddFrank_i + c \times Controls_i + d \times Court_i + \mathrm{error}_i,$$

where *DoddFrank* is an indicator variable equal to one for insider trades taking place within 2011–2013, and zero for the trades during the 2008–2010 period. The control variables are as in the baseline specification (16). We also include court fixed effects to control for the possibility that the legal jurisdiction may drive the strength of penalties assessed to insiders.

Columns (1) to (4) of Table VIII present the results. We observe that the enforcement shock affects trading decisions. In particular, we find that *Duration* decreases as hypothesized. The change is statistically and economically significant, since the coefficient decreases by 19.93% in 2011–2013 relative to its standard deviation. Both *Bet* and *Intensity* display negative coefficients, as hypothesized, but they are not statistically significant. On the other hand, we do not find evidence of a positive relation with *Splitting*. In sum, we find strong evidence that during the enforcement shock period informed trades occur earlier, on average, and there is weak evidence that informed volume decreases overall.

6.2 Evidence from the Newman Ruling

The time-series evidence in Figure 11 also identifies a sharp decrease in pecuniary and jail penalties during 2014–2015. This remarkable reversal in the severity of penalties resulted from a specific Supreme Court ruling involving two hedge fund managers: Todd Newman and Anthony Chiasson. Both managers were brought to trial but subsequently released. The Supreme Court judges' view was that no offense is committed unless a corporate insider acting as the tipper receive money or valuable property, such as jewelry, in exchange for leaking material information. Because the defendants were several layers removed from the original information leaks, and no evidence was found about payments, it was hard for prosecutors to prove with near certainty that these managers were aware of the wrongful acquisition of that information.

Such stricter interpretation of the law torpedoed a number of insider-trading prosecutions across the Second Circuit, which includes New York and Connecticut, where many hedge funds are based and most such cases are brought.[12] The consequences of the ruling were immediate and dire. U.S. Attorney of Manhattan, Preet Bharara, was forced to dismiss nearly a dozen of the hundred and eleven insider-trading cases that he had brought since assuming his post in August, 2009. Among the cases that were abandoned were several in which he had already obtained guilty pleas. Many argued that 2014 reduced significantly the expected legal risk associated with insider trading. This trend is formally supported by the time-series variation in assessed penalties and jail sentences.

If the Newman ruling reduced expected penalties, we should observe the opposite effect on strategic decisions relative to that of Dodd-Frank. To test the prediction formally, we define an indicator variable *Newman* equal to one for the period 2014–2015, and zero for the period 2011–2013.

[12]See, for example, https://www.nytimes.com/2016/08/02/business/dealbook/supreme-court-could-rewrite-insider-trading-law.html

Subsequently, we estimate the baseline regression model with *Newman* as a main control variable. The results are presented in columns (5) to (8) of Table VIII. Consistent with lower legal risk and less prudent behavior, the estimated coefficients for *Duration* and *Intensity* are positive and statistically significant. Both effects are economically large. Also, as predicted, the effect on *Bet* and *Splitting* are positive and negative, respectively, but statistically insignificant. The evidence therefore supports the view that traders responded to the weak enforcement environment post Newman ruling by trading more aggressively.

6.3 Evidence from the Whistleblower Reward Program

The sensitivity to legal risk could vary across traders, among other factors, depending on the trader's skills or ability. We conjecture that highly able traders internalize the risk of being detected and could develop superior skills at camouflaging their trades. Relative to poorly skilled individuals who might not fully grasp the relation between trades and detection risk, high-ability traders could be more sensitive to a positive shock to legal risk like that considered in Section 6.1. To test such hypothesis one needs to classify traders across skill levels. Naturally, SEC investigations do not provide such classification. In principle, one could rely on a skill measure based on the characteristics of detected trades, for example, whether traders display high or low *Splitting* values. However, such ex-post classification would pose additional identification challenges. For example, depending on market conditions, a highly skilled trader could find it optimal to concentrate trades on a relative short period if that decision lowered detection probability.

Instead, to select skilled traders, we rely on a different identification scheme based on the trader detection source. In particular, we exploit a a hand-collected sample of trades identified through the SEC Whistleblower Reward Program (WRP), implemented as part of the Dodd Frank Act in 2011. The underlying idea of the program is to use monetary payments to incentivize whistleblowers to provide regulators with *original information* on insider trading activity. The program defines original information as one that is (i) derived from the independent knowledge or analysis of a whistleblower, (ii) not known to the SEC from any other sources, and (iii) not exclusively derived from an allegation made in a judicial or administrative hearing, governmental report, hearing, audit, or investigation or from the news media. Since such insider traders are not identified by any other means, it seems plausible to regard this group as more highly skilled.[13] For the period 2011–2015, our sample contains 187 different cases, 47 of which are investigated through the WRP and 140 of which do not have a precise source of investigation. The latter could be the result of SEC/FINRA data analyses or based on other tips such as those coming from brokers or stock exchanges. Table IX summarizes various trading characteristics and shows that the two sets of cases are not very different from each other along most dimensions. The only notable difference is that WRP cases involve, on average, companies with greater market capitalization.

Subsequently, we assess whether skilled traders respond differently to changes in the enforcement environment following the adoption of Dodd-Frank Act. Formally, we estimate the following model:

$$\begin{aligned} StrategicDecision_i = a + b \times WhistleB_i + c \times DoddFrank_i + d \times WhistleB_i \times DoddFrank_i \\ + e \times Controls_i + f \times Court_i + \text{error}_i, \end{aligned}$$

where *WhistleB* is an indicator variable equal to one for traders identified through the WRP, and *DoddFrank* is defined as before. The coefficient of interest is d, which measures the sensitivity of strategic decisions to the trader detection source. Columns (1) to (4) of Table X present the results. Sophisticated investors are more likely to reduce their trade volume when facing greater enforcement risk. For *Bet*, the interaction term coefficient is negative and statistically significant at the 5% level. For *Splitting,* the coefficient of the interaction term is positive with a t-statistic slightly above 1.5, suggesting that this group of traders is more likely to spread trades more extensively when facing positive enforcement shock than the average individual in the sample.

