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ABSTRACT

Do illegal insiders internalize legal risk? We address this question with hand-collected data from 530 SEC (the U.S. Securities and Exchange Commission) investigations. Using two plausibly exogenous shocks to expected penalties, we show that insiders trade less aggressively and earlier and concentrate on tips of greater value when facing a higher risk. The results match the predictions of a model where an insider internalizes the impact of trades on prices and the likelihood of prosecution and anticipates penalties in proportion to trade profits. Our findings lend support to the effectiveness of U.S. regulations' deterrence and the long-standing hypothesis that insider trading enforcement can hamper price informativeness.

A VAST LITERATURE IN ECONOMICS and finance has argued that private information is transmitted into asset prices through the trading activity of

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informed agents. The canonical representation of this process is the Kyle (1985) model: knowing the value of an asset and internalizing the price impact, the informed trader cautiously spreads trades over time. However, the literature largely abstracts from *how* the information is produced. In the Grossman–Stiglitz (1980) tradition, a trader becomes informed by conducting costly fundamental research. In practice, private information can also be obtained in a breach of fiduciary duty, thus exposing regular investors to legal risk. But do *illegally* informed traders rationally internalize legal risks, as in Becker (1968)? If so, is this process reflected in their trades and prices?

These questions deserve formal study given their importance for market efficiency and welfare (Ausubel (1990), Fishman and Hagerty (1992), Leland (1992)), capital formation (Manove (1989), Easley and O'Hara (2004)), as well as for better understanding of the insider trading regulations (DeMarzo, Fishman, and Hagerty (1998)). These papers provide a rationale for the social investment of significant monetary and human resources in the associated battle against this activity. Ignoring the judicial branch and the Department of Justice, the U.S. Securities and Exchange Commission (SEC) Division of Enforcement alone employs over 1,300 skilled individuals and received federal resources for over $4.6 billion in the last decade. Ultimately, since regulators cannot stop insiders in real time, whether that social investment can be justified depends on its power to deter, which we argue should not be taken for granted.[1]

We aim to contribute to our understanding of these issues in three ways. First, we manually collect data from 530 illegal trading investigations prosecuted by the SEC on individual trades and the resulting legal outcomes. We characterize over 6,500 trades in 975 firms from 1995 to 2018, representing a fairly large universe of assets and market conditions. We examine in depth the information sets, timing, quantity traded, and penalties of illegal insiders. To our knowledge, a study with such scope has never been undertaken. Most importantly, the quality and granularity of the data allow us to overcome a formidable identification challenge: neither private information nor legal risks are readily observable. Second, we develop a stylized equilibrium framework of informed trading featuring an insider who internalizes his own trades' impact on prices, the probability of being prosecuted by a regulator, and the conditional value of a legal fine. The model allows us to benchmark the impact of the likelihood or severity of legal penalties on trading strategies. Third, we exploit two plausibly exogenous sources of variation in legal-risk exposure to test the model's predictions. Controlling for a host of behavioral predictors, we provide consistent evidence that legal risk influences insiders' trading behavior.

In Section I, we provide a detailed characterization of illegal insider trading, from the transmission of the private tip to the resolution of legal penalties. We

[1] Assessing the deterrence effect of laws and regulations is a cornerstone of the economics of crime literature. For a comprehensive review, see Freeman (1999) and Chalfin and McGrary (2017). The evidence discussed therein indicates that, in several criminal environments, crime does not clearly respond to the severity of sanctions.

highlight a few robust trends that later inform our modeling choices. First, insider tips contain economically powerful information connected to specific corporate announcements. For example, the average stock price change in the period between receiving a tip and its public announcement is 48.64% for mergers and acquisitions (M&As) and 17.64% for earnings. Second, insiders trade more than once, but do not trade continuously: the median insider trader places two trades over a median horizon of two weeks. Third, consistent with the prevailing legal framework, we observe a strong association between dollar trading profits and pecuniary penalties. The average and median profit values per trader are $1,271,755 and $95,109, respectively. For pecuniary penalties, the corresponding values are $1.67 million and $160,000.

The conceptualization of the economic links between insiders' actions and the regulatory framework from the data alone is challenging without a proper benchmark. In Section II, we build on the insights of Becker and Kyle and develop a model in which the equilibrium actions of a privately informed trader, a competitive market maker, and a regulator are jointly determined. The model features two periods to capture the insider's intertemporal concerns in the simplest fashion. The market maker observes the aggregate order flow and sets a clearing price to break even. The most significant contrast with conventional analyses is that, apart from an adverse realization of uninformed traders' order flow, the insider is concerned with the regulator's screening of abnormal order flow and penalties. If the prosecution is successful, the penalties are proportional to the realized profits.

In the early period, insider trades are guided by a private tip; in the late period, the insider further incorporates the price movement and whether early period transactions raised a red flag to the regulator. We analyze the impact of legal risk on the insider's behavior by considering changes in the severity of the penalties and the probability of successful prosecution. The equilibrium yields two predictions regarding trading strategies: following an increase in the expected legal punishment, the insider trades smaller quantities and trades relatively earlier. The intuition behind the first result is that the legal threat increases with the amount of trading, which incentivizes more cautious trading. The intuition for the second result is that the legal threat induces a smoother trade pattern across periods to mitigate the probability of prosecution. Absent legal risk, as in the Kyle (1985) model, the insider trades more intensely as the information deadline nears.

To test these two predictions, in Section III we propose two quasi-natural experiments that exploit plausibly exogenous variation in legal risk specific to insider trading. The first involves the 2014 U.S. Court of Appeals for the Second Circuit ruling on *United States v. Newman and Chiasson* (13-1837-cr(L)), the Newman ruling hereafter, which significantly narrowed the application of insider trading laws and was subsequently used as a precedent to clear several allegedly guilty individuals. Furthermore, the ruling likely affected insiders differently, depending on whether the private information was learned directly (least affected group) or acquired through connections (most affected group). We regard this ruling as a negative shock to legal risk. The second experiment considers the impact of Preet Bharara's tenure, the U.S. Attorney for the Southern District of New York (SDNY), who earned the reputation of a "crusader" prosecutor. His tenure affected insiders subject to SDNY jurisdiction. We regard this episode as a positive shock to legal risk. The consideration of both shocks is appealing because of complementarities regarding their anticipated effect, the specifics of trader cross-sectional impact, and the legal agents at play (judges vs. prosecutors).

The tests are based on a regression design in which the dependent variable captures either the volume or timing of the insider trades. We aim to identify whether heterogeneous groups of insiders display distinct trading behavior following each legal-risk shock. We include controls concerning trade activity, proxies for the model parameters, and a host of fixed effects accounting for the corporate event type, calendar year, and unobserved time-invariant trader heterogeneity.

The results in Section IV indicate that volume and timing measures display economically significant abnormal values in response to the legal shocks. Second, their qualitative responses conform well to the theoretical predictions. Following the Newman shock, traders acting on secondhand information behave *less* cautiously: informed dollar volume increases by 30.8% relative to its standard deviation. Conversely, traders *within* the SDNY jurisdiction reduced their trade aggressiveness during Bharara's tenure, as reflected by a 66.9% decrease in the normalized proportion of informed trading. In turn, the timing of trades shows a negative relation with the legal-risk shock sign in both tests, although only Newman's test results are statistically significant.[2] Specifically, insiders most affected by the Newman ruling trade closer to the public release time: the timing metrics display an increase equal to 93% to 95% of their corresponding standard deviations.

In Section V, we further assess the impact of legal risk from the perspective of engagement in criminal activity. A rogue but rational insider should be less willing to act on a private signal of a given economic value when the probability of enforcement or the anticipated penalty increases. Put differently, as a result of a positive (negative) risk shock, insiders should act on private signals of higher (lower) expected returns. The evidence suggests that insiders to some extent internalize the expected crime cost by comparing the average value of private tips under low and high legal-risk regimes. For example, compared to insiders in other jurisdictions, SDNY insiders' private signal values increased by 20.3% relative to its standard deviation after Bharara's appointment.

[2] The Internet Appendix (see Section 4) contains a complementary test of the model's predictions that exploits a plausibly-exogenous shock to legal risk regarding the SEC's implementation of the Whistleblower Reward Program (WRP) following the Dodd-Frank Act, which was enacted in 2010. The underlying idea of this program is to use monetary payments to incentivize whistleblowers to provide regulators with original information on insider trading activity. The test results on trade quantities and timing are qualitatively consistent with the model's predictions for a positive legal-risk shock and with the Bharara test results (also based on a positive shock) in Section IV. The Internet Appendix may be found in the online version of this article.