[13] Of course, there is also a chance that a trader in this sample is not sophisticated but simply lucky. The identification ability of this scheme relies on a population-wide feature: the probability of being detected by regulatory agencies decrease in one's trading skills.

6.4 Evidence from the Southern District of New York

Another dimension to evaluate the effect of legal risk is the cross-sectional variation in enforcement strength. We take advantage of the anecdotal evidence on insider trading prosecutions suggesting that the Southern District of New York (SDNY) has become a renownedly tough court under the reign of Preet Bharara, the U.S. Attorney of the same district. Bharara was appointed in 2009 and continued until 2017. As a U.S. Attorney, Bharara earned a reputation of a "crusader" prosecutor.[14] However, the 2014 Supreme Court Newman ruling discussed above weakened his power substantially. In this regard, we argue that potential illegal traders faced particularly strong legal risk during the early part of his tenure, spanning 2009–2013, a period we label as the *Bharara* period.

To evaluate the incidence of such cross-sectional variation in legal risk, we compare the strategic decisions of traders under SDNY jurisdiction to those investigated by other jurisdictions during the Bharara period and during adjacent periods. Under the hypothesis that the Bharara period had a positive impact on legal risk, one would expect that insiders located in the SDNY should behave more prudently then. Next, we estimate the following regression model:

$$\begin{aligned} StrategicDecision_i = b \times SDNY_i + c \times Bharara + d \times SDNY \times Bharara \\ + e \times Controls_i + f \times Court_i + \text{error}_i, \end{aligned} \tag{18}$$

where *SDNY* is an indicator variable equal to one if the insider case is subject to prosecution in the SDNY, *Bharara* is an indicator variable equal to one for the period 2009–2013, and zero for the adjacent periods 2006–2008 and 2014–2015[15]. The coefficient of interest is *d*. The set of controls mimics that in the baseline specification (16). To show the direct effect of SDNY, we exclude the constant term in the regression.

Columns (5) to (8) of Table X present the results. We find a statistically and economically

[14] See, for example, https://nypost.com/2015/10/05/supreme-court-rejects-insider-trading-case-in-setback-for-bharara/

[15] We choose this period to match the length of the ultimate power of Bharara. Because his power has weakened post 2013 we use the two years after 2013 and three years before 2009. The results are very similar if we use the five-year period of 2004-2008, instead. The results also weaken somewhat if we used the entire period of 2009-2015 as a treatment period, which is consistent with our view on his changing power to push through insider cases.

significant negative effect on insider trading quantities. Traders under the SDNY jurisdiction display values of *Bet* and *Intensity* are, respectively, 42.9% and 27.19% lower during Bharara's tenure relative to the standard deviations of these variables. The coefficients of *Splitting* and *Duration*, on the other hand, are statistically insignificant.

Overall, the results in the cross-sectional analyses provide supporting evidence on the role of traders' abilities and the legal profile of the court and prosecutors carrying insider trading investigation.

6.5 Evidence from Lawful Informed Traders

Not every insider trading prosecution is well grounded. Like in any legal issue, the judicial process can identify situations where no crime is committed. In the context of insider trading, such a situation corresponds to a well-informed individual that trades lawfully. We view such cases as providing a unique opportunity to understand the strategies of individuals that (i) are trading on precisely identified private information and (ii) are less likely to design their strategies with legal risk in mind. To the extent that such traders do not internalize legal risk, our model predicts that they should split their trades less extensively, display higher duration, and trade more aggressively.

Accordingly, we collect a set of 19 investigations that were brought to court by the SEC, but were eventually dismissed by a judge due to lack of supporting evidence.[16] Among others, our sample includes the cases of Newman and Chiasson discussed before, as well as the case of Michael Steinberg from the SAC Capital. To strengthen identification, we compare the trading strategies of these unconvicted traders to those drawn from a sample of convicted, but otherwise similar individuals. Specifically, we focus on the subset of traders with relatively low penalties corresponding to the 75th percentile of the distribution, excluding reckless insider traders such as Rajaratnam and Martoma. Such approach allows for a maximum penalty of $140,000 and results in 190 trades from 38 different investigations.

[16] Of course, the fact that a case was dismissed does not necessarily imply that, say, a second judge would also have concluded that the trader is not guilty. We are relying on a population-wide association between acting lawfully the probability of not being found guilty.

Formally, we estimate the following regression model:

$$StrategicDecision_i = a + b \times Lawful_i + c \times Controls_i + \text{error}_i, \tag{19}$$

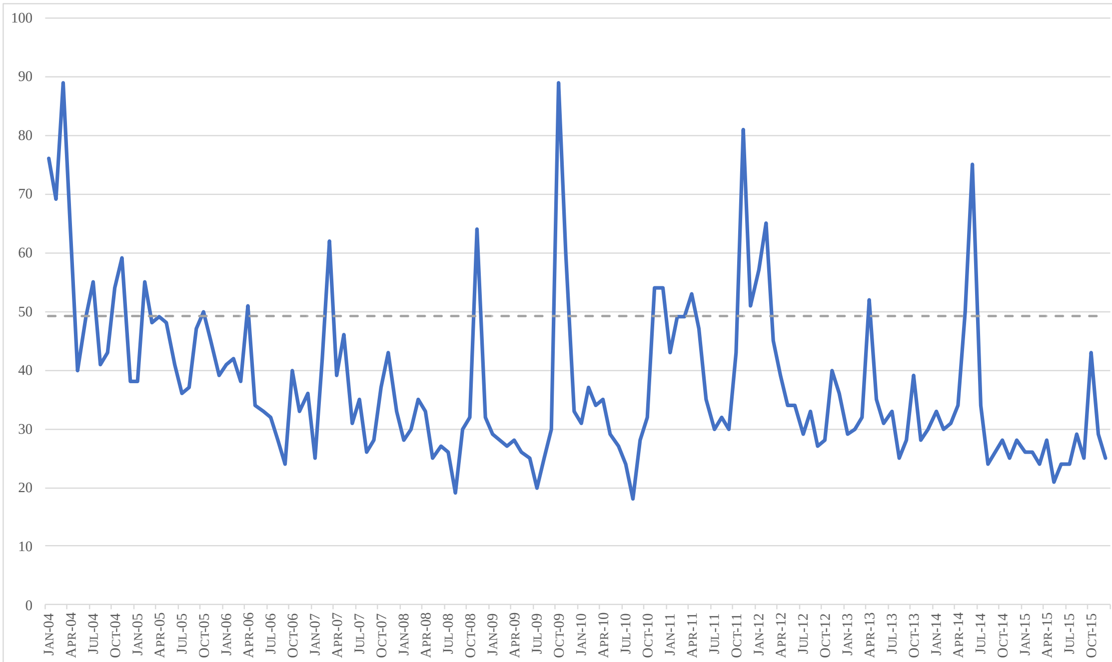
where *Lawful* is an indicator variable equal to one for trades deemed as legal by the corresponding federal court, and zero for trades performed by traders facing penalties. All control variables are as in Section 5.

The results, in Table XII, show that lawful traders exhibit less *Splitting*, higher *Duration*, and higher *Intensity*. All of the associated coefficients are statistically significant. The differences are also economically meaningful. Relative to the corresponding sample standard deviations, values of *Splitting* are 38.24% lower, while values of *Duration* and *Intensity* are higher by 61.12% and 68.42%, respectively. In sum, the evidence in this section provides further support to the notion that strategic decisions are affected by legal risk.

6.6 Evidence from Internet Search Trends

Our model and simple economic intuition suggest that if the probability of enforcement actions increases, legal risk should impact more heavily insider traders's strategies. In previous sections, we evaluated this prediction using a time-series variation in regulatory actions, a source of probability shock that can naturally be regarded as *objective*. In this section, instead, we empirically assess this prediction from the perspective of the *subjective* assessment of such probability. We proxy for the latter exploiting the time-series variation in the public's attention to insider trading, as measured by Google Trends. Specifically, we track online searches for the phrase "illegal insider trading" for the available period, 2004–2015. The monthly variation in the search activity is displayed in Figure 12. Although the series seems to be mean reverting, there are identifiable episodes with large spikes in values, several of which can be linked with the notorious insider trading cases discussed in previous sections.

Figure 12. Internet Search Intensity for 'Insider Trading': January 2004 to December 2015



Source: Google Trends.

Since the relation between online searches and the probability of legal enforcement is likely to be nonlinear, we specify a cutoff level equal to the 80th percentile of the unconditional distribution of the Google Trend measure and define an indicator variable, *InsiderTrend,* equal to one if the monthly value is above such cutoff. Subsequently, we estimate the following regression model:

$$StrategicDecision_{it} = a + b \times InsiderTrend_t + Controls_{it} + d_{year} + \text{error}_{it},$$

where d_{year} corresponds to a year fixed effect.

Table XI presents the results. The *Insider Trend* coefficient of *Splitting* is positive indicating that traders are more likely to split their trades in periods of higher perceived risk. Also, for *Bet* and *Intensity* the coefficient is negative and statistically significant, as predicted. Overall, the qualitative response of insiders' strategic decisions is consistent with the predicted response to a heightened subjective probability of enforcement actions.

6.7 Legal Risk and Private Signal Choice

In previous sections, we analyzed the role of expected costs, measured by legal risk, for the profile of insider trading strategies. We now assess the impact of legal risk from a different perspective: the ex-ante benefit from engaging in insider trading. Ceteris paribus, a rational trader that internalizes legal risk would be less willing to act on any given private signal if either the probability of enforcement or the conditional penalty increases. In other words, high expected legal costs require high expected benefits for an insider to take action. Consequently, following the seminal ideas in Becker (1968), we hypothesize that in response to increasing legal risk, insiders could rationally become more selective and, thus, concentrate on private signals of higher values. If some private signals with relatively low values are dropped, as they are not worth the risk, the consequence of such behavior should be an increase in the selected signals' average values.

We test this hypothesis by comparing the average value of PSV as in (1) for the subsamples described in Section 6.1: 2008–2010 representing low enforcement risk and 2011–2013 representing high enforcement risk. Formally, we conjecture that $\delta > 0$ in the following specification:

$$PSV_j = \text{constant}_j + \delta \times DoddFrank + \text{error}_j.$$

Table XIII shows the results. Consistent with our hypothesis, the average private signal value is significantly higher in times of high enforcement risk, 48.5% versus 34.83% in times of low enforcement risk. The difference is both economically and statistically highly significant.

For robustness, we replace *DoddFrank* by $InsiderTrend$, as defined in Section 6.6. The intuition is similar: Cases contemporaneous with $InsiderTrend = 1$ should display higher average values of PSV if traders pass on low-value signals when perceived legal risk is high. Table XIII shows that the difference between these two subsamples (43.66% versus 32.05%) is also economically and statistically significant.