In Section VI, we assess the robustness of our results from the perspective of the potential selection bias due to a nonrandom pool of cases that were investigated. First, we exploit the built-in volume-based detection rule in the model to isolate how changes in legal risk affect trading strategies for prosecuted cases. Notably, the model's predictions on trade quantities and timing hold for the latter. The outcomes also show how volume-based screening could lead us to underestimate the impact of legal-risk changes. Next, we recognize that traders who neglect legal risks will likely be overrepresented if the regulator actively screens for abnormal trade patterns. The outcomes of a model with a boundedly rational agent suggest that such overrepresentation would also lead us to underestimate the degree to which insiders internalize legal consequences. In sum, these analyses indicate that our empirical estimates are best viewed as a *lower bound* on the true effect of legal risk.

To empirically assess the lower bound on legal-risk sensitivity, we identify investigations referred to the SEC by sources likely to indicate unusual trading patterns. These include stock and options exchanges, brokers, and industry regulating agencies, such as the Financial Industry Regulatory Authority (FINRA) and the Options Regulatory Surveillance Authority (ORSA). We hypothesize that the individuals in these specific investigations are *less likely* to internalize legal risks than those detected through other, more direct means and those who went undetected. We find that this group of insiders responds to both legal-risk shocks and displays similar strategic responses, suggesting illegal insiders' legal-risk sensitivity is bound away from zero.

Although our paper focuses on trading strategies—over which insiders have direct control—asset prices could also reflect their actions. In Section VII, we examine the process of price adjustment. First, we establish that illegal insider trades affect prices at daily frequencies, both in the case of negative and positive private information. Second, we inquire into the dynamic process of information transmission into prices. If insiders internalize legal penalties, one should expect less information aggregation than in conventional analyses without legal risk (e.g., Back (1992)). We show that illegal insiders impound a significant amount of the private information, but not near the entirety. At the end of the trading period, the average cumulative return is no more than 40% of the information's initial value. We also find less information aggregation for cases associated with high legal risk, which is more evident in the case of the Newman ruling. Overall, these results suggest that the legal efforts to deter insider trading could indeed reduce price informativeness (e.g., Manne (1967)). This implies that regulators must unequivocally factor in the social costs resulting from reduced informational efficiency of securities prices against the potential liquidity and capital formation benefits of insider trading prosecution.

Our paper relates to several strands of literature. First, we contribute to the empirical literature on illegal insider trading.[3] One stream of the literature is

[3] Bhattacharya (2014) and Rauterberg, Fox, and Glosten (2018) provide excellent recent reviews of the illegal insider trading literature in economic and legal studies. An important but less directly

based on the direct analysis of investigation cases. Meulbroek (1992) provides the first comprehensive study of the impact of insider trading on stock returns and market efficiency. Del Guercio, Odders-White, and Ready (2017) find that the same-day price impact of illegal insider trades in recent years is lower than in Meulbroek's sample, and that measures of SEC budget resources are negatively correlated with the price run-up before M&A and earnings announcements. Our microlevel results on price aggregation are qualitatively consistent with these time-series relations.

Also related are the studies of Kallunki et al. (2018) on how wealth and income affect the decision to engage in insider trading, of Cornell and Sirri (1992) and Akey, Grégoire, and Martineau (2022) on stock liquidity, of Kacperczyk and Pagnotta (2019) on asymmetric information proxies, and of Ahern (2017) on insiders' networks. While these studies consider insider trading investigations in some capacity, they do not investigate the relation between insiders' strategies and legal risks, which is of our primary interest.

Another stream of studies in this literature examines the relation between a country's first-time enforcement of insider trading laws and capital markets' performance. For example, Bhattacharya and Daouk (2002) and Fernandes and Ferreira (2009) find that enforcement actions are negatively related to the cost of equity and that they can also enhance stock price informativeness. These aggregate findings indicate that insider trading laws affect how market participants invest. We complement this line of research by providing individual-level evidence on how the legal threat affects insiders specifically.

Second, we contribute to the theoretical literature on insider trading, which generally abstracts from legal-risk considerations.[4] A notable exception is DeMarzo, Fishman, and Hagerty (1998), who pioneered the analysis of optimal insider trading enforcement rules.[5] While their focus is on the normative regulation design, we focus on the positive effects of the prevailing regulations and provide empirical support for their otherwise assumed deterrence power. Carre, Collin-Dufresne, and Gabriel (2022) consider a one-period Kyle setting with insider penalties but adopt uniform noise distributions. This approach allows for analytical solutions when penalties depend on the insider trade size instead of profits, but the probability of detection does not. Broadly, our approach is distinct. We consider an intertemporal Kyle-like setting, enabling a connection between prosecution risk and the time distribution of trades. We

related literature examines the characteristics of legal trades by corporate insiders (e.g., Cohen, Malloy, and Pomorski (2012), Klein, Maug, and Schneider (2017)).

[4] See Foucault, Pagano, and Roell (2013) for a comprehensive survey of models of trading with asymmetric information.

[5] Also related is the model by Huddart, Hugues, and Levine (2001). Due to regulatory disclosure requirements, insiders are therein forced to disclose their trades after each trading round. The disclosure regulation induces the insider trader to add noise to its demand, which can result in transactions that are inconsistent with the insider's private information. While our focus is not on disclosure regulations, we find that insider trading enforcement can also reverse the trade direction. We show in Section 2.C of the Internet Appendix that this occurs when the near certainty of an investigation creates a rush for the insider to reduce trade profits to mitigate the chance of hefty penalties.

reflect the institutional framework by linking penalties to profits and prosecution probabilities to how the insider trades.

Third, we contribute to the microfounded empirical literature on private information and trading. Among the few studies that have carefully examined flows of private information concerning how agents trade over time are those of Koudijs (2015, 2016) and Bolandnazar et al. (2020). Generally, these studies consider the predictions of the Kyle model when traders face uncertainty on the information advantage horizon. Our work complements their findings by linking private information to legal risk, a separate but not mutually exclusive concern for insiders.

Finally, also related is an extensive literature that empirically analyzes financial misconduct. Among others, Dyck, Morse, and Zingales (2010) analyze the behavior of whistleblowers regarding corporate fraud. Karpoff and Lou (2010) discuss the importance of short sellers for the detection of financial report misrepresentation. Patel and Putniņš (2021) provide a structural estimation of the SEC insider trading detection rate. Kedia and Rajgopal (2011) study the role of constraints in the SEC budget for the commission of fraud by corporate managers. Egan, Matvos, and Seru (2018) analyze ex post penalties on financial advisers. To the best of our knowledge, this paper is the first to focus on the ex ante implications of legal risk for both trading behavior and private information transmission.

I. Investigations and Legal Penalties

This section describes the data collection process and provides a detailed characterization of insider trading investigations, from the content and timing of private tips to legal penalties. For brevity, we relegate further background on insiders' prosecution to Section 1 of the Internet Appendix (Section IA.1 hereafter). We also outline therein the main elements of a case using the example of Matthew Martoma, one of the most prominently featured insiders in recent decades.

A. Description of the Sample

To gain a broad perspective on insider trading investigations, we retrieve a list of SEC litigation press releases containing the term "insider trading." We use this list to obtain all the available civil complaint files on the SEC website from January 2001 to December 2018.[6] In cases in which the complaint file is not available, we rely on information from the corresponding U.S. District Court and/or web searches. This process results in a sample of 530 SEC investigations that were either litigated or settled out of court spanning trading

[6] We track all documents that provide updates on a previously released complaint file. Whenever updated information is available at a later date, we rely on the most recent version. Kacperczyk and Pagnotta (2019) used similar types of files (with releases until 2015) to study the relation between informed trading and empirical proxies of asymmetric information.

episodes between 1995 and 2018. The average number of investigations per year is 26.4, with the maximum number of cases (47) filed in 2012.

Each case content is organized by characterizing trades and information events. A *trade* is any single transaction record for which we can observe a date and link to a private information event. For most trades, additional information about the price, trade direction, quantity, trading profits, and closing date of the position is also available. An *information event* is a collection of one or more trades motivated by a unique piece of information about a firm-level event, such as a merger. In each case, we record the companies involved, the nature of the leaked information, and the public release date. An insider can be linked to multiple information events regarding one or more firms. Figure IA.6 shows that the distribution of the number of information events per insider has a mode and mean equal to 1 and 2.3, respectively.