We also note that one reaches the same conclusion by replacing PSV with *Strength*, that is, measuring the value of private signal from T_{first} instead of T_{info}. The bottom panel of Table XIII shows that the differences in mean values are significant, although quantitatively more moderate: 31.9% versus 25% for $DoddFrank$ and 26.37% versus 22.09% for $InsiderTrend$.

Overall, the evidence on the distribution of private signals complements our evidence on strategic trading in previous sections and further supports the notion that insider traders internalize legal risk.

7 A Brief Discussion of Implications

In this section, we provide a short discussion of implications from our work and suggest directions for future research.

Strategic use of private information. The simple framework developed in Section 4 highlights the role of information risk and legal risk but also embeds the basic ingredients of the canonical Kyle model. Therefore, several of our findings in Section 5.4 are informative about the empirical connections between such ingredients and insiders' strategies. To sum up, we find that the basic predictions from the Kyle model on strategies are confirmed in the data. In particular, the value of information, its precision, the volatility of asset prices, and the amount of noise trading play an important role in the design of trading strategies. Thus, our results complement the supporting evidence by Koudijs (2015), which is based on return correlations.

At the same time, having controlled for the ingredients of Kyle's model, we do not find strong evidence that personal characteristics, frequently highlighted in the behavioral finance literature, such as gender, age, or corporate role, play an equally central role. Yet, we show empirically that, while given several weeks to trade in most cases, a significant fraction of investors do not split trades at all. We note that, while interesting per se, such a finding is not direct evidence of lack of rationality or a violation of the Kyle model. Unmodeled frictions, such as attention costs, for example, could induce rational investors to limit the scope of order splitting.

Relation to other informed traders. While illegal insiders are a subset of a broader group of informed traders, we do not claim that our findings can be automatically extrapolated to any type of such traders. For example, the properties and duration of private signals could be different elsewhere. A hedge fund manager that generates his own signal through fundamental research, and expects the market price gap to disappear over several years, could behave more cautiously. For example, portfolio turnover of mutual fund and hedge fund managers is much lower than that of high-frequency or algo traders. On the other hand, the perceived absence of legal risk and the fear of information disappearing could result in such manager behaving more aggressively. To this end, Yan and Zhang (2009) show that active fund managers with shorter investment horizons generate higher alphas. The net effect of these factors is not obvious ex ante: Insider traders could be more or less aggressive than other informed traders.

We can, however, provide some perspective on the generalizability of our findings regarding the role of legal risk. The test on lawful traders in Section 6.5, who are unlikely to internalize legal risk, provides a valuable insight since we find that lawful traders trade somewhat more aggressively. At the same time, unreported results suggest that, otherwise, lawful traders display similar patterns of strategic behavior to those who face penalties. For example, information risk reduces the value of *Duration* and *Splitting* in both cases. Therefore, the available evidence, while limited in scope, suggests that our findings can still be helpful to understand the strategies of other informed traders. It would be interesting for future research to provide direct evidence from different groups of informed traders.

Regulatory actions. Perhaps the most important implication of our study is that regulatory and legal actions *do affect* insider trading. Exploiting multiple plausibly exogenous sources of variation in legal risk, we show that an increase in such risk induces insiders to adjust their strategies. They become more conservative. Such finding provides useful empirical validation of the deterrence power of the SEC's actions. Moreover, by developing similar institutional frameworks, regulatory agencies in countries where the enforcement of insider trading laws is currently weak can, therefore, hope to influence the investment environment in their capital markets.

A logical consequence of this finding is that, if a regulatory body decides to strengthen its data-based ability to detect illegal trading, the effect on insider strategies could, in turn, make it more difficult for the regulators to detect such misconduct. It is an open empirical question whether such a cat-and-mouse game leads to a greater proportion of illegal trade detection over the long-run, and whether it represents an efficient use of regulatory resources more broadly. Such evaluation could build on the analyses by DeMarzo et al. (1998) and Carre et al. (2018). In light of the growing sophistication of trading technologies (e.g., trading algos, exchange routing systems, complex order types), however, our results rationalize the adoption of detection mechanisms that are independent of the dynamics of trading, such as the Whistleblower Reward Program introduced with the Dodd-Frank Act.

The informativeness of asset prices and welfare. The debate whether insider trading should be illegal, and under what circumstances, has a long tradition in economics and finance. The dominant view that promotes enforcement actions highlights the potential to reduce the cost of firms' capital and increase investment (e.g., Ausubel (1990); Easley and O'Hara (2004); Manove (1989)). Others emphasize the potential social costs derived from weaker informational efficiency of securities prices (e.g., Manne 1967, Leland 1992, Bernhardt et al. 1995).

Our goal is not to settle this debate. However, we believe that our results provide valuable insights regarding the potential costs impounded on price informativeness. From an ex-ante perspective, and consistent with Becker's view of rational crime, the results in Section 6.7 suggest that insider traders could *refrain* from trading whenever the value of their private signal is relatively low. Such choices could hamper stock price informativeness at the individual firm level, a concern that is particularly pressing given the recent explosion in popularity of ETFs and similar portfolio-level investment vehicles. This notion echoes predictions of a theoretical model in Kacperczyk, Nosal, and Sundaresan (2018) who show, in general equilibrium, that the shift of holdings from informed to uninformed investors reduces prive informativeness. Second, by affecting the design of trading strategies, regulations are likely to affect price informativeness *even* when insider trading occurs. Indeed, theoretically and empirically, we find that legal risk induces insiders to trade lower quantities and to concentrate relatively more volume earlier. Such implications can help to rationalize the price adjustment paths of Section 3, with flatter return slopes and lower total information aggregation than the canonical Kyle model would suggest. Further studying the general equilibrium effects of enforcement, in particular, its impact on other market participants, such as long-term investors and market makers, would be a promising research endeavor that would hel to clarify the legal effects on price informativeness, firms' performance, and capital allocation.