Manual data extractions from these investigations yield 6,553 unique trades involving 957 firms and 1,303 traders. We note that our complete data set is not a balanced panel; hence, the number of observations could differ across various tests. Panel A of Table I displays the sample characteristics. The distribution of the number of firms per case is highly asymmetric. While the mean is slightly over 2, approximately 80% of the cases involve a single firm, and 4% of cases involve 10 firms or more. The distribution of trades over time is fairly even, with a total of over 100 trades per year between 1999 and 2018. The number of trades per trader has a mode of one and mean and median values of 5.05 and 2, respectively, with a maximum of 115 trades. The mean and median numbers of trades per firm are 6.83 and 3, respectively.

B. Private Information and Trade Horizons

Panel B of Table I details the corporate event types for the affected firms. The most frequent event categories are M&As (53.22%), followed by earnings announcements (21.91%). The general business event category (10.16%) includes, among other things, information on product releases, patents, and U.S. Food and Drug Administration medical trials. Given the importance of M&As in our sample, unsurprisingly, the majority (74.31%) of private signals are positive (Panel C). The three most well-represented industry sectors in our sample are chemicals, business services, and electronic equipment, which account for 40% of all trades (Panel D). Notably, our sample involves companies spanning almost all industrial sectors.

Next, we characterize the relevant dates in a given investigation, as in Figure 1. The event begins with date T_{info}, when the trader receives a private signal about a given firm's fundamentals. Such an advantage disappears at the date T_{public}, when that 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 $T_{\text{last}} \leq T_{\text{public}}$. 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 days.

Table I

Corporate Events, Industries, and Trading Instruments: Summary Statistics

This table provides summary statistics for the sample of SEC insider trading investigations. The sample period covers 1995 to 2018. Panel A shows general characteristics. Firms per case is the number of distinct companies reported in a given case; traders per case is the number of individuals involved in insider trading; trades per trader is the number of trades executed by an individual across cases; trades per firm is the number of trades executed by all insiders trading a given firm's assets; assets per trader is the number of different assets traded by a given individual. Panel B shows the distribution of corporate event types motivating privately informed trades. Panels C and D show the distribution of the private information sign and trades by industry, respectively. Panel E shows the distribution of trading instruments used by insider traders.

Panel A: General Characteristics	Mean	Median	*SD*	Min	Max
Firms per case ($N = 957$)	2.10	1	3.77	1	40
Traders per case ($N = 1{,}303$)	2.44	1	3.01	1	32
Trades per trader	5.05	2	8.76	1	115
Trades per firm	6.83	3	10.38	1	197
Assets per trader	1.83	1	2.57	1	26

Panel B: Corporate Event Type	Number of Cases	Percentage
Mergers and acquisitions	702	53.22
Earnings announcements	289	21.91
General business events (patents, trials)	134	10.16
Shares offerings and tenders	94	7.13
Dividend changes and buybacks	39	2.96
Other (restatements/fraud/manipulation)	61	4.62
Panel C: Information Sign		
Good news	1,030	74.31
Bad news	356	25.69
Panel D: Distribution of Trades by Industry: Top 10 Codes (SIC2 Codes)		
Chemicals (28)	879	14.78
Business services (73)	862	14.49
Electronic equipment (36)	642	10.79
Measuring and controlling equipment (38)	372	6.25
Industrial and commercial machinery (35)	264	4.44
Engineering and management services (87)	212	3.56
Depositary institutions (60)	210	3.53
Nonclassifiable establishments (99)	173	2.91
Food and kindred products (20)	172	2.89
Communications (48)	168	2.82

Panel E: Trading Instrument	Number of Cases	Percentage
Stocks	4,109	66.42
Options	2,025	32.74
ADS	37	0.60
Bonds	15	0.24

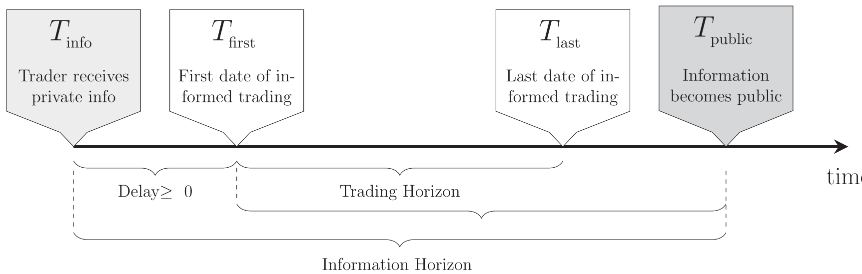


Figure 1. Timeline of an insider trading case. This figure shows the timeline of a generic insider trading case.

The left panel of Figure 2 displays the distribution of information horizons for the entire sample. The mean and median values are 25.14 and 11. The middle and right panels display the distributions for earnings and M&A events, respectively. Private information is longer lived for M&A events: the mean value of 30.44 is more than twice that value for earnings (13.1 days). Given the unscheduled nature of M&A announcements, some of which are delayed for months, we observe more significant skewness in the distribution's right tail. The median period from any given trade until T_{public} is seven days, and the median trading horizon is eight days.

C. Trading Instruments and Profits

There are 6,186 trades for which the trading instrument is known. Panel E of Table I shows that most trades are executed via stocks (66.42%) or options (32.74%). The remaining few are trades in American depositary shares (ADS) and bonds.

In most investigations, the SEC reports the aggregate profit figure corresponding to each trader, which can span more than one information event. The average trader profit is $1,271,755, and the median value is $95,109. About 49% of trades elicit at least $100,000 in profits. For a subset of 32% of the trades, we can calculate per-trade profits using the information on traded assets' quantities and prices, whose mean and median values are $358,632 and $19,250, respectively.

D. Civil and Criminal Penalties

Legal penalties materialize in two forms. Pecuniary penalties determined in civil court investigations are set in proportion to trading profits. Section 21A of the Securities Exchange Act of 1934 prescribes civil penalties of up to three times the profit or loss avoided. Nonpecuniary penalties result from a criminal investigation and usually take the form of prison time or probation. Criminal penalties can be up to $5 million and 20 years of imprisonment. Probation does not usually last longer than five years. In the absence of strong evidence, civil

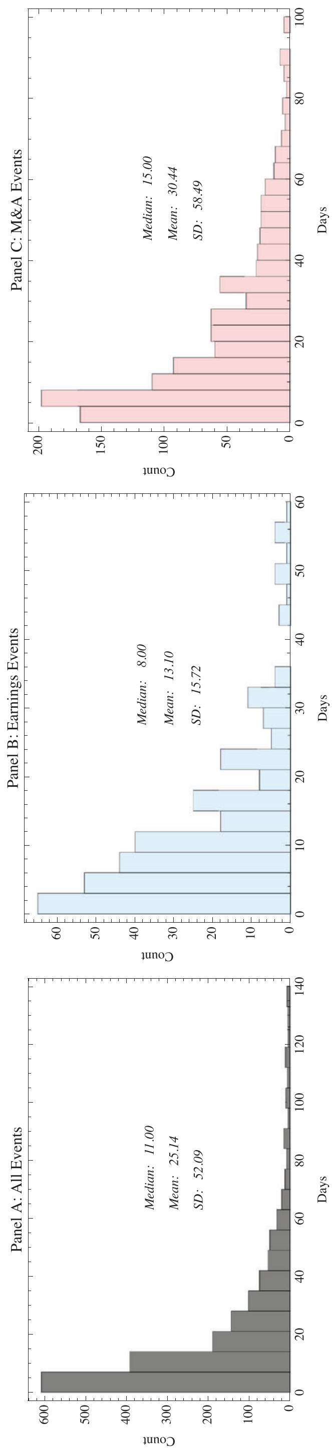


Figure 2. Distribution of private information horizons. This figure displays the distribution of private information horizons, $T_{\text{public}} - T_{\text{info}}$, measured in days. Panel A corresponds to all the information events. Panels B and C correspond to earnings and M&A events, respectively. (Color figure can be viewed at wileyonlinelibrary.com)

Table II

Insider Trading Penalties: Summary Statistics

This table provides general characteristics of the sample of insider trading penalties. Individual records are obtained from various sources, including SEC complaint files, web searches of court reports and newspaper articles, and searches of legal databases such as LexisNexis and Securities Law360. The sample period covers 1995 to 2018. Panel A reports the total number of cases in our sample, the number of cases that received at least one prison sentence, the number of cases that received at least one verdict of probation, and the number of cases where at least one trader was dismissed. Panel B shows the three most active courts regarding sentences for individual traders. Panel C reports information on traders' penalties: the average dollar penalty per trader, the total dollar penalty assigned for a full case, the standard deviation of penalties across traders within a given case, the percentage of traders assigned a prison penalty, the percentage of imprisoned traders within a given case, the percentage of traders who received probation, and the percentage of cases dismissed.