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Proof of Proposition 1

We verify that the system of equations (8) to (12) is a unique linear equilibrium by following the three-step strategy in the proof of Theorem 2 in Kyle (1985). The key differences with the latter are found in the first step.

1) Trading strategy. First, we use backward induction to find optimal informed trades based on the conjectured pricing rule. Consider the informed trader problem at time $t = 2$. The expected penalty can be written as $K(x_1, x_2) = qc\left(x_1^2 + x_2^2 + 2x_1x_2\right)$. Substituting K in equation (7), and re-arranging, the objective function can be written as:

$$\max_{x_2 \in \mathbb{R}} \left(v - p_1 - 2qcx_1\right) x_2 - \gamma_2 x_2^2,$$

where $\gamma_t := (\lambda_t + qc)$. The optimal order x_2 must satisfy the following first-order condition:

$$x_2^* = \frac{(v - p_1 - 2qcx_1)}{2\gamma_2}. \tag{20}$$

Note that, unlike in the traditional Kyle model, the optimal x_2 depends on the value of x_1 because enforcement risk creates a new intertemporal dependency. Satisfying the second order condition requires $\gamma_2 > 0$.

Using (20), the value function V_2 can be expressed as

$$\begin{aligned} V_2 &= \mathbb{E}\left[x_2^*\left(v - p_1 - \lambda_2(u_2 + x_2^*)\right) \mid v, p_1\right] - qc\left(x_1^2 + x_2^{*2} + 2x_1x_2^*\right), \\ \Rightarrow V_2 &= \frac{\left(v - p_1 - 2qcx_1\right)^2}{4\gamma_2} - qcx_1^2. \end{aligned} \tag{21}$$

Consider now the insider problem at $t = 1$. Using equation (21) we can re-express the program in equation (6) as

$$\max_{x_1 \in \mathbb{R}} \mathbb{E}\left[\left(v - p_0 - \lambda_1 y_1\right) x_1 + \frac{(1-\rho)}{4\gamma_2}\left(v - p_1 - 2qcx_1\right)^2 |v\right] - qcx_1^2. \tag{22}$$

Expanding the term $(v - p_1 - 2qcx_1)^2$, evaluating the expectation, and dropping constant terms, one can write (22) as

$$\max_{x_1 \in \mathbb{R}} \left\{ (v - p_0)\, x_1 \left(1 - 2\theta \left(\gamma_1 + qc\right)\right) + \left(\theta \left(\gamma_1 + qc\right)^2 - \gamma_1\right) x_1^2 \right\},$$

where $\theta_2 = \frac{(1-\rho)}{4\gamma_2}$. The first-order condition is

$$(v - p_0)\left(1 - 2\theta \left(\gamma_1 + qc\right)\right) = 2\left(\gamma_1 - \theta \left(\gamma_1 + qc\right)^2\right) x_1,$$

implying that

$$x_1^* = \frac{(v - p_0)\left(1 - 2\left(\gamma_1 + qc\right)\theta\right)}{2\left(\gamma_1 - \left(\gamma_1 + qc\right)^2 \theta\right)}. \tag{23}$$

Therefore, $\alpha_1 = -\beta_1 p_0$ and

$$\beta_1 = \frac{\left(1 - 2\left(\gamma_1 + qc\right)\theta\right)}{2\left(\gamma_1 - \left(\gamma_1 + qc\right)^2 \theta\right)}.$$

The second-order condition can be expressed as $\lambda_1 > \theta \left(\lambda_1 + 2qc\right)^2 - qc$.

To find α_2 and β_2, we combine equations (23) and (20) to obtain

$$x_2^* = \frac{1}{2\gamma_2}\left(v\left(1 - 2qc\beta_1\right) - p_1 + 2qc\beta_1 p_0\right).$$

Therefore,

$$\begin{aligned} \beta_2 &= \frac{1}{2\gamma_2}\left(1 - 2qc\beta_1\right), \\ \alpha_2 &= \frac{1}{2\gamma_2}\left(2qc\beta_1 p_0 - p_1\right). \end{aligned}$$

2) Learning and prices. Based on the insider strategy and using a market efficiency condition, we address the market maker learning problem and derive the pricing rule. In period $t = 1$, informational efficiency requires that the asset satisfies $p_1 - p_0 = \mathbb{E}\left[v - p_0 | \alpha_1 + \beta_1 v + u_1 = y_1\right]$. Given the normal distribution assumption for v and u_1, the projection theorem implies that λ_1 must be given by (10). In period $t = 2$, based on the signals y_1 and y_2, informational efficiency requires that $p_2 - p_1 = \mathbb{E}\left[v - p_1 | \alpha_2 + \beta_2 v + u_2 = y_2\right]$. Then,

$$\mathbb{E}\left(v - p_1 | y_1, y_2\right) = \frac{\beta_2 \sigma^2_{v|y_1}}{\beta_2^2 \sigma^2_{v|y_1} + \sigma_u^2} y_2, \tag{24}$$

Using equation (24) and $\sigma^2_{v|y_1} = \frac{\sigma_v^2 \sigma_u^2}{\beta_1^2 \sigma_v^2 + \sigma_u^2}$ yields $\lambda_2 = \frac{\beta_2 \sigma_v^2}{\left(\beta_2^2 + \beta_1^2\right)\sigma_v^2 + \sigma_u^2}$.