Panel A: Investigations	Number	Percentage
Total cases	530	100
Cases with prison sentence	84	15.85
Cases with probation	22	4.15
Dismissed	22	4.15

Panel B: Most Active Courts (N = 54)	Number	Percentage
Southern District of New York	307	23.91
Northern District of California	116	9.03
District of New Jersey	107	8.33

Panel C: Trader Penalties	Mean	Median	*SD*	Min	Max
Trader penalty (USD m.)	1.67	0.16	7.71	0	156.61
Total penalties per case (USD m.)	3.41	0.31	13.40	0	212.72
SD of penalties within case (USD m.)	1.50	0.11	4.49	0	31.17
Prison sentence (%)	10.12	–	–	–	–
Percentage of prisoned traders (within case)	11.26	0	28.74	0	100
Probation (%)	23.55	–	–	–	–
Dismissed (%)	16.82	–	–	–	–

courts sometimes dismiss cases brought in by the SEC. Panel A of Table II summarizes the investigation outcomes in our sample. About 16% of cases receive a prison penalty, another 4% receive probation, and about 4% of the originated cases are subsequently dismissed.

The assignment of cases to courts is largely based on geographic proximity to the trader's permanent address. We collect records on the corresponding courts, since, in principle, the severity of the penalties that a trader anticipates could depend on the ruling court. Since most ruling decisions occur at the level of divisional courts, we aggregate observations accordingly. The origin of verdicts has a diverse representation, with 54 divisional courts. Panel B of Table II summarizes some of the data. The most prominently featured courts are the

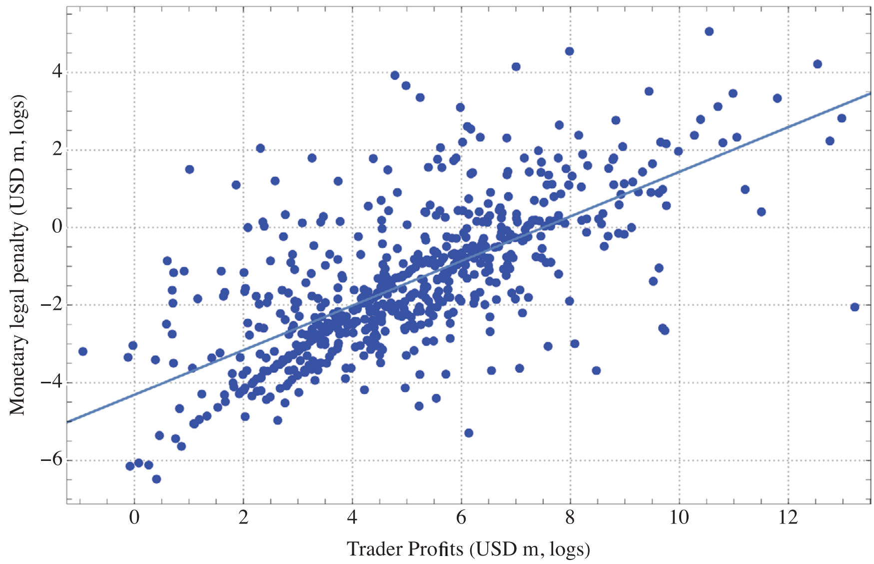


Figure 3. Insiders' trade profits and monetary penalties. This figure shows the (logarithmic) empirical relation between insider trading profits and monetary legal penalties in the sample. (Color figure can be viewed at wileyonlinelibrary.com)

SDNY, with 23.91% of traders, the District Court of the Northern District of California (9.03%), and the District Court of the District of New Jersey (8.33%).

We also collect detailed information on each penalty type for each defendant in the sample. The SEC complaint files report some of the relevant information. However, since many files miss critical records, we performed additional website searches for court reports and newspaper articles, and searched legal databases such as LexisNexis and Securities Law360. We obtain precise dollar figures for 1,039 traders, summarized in Panel C of Table II. The average monetary penalty for a given trader amounts to $1.67 million, with a median of $160,000. The largest individual penalty corresponds to Raj Rajaratnam of the Galleon Group, at approximately $156.6 million. The average total penalty per case, including all involved traders, equals $3.41 million, with a median of $310,000. Penalties can vary across traders in a given case; the average within-case standard deviation equals $1.5 million. More than 10% of traders in our sample received a prison penalty, with an average duration of 3.5 years. An additional 23.55% of traders received probation and 16.82% of their accusations were dropped.

To conclude this section, Figure 3 provides a graphical representation of the relationship between insider trading profits and monetary penalties, using a logarithmic scale. We find a robust positive relation between the two, which motivates an analogous theoretical assumption in the next section. We also observe substantial dispersion in outcomes in the figure, indicating that monetary penalties cannot be simply explained as a fixed and deterministic multiple of profits. The latter finding is consistent with the law providing courts with some discretion to determine the pecuniary amount.[7]

II. Model

This section introduces a simple theoretical framework to benchmark insiders' strategic decisions. Following the contributions of Kyle (1985) and Becker (1968), we consider a profit-driven informed trader who internalizes both the price impact of trades and possible legal threats.

A. Information and Enforcement Environments

We consider a discrete-time market for an asset with a liquidation value $\tilde{v}$ at time T_{public} that equals $v > 0$ with probability one-half, and $-v$ otherwise.[8]

Traders. The insider observes the realization of $\tilde{v}$ at time T_{info} before the market is active and submits market orders x_t on each date $t = 1, 2$, understanding that each order can impact the asset price, p. Nonstrategic liquidity traders submit market orders of size $u_t \sim N(0, \sigma^2)$ on each date.

Regulator. Apart from price impact concerns, the informed trader faces *legal risk* due to the potential enforcement actions of a *regulator*. The latter does not observe traders' information sets but can learn about the insider's actions by screening public trading activities to initiate internal investigations.

Similar to the work of DeMarzo, Fishman, and Hagerty (1998), the investigation process is based on an abnormal total volume rule that is common knowledge. We represent the investigation trigger event with $\delta_t := 1_{\{|y_t|>\bar{y}\}}$, where $y_t = x_t + u_t$ and $\bar{y} > 0$ is a policy threshold, and $q_t := \mathbb{P}(\delta_t = 1)$. Abnormal order flow, however, only constitutes indirect evidence and is not sufficient for prosecution. We assume that, conditional on detecting abnormal volumes, with probability D, the regulator gathers sufficient compromising evidence—such as phone calls and text messages—to meet institutional requirements. Thus, the probability of a successful prosecution, Q, can be represented as

$$Q(x_1, x_2) = (q(x_1) + (1 - q(x_1))q(x_2))D. \tag{1}$$

Regardless of the detection period, regulators' access to the insider's broker account reveals x_1 and x_2.

[7] More precisely, Section 21A of the Securities Exchange Act of 1934 specifies that the penalty should be determined by the court "in light of the facts and circumstances." See, for example, https://www.govinfo.gov/content/pkg/COMPS-1885/pdf/COMPS-1885.pdf and https://www.law.cornell.edu/uscode/text/15/78u-1.

[8] We share features of Kyle-type models, including the market participants and the price formation mechanism. While most studies consider a normal distribution of the asset value to obtain a unique linear equilibrium, the literature previously considered settings with a binary distribution. Examples include Back and Baruch (2004) and Chakraborty and Yilmaz (2004). Binary payoffs are also commonplace in sequential trade models of informed trading pioneered by Glosten and Milgrom (1985). We fundamentally depart from these papers by incorporating legal risk into the insider's optimization problem.

Upon successful prosecution, the legal penalty, P, is given by

$$P(\pi_1, \pi_2) = \left(c \sum_t \pi_t\right) \times 1_{\{\sum_t \pi_t > 0\}}, \tag{2}$$

where $\pi_t := x_t(v - p_t)$. The penalty in equation (2) is proportional to the accrued trade profits, $\sum_t \pi_t$. We consider the institutional parametric condition $c > 1$, which ensures that conditional on an enforcement action, insider trading remains unprofitable. The indicator function in equation (2) implies that the penalty can only be enforced when the insider has realized positive trade profits.

Legal Risk. Based on this regulatory environment, we refer to the insider's exposure to legal risk in relation to the two model parameters driving the expected legal penalty, c and D.

Market Maker. A competitive market maker sets the asset price p_t on each date $t = 1, 2$ without observing traders' information sets. At $t = 1$, the market maker updates a prior $\mathbb{E}(\tilde{v}) = 0$ according to y_1. To simplify the exposition, we assume that the market maker updates beliefs at $t = 2$ based on the observed cumulative aggregate order flow[9] but not δ_1.[10] Thus, $p_t = \mathbb{E}[\tilde{v}| \sum_{s \leq t} y_s]$.

Value Functions and Equilibrium. As in the Kyle (1985) model, the informed trader internalizes the price impact of each trade, but also their impact on investigation outcomes. Given the regulatory environment, at the beginning of $t = 1$, the informed trader has a value function given by

$$\begin{aligned} V_1(v) = \max_{x_1 \in \mathbb{R}} \mathbb{E}_{u_1|v} \Bigg\{ & \pi_1(x_1) + q(x_1) \quad \underbrace{(V_2(v, y_1, \delta_1 = 1))}_{\text{cont. value after investigation trigger}} \\ & +(1 - q(x_1)) \quad \underbrace{V_2(v, y_1, \delta_1 = 0)}_{\text{cont. value w/o investigation trigger}} \Bigg\}. \end{aligned} \tag{3}$$

Note that the continuation value V_2 depends on δ_1, since, upon observing this variable, the informed trader assesses the prosecution probability to be equal to $D \times q(x_2)^{1-\delta_1}$.

[9] Using the cumulative order flow simplifies matters by reducing the dimensionality of the market maker's problem at time $t = 2$. This allows for the visual representation of all equilibrium objects using two-dimensional graphs, and significantly reduces the equilibrium computational time. Alternatively, one can consider a market maker who updates beliefs based on $\{y_1, y_2\}$. Because the latter is a finer signal, all else held constant, the insider could perceive more price impact risk and trade lighter quantities in the equilibrium. However, our focus is on the relation between legal risk and trading strategies, which remains qualitatively unaltered.

[10] While one can allow δ_1 to influence p_2, assuming otherwise could be more realistic in some circumstances. For example, it is plausible to regard the market maker as relatively less aware of insiders' screening policies than the actual criminal. Even if aware of such a rule, the market maker could question its relevance in the price-setting process if, probabilistically, most informed traders are acting on legally acquired knowledge instead of misappropriated information.

At $t = 2$, the value function is given by

$$V_2(v, y_1, \delta_1) = \max_{x_2 \in \mathbb{R}} \mathbb{E}_{u_2, \delta_2 | \{v, y_1, \delta_1\}} \{\pi_2(x_2) - P(\pi_2; \pi_1)\}. \tag{4}$$

The equilibrium notion is that of a standard Bayesian Nash equilibrium: taking the pricing and enforcement rules as given, the informed trader selects trades according to equations (3) and (4); given the informed trader strategy, the market maker prices the asset according to its expected value, and the regulator prosecutes the insider with a probability given by equation (1) and enforces penalties as in equation (2).

B. Impact of Legal Risk on Trading Strategies

We design a fixed point algorithm to compute the equilibrium outcomes, as described in Section IA.2.A. Since the environment for positive and negative news is entirely symmetric, we focus on symmetric strategies regarding the information sign. The equilibrium components are illustrated in Figure 4.[11] To facilitate interpretation, we also display the equilibrium outcomes of the particular case of the model without legal risk (that is, $c = 0$ or $D = 0$).[12]

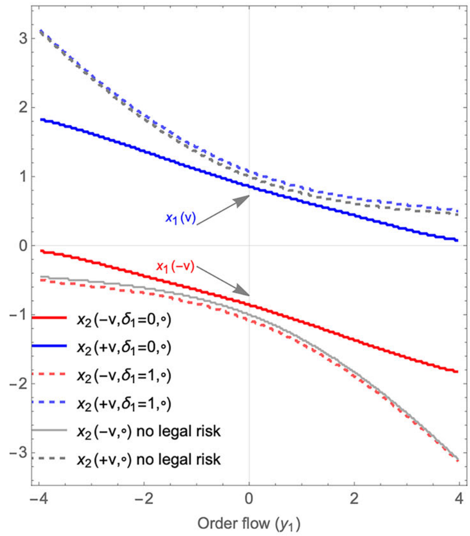
The left panel of Figure 4 displays insiders' trades in each period. To illustrate, consider the case of positive news on the top side. In the first period, the trade size is entirely determined by the asset value v. In the second period, trade size also depends on y_1 and δ_1. For a given δ_1 value, the informed trader places a less aggressive trade when prices have moved upward due to a high y_1 value. Surprisingly, for a given y_1, we find that $x_2(v, y_1, \delta_1)$ is lower when $\delta_1 = 0$. The intuition is that, when $\delta_1 = 0$, the informed trader is concerned about the impact of x_2 on *both* the asset price and the likelihood of prosecution. Instead, when $\delta_1 = 1$, the informed trader understands that regulatory screening will expose his/her trades, and prosecution will then occur with probability D. Therefore, one of the motivations to moderate trade aggressiveness, that is, reducing the probability of detection, is eliminated.

The middle panel of Figure 4 shows the market maker's pricing rule. We can see that the second period's pricing rule is steeper and approaches the liquidation value more quickly, which is intuitive since imbalances in $y_1 + y_2$ are more informative than those in y_1.

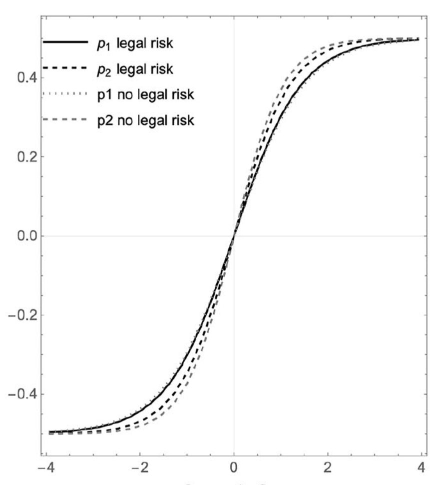
Finally, the prosecution probability Q shown in the right panel of Figure 4 reflects the insider's aggressiveness. Consider again the case with positive news.

[11] Although we are not able to establish the equilibrium uniqueness, we numerically checked that the qualitative relations reported in this section are robust to alternative parameter values.

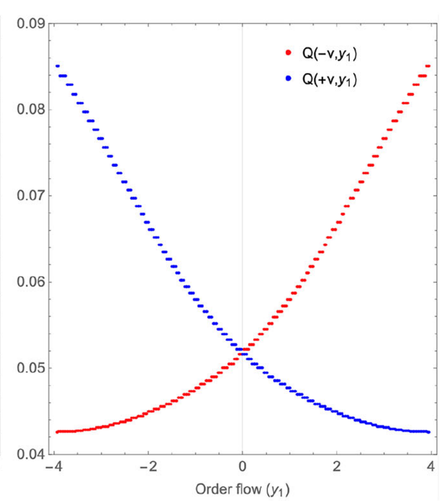
[12] Unlike in the canonical Kyle (1985) model with a normally distributed asset value, with a binary payoff, the market maker's pricing rule and the insider's trades are nonlinear in the order flow even when there is no legal risk (e.g., Back and Baruch (2004)). With legal risk, the model solution is generally nonlinear irrespective of the asset payoff distribution. An exception is given by an environment with $v \sim N(0, \sigma^2)$, a penalty function $P(x_1, x_2) = (x_1 + x_2)^2$, and detection occurring with an exogenous probability $Q \in [0, 1]$. The solution to this case is omitted but available upon request.



Panel A: Informed Trades

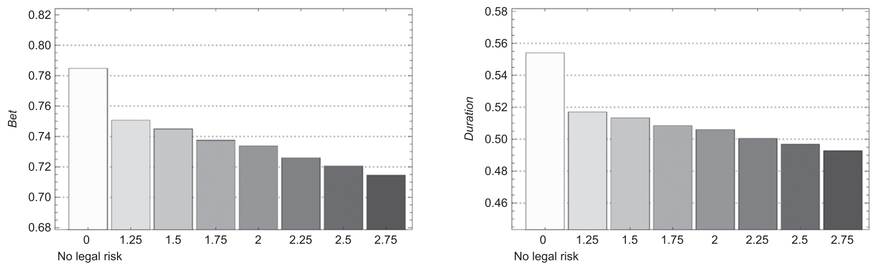


Panel B: Asset Price

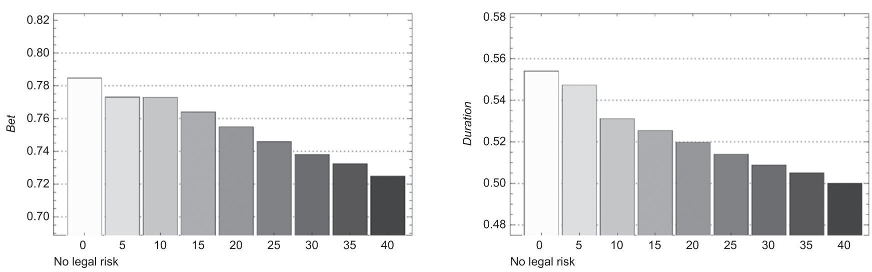


Panel C: Prosecution Probability

Figure 4. Equilibrium objects. This figure displays the main equilibrium objects. Panel A shows the insider's trades $x_1(v)$ and $x_2(v, y_1, \delta_1)$. The blue (red) lines represent the case with positive (negative) private information. The counterfactual trades corresponding to an equilibrium without legal risk are shown in gray. Panel B shows the market maker's pricing rule with and without legal risk. Panel C shows the prosecution probability in equation (1) for a given realization of $\tilde{v}$ and y_1. Parameter values are as follows: σ and the length of the asset value support $(2v)$ are equal to one, $\bar{y} = 2$, $D = 0.35$, and $c = 2$. (Color figure can be viewed at wileyonlinelibrary.com)