3) Having characterized the linear structure of trading strategies and pricing rule in 1) and 2), the existence of a unique way to iterate the system backward follows from the arguments given in Kyle (1985). ■

Table I
Insider Trading Investigations and Penalties: Summary Statistics

We classify the sample of SEC insider trading cases. Firms per case is the number of distinct companies reported in a given case; traders per case is the number of distinct traders involved in a given case; trades per trader is the number of trades executed by insider in all cases he/she appears in the data; trades per firm is the number of trades executed by all insiders trading a given firm's shares; trader finance background is the percentage of insiders who have finance job; trader top executive is the percentage of insiders who hold executive positions in their respective companies; reported profit is the dollar profit realized on a given trade (in '000).

A. General characteristics	mean	median	SD	min	max
Firms per case (N=840)	2.07	1	3.15	1	26
Traders per case (N=1079)	5.71	4	5.21	1	25
Trades per trader	20.22	10	24.32	1	97
Trades per firm	18.53	13	21.24	1	126
B. Penalties	mean	median	SD	min	max
Trader penalty (USD m.)	2.85	0.20	14.03	0	156.61
Total penalties per case (USD m.)	11.74	1.25	32.68	0	177.21
SD of penalties within case (USD m.)	3.16	0.08	11.37	0	89.64
Jail sentence (%)	10.48	-	-	-	-
Percentage of jailed traders (within case)	10.43	0	22.24	0	100
Probation (%)	23.55	-	-	-	-
Dropped (%)	12.40	-	-	-	-
C. Most active courts (N=77)	number	percentage			
Southern District of New York	144	30.44%			
District of Columbia	29	6.13%			
Central District of California	26	5.50%			

Table II

Summary Statistics: Corporate Events, Firms, and Trading Instruments

We classify the sample of SEC insider trading cases based on event type (M&A, earnings announcements, general business events, shares offerings, and dividend changes), information sign (good news/bad news), and trading instrument (stocks, options, ADS, and bonds).

Event type	Number of cases	Percentage
Mergers & Acquisitions	360	55.90
Earnings announcements	97	15.06
General business events (patents, trials)	69	10.71
Shares offerings & tenders	52	8.07
Dividend changes & buybacks	14	2.17
Other (restatements/fraud/manipulation)	52	8.07
Information sign		
Good news	664	71.86
Bad news	260	28.14
Trading instrument		
Stocks	3,392	67.06
Options	1,610	31.83
ADS	44	0.87
Bonds	12	0.24
Distribution of trades by industry (SIC2 codes)		
Chemicals (28)	752	16.09
Business Services (73)	673	14.40
Electronic Equipment (36)	494	10.57
Measuring and Controlling Equipment (38)	318	6.80
Industrial and Commercial Machinery (35)	220	4.71
Depositary Institutions (60)	192	4.11
Wholesale Trade: Durable Goods (50)	138	2.95
Engineering and Management Services (87)	132	2.82
Wholesale Trade: Nondurable Goods (51)	127	2.72
Oil and Gas Extraction (13)	103	2.20

Table III
Insider Traders: Personal and Professional Background

This table reports the numbers of insider traders in our sample distributed according to their job category. In **Panel A**, we break down the sample by the corporate function; **in Panel B**, we break down the sample according to the types of finance jobs; in Panel C, we summarize the data according to non-finance jobs. The sample period is 1995–2015.

Personal background	**Value**
Average age traders	47.16
Median age traders	46
Median age tippers	45
Gender (% of males)	91.89
Corporate function	**Number of traders**
Employee/Low-level management	105
Mid-level management	84
Vice president	67
CEO	38
Director	32
President	32
CFO	24
Other	28
Jobs in the financial sector	
Portfolio manager/Hedge fund	59
Broker or dealer	30
Analyst	21
Trader	16
Financial Advisor	7
Other	16
Non-finance jobs	
Business owner/self employed	52
Lawyer/Attorney	42
Medical doctor / dentist	24
Accountant	14
Sales	13
Engineer /IT	12
Real estate broker	11
Other	26

Table IV
Dependent and Control Variables: Summary Statistics

Splitting is the difference in number of days from the first to the last trade, scaled by the number of days from the date of information arrival until the day information is public. *Intensity* is the maximum over all traded assets of the asset-specific trade size relative to the volume in the same asset. *Duration* is the time-weighted average of relative trade sizes over the two equal-length time periods splitting the time between the first and the last time the insider trades. *Strength* is the return on information recorded from the open of the day when the insider trades until the open of the day following the public disclosure of information; *Alt Strength* is the return on information recorded from the open of the day when the insider receives information until the open of the day following the public disclosure of information; *Realized Volatility* is the 30-minute return volatility of a traded stock; *Volume Vol* is the volatility of trading volume; *Tipper Insider* is an indicator variable equal to one if the insider is either a tipper or a trader in a case; *Expert* is an indicator variable equal one if the trader is a corporate insider and zero otherwise; *Traders* is the number of distinct traders involved in trading of a given stock and case; *Age* is the age of trader in years; *Gender* is an indicator variable if a trader is male, and zero if a trader is female; *Ln(mkt. cap)* is the natural logarithm of the firm's market capitalization. *PredPenalty* and *PredJail* are derived in Table VI.