Panel A: Severity of the Penalty (c)



Panel B: Conditional Probability of Prosecution (D,%)

Figure 5. Legal-risk parameters and strategic outcomes: Empirical predictions. This figure shows the impact of changes in the legal-risk parameters c (Panel A) and D (Panel B) on the values of *Bet* and *Duration* as given by equation (5). Other parameter values are as in Figure 4.

Trades in the first period expose the insider with probability $q(x_1(v))$ and lead to prosecution with probability $q(x_1(v)) \times D$. In the second period, if $\delta_1 = 0$, the trade-related prosecution probability is $q(x_2(v, y_1\delta_1 = 0)) \times D$. Therefore, Q decreases with y_1 via the effect on x_2.

Next, we exploit these equilibrium connections to derive empirical predictions for the two following *strategic outcomes*:

$$Bet := \frac{1}{2}\mathbb{E}(|x_1| + |x_2|) \quad , \quad Duration := \mathbb{E}\frac{|x_2|}{|x_1|+|x_2|}, \tag{5}$$

where *Bet* is the average informed trading volume and *Duration* is the proportion of late trading volume.

The simulation of trading sessions permits the computation of the moments defined in equation (5). Figure 5 displays the outcomes for the same trading environment but different legal risk. Panels A and B show, respectively, the impact of changes in the severity of the penalty, c, and in the conditional probability of prosecution, D. Within each panel, the leftmost value regards the case without a legal threat ($c = 0$ or $D = 0$), and legal risk increases moving to the right as the expected penalty increases.

What is the impact of an increase in legal risk? Most straightforward is the negative effect on *Bet*: the insider internalizes higher expected legal costs by reducing the total traded amount. The distribution of trade volume across periods captured by *Duration* is also affected. To provide intuition, we relate to the Kyle (1985) model. The insider therein trades a larger size as the information expiration date approaches to optimally manage price impact. The same holds in our setting when the legal risk is negligibly small: considering the parameter c, $\lim_{c\to 0} |x_2| - |x_1| > 0$ ($\lim_{c\to 0} \mathit{Duration} > \frac{1}{2}$). All else being equal, an increase in legal risk incentivizes the insider to trade more balanced amounts, thereby reducing the probability of triggering an investigation due to an abnormally high order flow imbalance. Doing so requires reducing x_2 in a more significant proportion than x_1; thus, *Duration* decreases.

We summarize these empirical predictions as follows:

PREDICTION 1: *The value of Bet decreases with legal risk.*

PREDICTION 2: *The value of Duration decreases with legal risk.*

III. Empirical Methodology

To test the model's predictions, we require empirical measures of legal risk. Finding such measures is generally not feasible; hence, we resort to two experiments that offer plausibly exogenous shocks to such risks. The first involves the Newman ruling, which we argue has unilaterally changed the perception of legal risks for some traders. The second involves Preet Bharara's tenure at SDNY and is based on traders' differential treatments across legal jurisdictions. Notably, both shocks are specifically related to insider trading, and less directly connected to other macrolevel events. In this section, we provide institutional background on these events, describe the construction of proxies for the model's strategic outcomes, and outline the methodology of our baseline tests.

A. Shocks to Legal Risk

The Newman Ruling. In December 2014, a surprising decision by the U.S. Court of Appeals for the Second Circuit dismissed the penalties of two hedge fund managers, Todd Newman and Anthony Chiasson. Both managers had appealed their SDNY insider trading prison sentences in 2013. The court's view was that to prove a violation of insider trading laws, prosecutors must prove that a corporate insider acting as the tipper received money or valuable property in exchange for leaking material information and that the defendants were aware that the information was wrongfully acquired.[13] Because the de-

[13] In the Newman-Chiasson decision (Nos. 13-1837-cr and 13-1917-cr), the court of appeals judges wrote, "We hold that to sustain an insider trading conviction against a tippee, the Government must prove each of the following elements beyond a reasonable doubt: that (1) the corporate insider was entrusted with a fiduciary duty; (2) the corporate insider breached his fiduciary duty by (a) disclosing confidential information to a tippee (b) in exchange for a personal benefit; (3) the tippee knew of the tipper' s breach, that is, he knew the information was confidential and divulged for personal benefit; and (4) the tippee still used that information to trade in a security or tip another individual for personal benefit." The explicit requirement to prove material compensation to

fendants were several layers removed from the original information leaks and prosecutors found no evidence of payments for tips, these fund managers were freed from prison.

This stricter interpretation of the law came as a shock that quickly torpedoed several insider trading prosecution cases. Cases in which prosecutors had already obtained guilty pleas were abandoned. Indeed, in an unsuccessful rehearing attempt in April 2015, prosecutors argued that this decision "will dramatically limit the Government' s ability to prosecute some of the most common, culpable, and market-threatening forms of insider trading," and "arguably represents one of the most significant developments in insider trading law in a generation." [14] Consistent with these views, other pundits have argued that this ruling significantly reduced the expected legal hazard of insider traders.[15]

An appealing feature of the Newman shock is that, unlike regulations motivated by shocks to the financial sector, this ruling did not coincide with other significant market events and was largely unexpected by the finance community. In this regard, the event represented a reasonably exogenous shock to the legal environment. Notably, the ruling was subsequently weakened in December 2016, when another decision, the Supreme Court's ruling in *United States v. Salman*,[16] reversed some, but not all, conditions specified in the Newman ruling.[17] Therefore, we argue that the two-year period 2015 to 2016, the *Newman period*, represents the regime with the lowest legal risk. Empirically, Panel A of Figure 6 shows a sharp decline in monetary and prison penalties over such a period relative to the preceding five-year average.

By its nature, the Newman ruling must have affected insider traders differently. While it is not feasible to assess the risk reduction on a trader-by-trader basis,[18] for identification purposes, we argue that the decline in legal risk must have been stronger for those traders who received a tip from another party.

the tipper seemingly contradicted the Supreme Court' s 1983 decision in *Dirks v. SEC* (463 U.S. 646 (1983)), which argued that liability can exist when an insider makes "a gift of confidential information to a trading relative or friend".

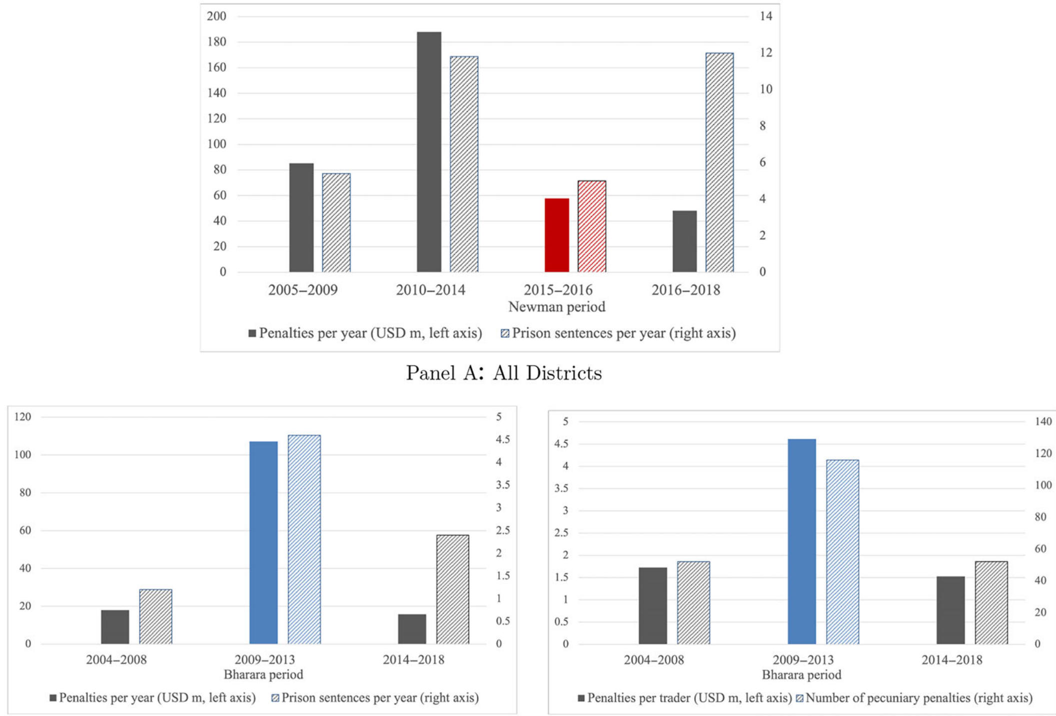
[14] See, for example, https://www.nytimes.com/2015/04/04/business/dealbook/appeals-court-rejects-request-to-rehear-landmark-insider-trading-case.html?_r=0 and https://nypost.com/2015/04/03/preet-bharara-dealt-rare-setback-by-federal-appeals-court/.

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

[16] See 792 F.3d 1087 (2015).

[17] On the Supreme Court's ruling in the Salman case, Mary Jo White, then chairman of the SEC, optimistically commented, "The decision reaffirms our ability to continue to aggressively pursue illegal insider trading and bring wrongdoers to justice." See, for example, https://www.wsj.com/articles/supreme-court-backs-prosecutors-over-tips-from-friends-and-family-in-insider-trading-cases-1481038798.

[18] First, the relationship between the tipper and the trader is not fully detailed in all cases. Second, some traders could face ambiguity regarding the legal characterization of such a relation. For example, as noted above, the Supreme Court decided in *Dirks v. SEC* that liability can exist in the absence of monetary compensation when an insider gifts confidential information to a trading relative or friend. There is ambiguity in applying this view in practice (e.g., regarding the precise definition of "friend"). Is, say, a Facebook or LinkedIn contact a friend?



Panel A: All Districts

Panel B: SDNY: Average Penalties Per Year

Panel C: SDNY: Average Penalties Per Trader

Figure 6. Monetary penalties and prison sentences 2004 to 2018: All districts and SDNY. This figure displays the monetary insider trading penalties and the number of prison sentences. Panel A corresponds to all districts and highlights the Newman ruling period in red. The solid columns display the average value of monetary penalties per year, and the dashed columns the yearly average number of prison sentences. Panel B presents the same information corresponding to SDNY and highlights the five-calendar-year window including the Bharara period in blue. Panel C displays SDNY yearly average monetary penalties per trader (solid columns) and the annual number of traders with monetary penalties (dashed columns). The penalty data are available at the yearly frequency. Therefore, the highlighted legal shock periods are similar but do not match exactly the definitions of the variables *Newman* and *Bharara* in this section. Sources: SEC, district courts, LexisNexis, and Securities Law360. (Color figure can be viewed at wileyonlinelibrary.com)

Conversely, those who traded on self-acquired information would essentially be unaffected. Accordingly, we hand-collect records regarding the type (i.e., source) of information acquisition from the investigation source files. Approximately 20% of our observational units correspond to the trades of insiders who acquire information on their own.

Bharara's Tenure at the SDNY. Not all insider trading prosecutors act with the same conviction or possess the same ability to prove financial crime in court. The SDNY became renowned as a tough court during the tenure of Preet Bharara, who was described by some as a crusader prosecutor. For example, according to *The New York Times*, Bharara was one of "the nation's most aggressive and outspoken prosecutors of public corruption and Wall Street crime."[19]

Bharara enjoyed a flawless multiyear trial record in insider trading cases from the time he was sworn in to the position in August 2009. However, such seeming invincibility ended in 2014, when a jury acquitted Rengan Rajaratnam of insider trading charges and effectively ended the long-standing "perfect hedge" investigation—which was one of the largest in recent decades and imprisoned his sibling, Raj Rajaratnman.[20] The judicial setbacks in 2014 also included the Newman ruling, discussed above, which substantially weakened Bharara's power[21] (his tenure ended in March 2017). Hence, for identification purposes, we argue that illegal traders prosecuted by the SDNY faced exceptionally high legal risk from August 2009 to the end of 2013, a period we call the *Bharara period*.

The time-series variation in pecuniary penalties and the number of prison sentences for cases processed by the SDNY, reported in Panel B of Figure 6, provide empirical support for our claim. The graph shows a remarkable increase in the value of these penalties over the five-year treatment period relative to the preceding one and an equally marked decrease from 2014 onward.[22] Panel C shows that not only the number of SDNY monetary penalties increased sharply over the Bharara period, the average penalty per trader more than doubled relative to that between 2004 and 2008.[23]

[19] See https://www.nytimes.com/2017/03/10/nyregion/preet-bharara-us-attorney.html.

[20] See, for example, https://dealbook.nytimes.com/2014/07/08/jury-clears-rengan-rajaratnam-in-insider-trading-case/.

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

[22] We note that, from 2011 on, the considered Bharara period is contemporaneous with the implementation of the SEC' s WRP as part of the Dodd-Frank Act. While implementing this program could have increased the arrival frequency of whistleblowers, what is essential for our purposes is that it affects *all* legal jurisdictions, not just the SDNY. On the other hand, our empirical strategy studies the differential response of traders located in the SDNY to Preet Bharara's actions. Quantitatively, the sharp drop in SDNY penalties from 2014 on—occurring without any specific changes to the WRP—suggests that the marginal impact of the WRP is likely of moderate size relative to the Bharara effect. We address the WRP adoption more fully in Section IA.4.

[23] In contrast, the number of penalties per year across all districts decreased by 38.7% over the Newman period compared to that during the prior five-year average period. The per-trader monetary penalties across all districts display much less time variation around the Newman shock.

In our view, the consideration of both shocks is appealing because of helpful complementarities. What is most apparent, these shocks are of the opposite sign, which enables us to study whether insiders' reactions to both an increase and a decrease in legal risk are symmetric. In addition, the Newman ruling considerably raised the bar for the successful prosecution of an insider, which best relates to the probability D in our model. Bharara's tenure is also associated with the greater severity of the effective penalties, captured by c. Hence, we can assess whether insiders respond to these specific factors.

B. Insider Trading Strategies: Empirical Proxies

In this section, we construct empirical counterparts to the strategic outcomes in equation (5). We also define closely related metrics to account for features in the data not present in the model. Even though we suppress subscripts, unless otherwise noted, all the trading variables relate to a single information event/trader tuple.

The variable $\hat{Bet}$ is the total dollar value that an insider trades over the trading horizon $[T_{\text{first}}, T_{\text{last}}]$. Even though this measure provides information about an insider's wealth exposure, it might not accurately reflect the market impact of individual trades; dollar volumes can systematically vary across firms, times, and security types, which can affect the trader's behavior as well. We therefore define a second, normalized volume measure as follows:

$$\hat{Bet}Norm := \max_{a} \left\{ \frac{Informed\ vol_a}{Normal\ vol_a} \right\}, \tag{6}$$

where $a \in \{\text{stocks, calls, puts}\}$, and normal volume is defined as the average daily dollar volume for the same asset over the previous calendar year.[24] We include the max operator because some traders use both stocks and options simultaneously. For options, we compute the normal volume across all contracts with the same underlying stock. To allow for comparability across contracts, which could have distributions of volumes of different magnitudes, we standardize the values in equation (6) in the regression analyses that follow by subtracting the unconditional mean and dividing the differences by the unconditional standard deviation (reported coefficients of $\hat{Bet}Norm$ all correspond to standardized values).

To proxy for *Duration*, we consider two measures that mimic our model's two-period horizon, facilitating cross-comparisons. First, we consider the following ratio:

$$\hat{D}uration := \frac{Informed\ vol\ [T_{\text{info}} + 7, T_{\text{public}}]}{Informed\ vol} \times 1_{\text{split}} \in [0, 1], \tag{7}$$

where 1_{split} is an indicator function that equals one if insider trade quantities are observed on more than one date for a given information event, and zero

[24] If the insider traded over a range of dates, but only the total volume is available, we compute Informed vol on daily basis using linear interpolation.

otherwise. If the insider trades on a single date, the measure is not well defined. We note that the seven-day threshold is below the mean and median values for the information horizon reported in Section I.B. By construction, the value of this measure can be affected by whether the trader delays action upon becoming privately informed—the median value of such delay is near two calendar days.