Characteristic	mean	median	st. dev.
Dependent Variables			
Splitting	0.462	0.484	0.387
Duration	1.227	1	0.291
Bet	4,516.28	318.82	15,759
Intensity	-0.057	-0.099	0.228
Action Delay	0.309	0.166	0.344
Controls			
Strength	30.61	24.74	54.96
Realized Volatility	15.15	5.24	41.91
Volume Vol.	134.99	54.32	255.65
Ln(mkt. cap)	13.89	13.88	1.82
Tipper Insider	24.51	0	43.02
Inforisk	76.95	100	42.12
PredPenalty	6.34	4.08	12.59
PredJail	0.305	0.261	0.256
Traders	5.20	3	4.74
Executive	0.248	0	0.432
Finance	0.262	0	0.44

TABLE V
Information Risk and Action Delay

The dependent variable is *Action Delay* (defined as the difference in number of days from the date when the trader receives information until the first time she trades, scaled by the number of days from the date of information arrival until the day information is public). All controls are defined in Table IV. We estimate the regression using Tobit model. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

	Action Delay		
	(1)	(2)	(3)
Inforisk	-0.186***	-0.097***	-0.115**
	(0.042)	(0.028)	(0.050)
Number Traders	-0.001	0.002	0.001
	(0.002)	(0.002)	(0.003)
Strength		-0.057***	-0.069**
		(0.016)	(0.028)
Realized Volatility		0.275***	0.353***
		(0.091)	(0.132)
Volume Vol.		-0.004	-0.001
		(0.005)	(0.009)
Ln(mkt. cap)		0.009	0.012
		(0.008)	(0.015)
Tipper Insider			-0.018
			(0.028)
Age			0.001
			(0.001)
Gender			0.074
			(0.065)
Executive			0.023
			(0.032)
Finance			0.058*
			(0.031)
Observations	3,006	2,306	1,764

Table VI

Determinants of Monetary Penalties and Jail Sentences

Penalty is a dollar amount of assessed penalty (in $million). *Jail* is an indicator variable equal to one if an insider receives a jail sentence, and zero, otherwise. All controls are defined in Table IV. Court fixed effects are related to the court in which the settlement takes place. We estimate all regressions using OLS model. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

	Penalty		**Jail**	
SDNY		12.763***		0.236***
		(0.034)		(0.034)
District Columbia		7.649**		0.069**
		(3.579)		(0.033)
Central California		5.150**		0.306***
		(2.554)		(0.09)
Inforisk	-1.492	-1.458	-0.021	-0.084
	(3.546)	(3.450)	(0.075)	(0.062)
Strength	-0.628	-0.637	-0.035	-0.020
	(0.699)	(0.959)	(0.047)	(0.042)
Realized Volatility	-2.421	-2.401	-0.121	0.044
	(2.677)	(3.674)	(0.151)	(0.136)
Volume Vol.	2.012	1.657	0.019	0.018
	(1.420)	(1.227)	(0.014)	(0.012)
Ln(mkt. cap)	1.864	1.952	0.001	0.016
	(1.356)	(1.363)	(0.018)	(0.016)
Tipper Insider	2.215	3.560	-0.107	-0.033
	(2.261)	(3.910)	(0.072)	(0.062)
Age	0.370	0.470	0.002	0.001
	(0.302)	(0.403)	(0.003)	(0.003)
Gender	7.884	11.625	0.013	-0.019
	(6.791)	(9.701)	(0.127)	(0.137)
Executive	-6.259	-7.143	-0.101	-0.110
	(4.869)	(5.345)	(0.082)	(0.069)
Finance	10.206	9.591	0.038	0.022
	(8.054)	(7.369)	(0.099)	(0.088)
Court F.E.	No	Yes	No	Yes
Observations	2,660	2,660	2,833	2,833

Table VII
Determinants of Trading Strategies

The dependent variables are *Splitting*, *Intensity*, and *Duration*. All variables are defined in Table IV. We estimate the regression models using Tobit model (in columns 1-2, and 5-6) and OLS (in columns 3-4). ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

	Splitting	**Duration**	**Bet**	**Intensity**
	(1)	(2)	(3)	(4)
Information Risk	-0.083**	-0.107***	1,103.186	0.006
	(0.039)	(0.040)	(2,108.466)	(0.011)
PredPenalty	0.004**	-0.002	-232.314*	-0.005***
	(0.002)	(0.003)	(136.503)	(0.002)
PredJail	0.047	-0.125**	-2,665.627	0.060
	(0.049)	(0.054)	(2,272.421)	(0.053)
Strength	0.041	0.073**	-2,017.656*	-0.020**
	(0.032)	(0.030)	(1,030.750)	(0.010)
Realized Volatility	-0.147*	-0.145*	2,189.454	-0.048
	(0.075)	(0.080)	(2,428.529)	(0.051)
Volume Vol.	0.009*	0.015**	1,579.271**	0.006**
	(0.005)	(0.006)	(756.029)	(0.003)
Ln(mkt. cap)	-0.001	-0.019	1,797.864***	-0.039***
	(0.009)	(0.013)	(680.191)	(0.007)
Tipper Insider	0.027	0.053*	3,851.283**	-0.028**
	(0.031)	(0.031)	(1,719.858)	(0.013)
Age	-0.001	0.001	79.150	0.001
	(0.001)	(0.001)	(57.690)	(0.001)
Gender	0.009	0.027	-1,331.027	-0.100
	(0.048)	(0.059)	(3,731.860)	(0.067)
Executive	-0.046	-0.017	-212.838	0.005
	(0.030)	(0.034)	(1,646.695)	(0.015)
Finance	-0.002	0.040	551.193	0.050**
	(0.029)	(0.038)	(1,754.454)	(0.020)
Observations	2,035	1,804	1,841	2,766

Table VIII

Trading Strategies and the Enforcement Strength: Time Series Evidence

The dependent variables are *Splitting*, *Intensity*, and *Duration,* defined in Table VII. *DF* is an indicator variable equal to one for the period 2011-2013, and zero for the period 2008-2010. *Newman* is an indicator variable equal to one for the period 2014-2015, and zero for the period 2011-2013. All controls are defined in Table IV. We estimate the regression using Tobit model (in columns 1, 3, 4, and 6) and OLS (in columns 2 and 5). ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

	Splitting	**Duration**	**Bet**	**Intensity**	**Splitting**	**Duration**	**Bet**	**Intensity**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DoddFrank	-0.023	-0.058**	-2,139.344	-0.062				
	(0.047)	(0.021)	(3,942.669)	(0.040)				
Newman					-0.027	0.241*	901.846	0.113**
					(0.059)	(0.089)	(651.870)	(0.028)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,004	786	805	1,321	263	190	193	452

Table IX

SEC Whistleblower Cases: Summary Statistics

We consider the insider trading trades over the period 2008-2013. We define two sets of insider trading cases: WB=1 are cases that have been investigated by the SEC based on Whistleblower Reward Program; WB=0 are the cases with unknown origin of investigation sampled during the sample time period.

Characteristic/Sample	WB=1	WB=0
Number of Cases	47	140
Distance from news to trade	6.82	7.60
Distance from trade to event	15.48	17.46
Distance from first to last trade	7.59	6.85
Trades per firm	5.61	7.33
Trades per trader	8.29	9.92
Market capitalization (in Billions)	10.27	5.82
Reported profits (in Millions)	0.98	1.31

Table X
Trading Strategies and Enforcement Strength: Cross-Sectional Evidence

The dependent variables are *Splitting*, *Intensity*, and *Duration,* defined in Table VII. *DF* is an indicator variable equal to one for the period 2011-2013, and zero for the period 2008-2010. *WB* is an indicator variable for insider trades detected through the Whistleblower Program, and zero for trades detected through other means. *PB* is an indicator variable equal to one for the period 2009-2013, and zero for the period 2006-2008 and 2014-2015. *SDNY* is an indicator variable for traders convicted by Southern District of New York, and zero for traders convicted in other courts. All controls are defined in Table IV. We estimate the regression using Tobit model (in columns 1 and 3) and OLS (in columns 2 and 4). ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

	Splitting	**Duration**	**Bet**	**Intensity**	**Splitting**	**Duration**	**Bet**	**Intens**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DoddFrank	-0.027	-0.075**	-276.982	-0.065				
	(0.050)	(0.020)	(3,068.057)	(0.042)				
WhistleB	0.008	-0.057	10,696.173***	-0.008				
	(0.082)	(0.080)	(1,070.807)	(0.014)				
DoddFrank*WhistleB	0.167	0.121	-9,114.724**	0.022				
	(0.108)	(0.149)	(4,698.975)	(0.035)				
SDNY					0.274**	0.540***	1,808.513	0.080*
					(0.089)	(0.110)	(6,315.028)	(0.01
Bharara					-0.047	-0.108**	712.662	0.01
					(0.050)	(0.047)	(2,020.668)	(0.01
SDNY*Bharara					0.014	0.103	-6,761.785**	-0.062*
					(0.128)	(0.071)	(2,127.852)	(0.01
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Court F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,004	786	805	1,321	1,457	1,132	1,166	1,97

Table XI
Trading Strategies and Perceived Legal Risk

The dependent variables are *Splitting*, *Intensity*, and *Duration,* defined in Table VII. *Insider Trend* is an indicator variable equal to one for the period with google trends of the phrase "insider trading" greater than the 80% of the unconditional distribution, and zero otherwise. All controls are defined in Table IV. In some specifications, we additionally include year fixed effects. We estimate the regression using Tobit model (in columns 1-2 and 5-6) and OLS (in columns 3 and 4). ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

	Splitting	**Duration**	**Bet**	**Intensity**
InsiderTrend	0.036*	0.002	-1,635.289**	-0.030*
	(0.021)	(0.019)	(819.410)	(0.017)
Controls	Yes	Yes	Yes	Yes
Year F.E.	No	No	Yes	Yes
Observations	2,116	1,627	1,670	2,864

Table XII

External Validity: Evidence from Lawful Trades

The dependent variables are *Splitting*, *Intensity*, and *Duration*. *Dismissed* is an indicator variable equal to one for trades that are performed by traders for whom the Federal court found no evidence of illegal behavior, and zero for trades performed by traders convicted of illegal insider trading and facing small penalties. All control variables are defined in Table IV. We estimate the regression using Tobit model (in columns 1 and 3) and OLS (in column 2). ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

	Splitting	**Duration**	**Bet**	**Intensity**
Lawful	-0.148*	0.178*	9,671.051	0.156**
	(0.077)	(0.104)	(9,199.476)	(0.073)
Controls	Yes	Yes	Yes	Yes
Observations	169	151	152	242

Table XIII

Signal Strength and Enforcement

Low Strength refers to cases which were originated during the period 2008-2010; and *High Strength* refers to cases which were originated during the period 2011-2013. *Low Risk* refers to cases when google trends indicator for insider trading is below 80% value of the distribution; and *High Risk* refers to cases when google trends indicator for insider trading is above 80% value of the distribution. *Strength* is defined in Table *IV*. p-values correspond to the statistical difference in means between the two periods.

	DoddFrank=0	DoddFrank=1	diff. p-val.	InsiderTrend=0	InsiderTrend=1	diff. p-val.
PSV mean (%)	34.83	48.50	0.011	32.05	43.66	0.005
Observations	958	387		1667	424	-
Strength mean (%)	25.00	31.90	0.017	22.09	26.37	0.044
Observations	1,393	686	-	2,721	759	-

Appendix to Section 4

Figure 13. Equilibrium: Information and Enforcement Risks