One possible limitation of expression (7) is that a parametric threshold splitting the trading period might not be ideal for corporate information events of very short or very long horizons. Therefore, we also consider a nonparametric partition of the information horizon $[T_{\text{info}}, T_{\text{public}}]$ into two equal subperiods, early and late, and compute the trading volume within each subperiod. We then compute:

$$\hat{D}urNorm := \frac{Informed\ vol_{\text{late}}}{Informed\ vol} \times \mathbf{1}_{\text{split}} \in [0, 1]. \tag{8}$$

This normalization has the advantage of facilitating comparisons across corporate information events of significantly different timings.

Intuitively, values of $\hat{D}uration$ and $\hat{D}urNorm$ close to zero (one) indicate that a high proportion of the informed trading volume is executed closer to T_{info} (T_{public}). Because Informed vol is based on dollar figures, we compute the measures in equations (7) and (8) separately for stock and option trades. Figure IA.5 characterizes the empirical distributions of these proxies.

C. Regression Setting

We now present the design of our empirical tests. Each test aims to capture the effect of shocks to legal risk, as described in Section III.A, on the strategic metrics of Section III.B.

To assess the impact of the Newman ruling, we estimate the following regression:

$$\begin{aligned} StratOutcome_{ij} = & a_1 \times Newman_i + b_1 \times EventType_i + c_1 \times Trader_j + d_1 \times Year_i \\ & + \delta_1 \times \underbrace{Newman_i \times NewmanAgent_j}_{\text{InteracNewman}} + e_1 \times \mathbf{Controls}_{ij} + \varepsilon_{1,ij}, \end{aligned} \tag{9}$$

where each unit of observation is associated with a trade i by insider j; *Newman* is an indicator variable equal to one for the period 2015 to 2016, and zero for the period 2013 to 2014; *NewmanAgent* is an indicator variable that equals one if the trader received information from another tipper, and zero otherwise. A two-year control time window reduces the possibility of capturing additional regulatory changes over more extended periods. Our coefficient of interest is δ_1, capturing the differential impact that the Newman ruling had over those traders who experienced the most significant reduction in risk.

We include year fixed effects, *Year*, and cross-sectional fixed effects, as follows. *EventType* absorbs possible differences in the way insiders trade around corporate events, such as M&As or earnings announcements. Trader fixed effects, *Trader*, capture any unobserved time-invariant, insider-level characteristics that could affect their trading behavior.[25] Examples of such characteristics are wealth, income level, access to leverage, trading experience, marital status, and how the court in the trader's legal jurisdiction could affect perceived legal risks.[26]

The vector **Controls** includes two variables motivated by our theoretical model. To proxy for the volatility of noise trading, we use the average annualized volatility of the daily trading volume over the previous calendar year, *Volume Vol*.[27] To account for the size of private signals, we compute the percentage change in the corresponding stock price from the opening price on date T_{first} to the opening price immediately after the information becomes public, on date $T_{\text{public}} + 1$. We denote the absolute value of such a return, adjusted by the S&P500 index, as *Strength*.[28]

To sharpen our identification, we include additional control variables that could be correlated with trading behavior. Two of the controls capture ex-ante heterogeneity in the liquidity and volatility levels of the traded assets: *Ln(MktCap)* represents the average value of the (logarithm) of market capitalization, and *Volatility* corresponds to daily stock return volatility. The average values are computed over the previous calendar year.

Our second test is based on the Bharara shock. We compare the strategic decisions of traders subjected to SDNY jurisdiction to those of traders investigated by other jurisdictions during the Bharara period *and* during adjacent periods. To this end, we estimate the following regression model:

[25] Recall that a given insider can appear more than once in our panel if the insider trades on different information events concerning the same or multiple firms (see examples in Section IA.3.D). We also note that an insider could appear to be trading on separate corporate events before, after, or before *and* after the legal shock. Therefore, adding trader fixed effects brings the regression specification closer to an idealized setting where the set of insider traders is unaltered across time. The Newman test has 12 traders who appear in the periods before and after the legal shock (corresponding to 298 observations), not necessarily motivated by the same information event across periods, and 161 traders who trade only in one of those periods (1,271 observations). In the Bharara test, 57 traders span both periods (1,148 observations), and 657 traders span one period (3,469 observations).

[26] We note that insiders who trade on multiple firms were not necessarily caught multiple times (to the best of our knowledge, investigations in which the defendants were previously found guilty of insider trading are very rare). Large-scale investigations such as Rajaratnam' s Perfect Hedge or Cohen' s SAC Capital, often start with one episode of insider trading that subsequently reveals the existence of more. Even if the original red flag originated in abnormal trade patterns, prosecutors can later learn about other episodes through different investigative means, such as confessions of the trader, tippers, or direct analyses of the defendant' s brokerage accounts.

[27] We also considered the fraction of retail trading to measure noise trading. The results are qualitatively identical.

[28] The estimation results are similar using unadjusted returns.

Table III

Dependent and Control Variables: Summary Statistics

The definition of variables in this table is as in Appendix. The construction of the dependent variables and controls is discussed in Sections III.B and III.C. The values of $\hat{Bet}$, $\hat{Bet}Norm$, PSV, and (nonbinary) controls variables are winsorized at the 1% level. The summary statistics for $\hat{Bet}Norm$ in Panel A correspond to standardized values of this variable, using the mean and standard deviation of the unwinsorized sample

Characteristic	Mean	Q25	Q50	Q75	*SD*
Panel A: Dependent Variables					
$\hat{Bet}$	3,089.99	37.52	151.68	745.47	12,418.49
$\hat{Bet}Norm$	−0.051	−0.091	−0.089	−0.073	0.248
$\hat{D}uration$	0.721	0.540	0.751	1	0.276
$\hat{D}urNorm$	0.449	0.281	0.471	0.546	0.239
PSV	45.48	19.15	30.46	52.77	73.84
Panel B: Control Variables					
$Strength$	29.92	6.09	23.66	46.44	51.48
$Volatility$	51.26	32.82	44.96	62.92	25.22
$VolumeVol$	114.71	18.68	53.80	108.09	201.09
$Ln(MktCap)$	13.85	12.67	13.88	14.86	1.8
$NewmanAgent$	0.813	–	–	–	–
$SDNY$	0.321	–	–	–	–

$$StratOutcome_{ij} = a_1 \times Bharara_i + b_2 \times EventType_i + c_2 \times Trader_j + d_2 \times Year_i + \delta_2 \times \underbrace{Bharara_i \times SDNY_j}_{\text{InteracBharara}} + e_2 \times \mathbf{Controls}_{ij} + \varepsilon_{2,ij}, \quad (10)$$

where $SDNY$ is an indicator variable equal to one if the insider case was subject to prosecution in the SDNY, and $Bharara$ is an indicator variable equal to one for the period August 2009 to December 2013, and zero for the periods January 2006 to July 2009 and 2014 to 2015.[29] All the other regressors are as defined above. Our coefficient of interest is δ_2.

To allow for the correlation of residuals across individual traders, we cluster standard errors by the trading date in the estimation of regression models (9) and (10). To mitigate the impact of extreme observation values on our estimates, we winsorize $\hat{Bet}$, $\hat{Bet}Norm$, and the variables in **Controls** at the 1% level. Table III provides descriptive statistics.

[29] As explained in Section III.A, the treatment period matches the span of Bharara's ultimate power. To balance the length of the treatment period, we use the two years after 2013 and the three years before 2009 as a control window. The results are very similar if, instead, we use the five-year period from 2004 to 2008. In turn, the results weaken somewhat if we use the entire period from 2009 to 2015 as a treatment period, which is consistent with our view of Bharara's weakening power due to the Newman ruling.

We provide in Section IA.3 additional analyses to validate our empirical results. First, we analyze case characteristics across groups affected and unaffected by the Newman and the Bharara shocks. Table IA.I shows that cases are similar along most dimensions, except that $SDNY = 1$ cases display more firms per case, and $NewmanAgent = 1$ cases display relatively more M&A events. Any time-invariant heterogeneity due to the latter should be absorbed by $EventType$.

Second, we assess sample balancedness. Table IA.II presents group-specific statistics for the time-varying regressors in equations (9) and (10) and a host of stock characteristics and liquidity measures. We find that the respective subsamples do not differ significantly, suggesting that any treatment effects we identify are unlikely a reflection of ex ante differences driving heterogeneous trading patterns among trader groups.

Finally, we test for pretreatment trends in the outcomes variables by estimating a specification similar to equations (9) and (10) that includes leads and lags of the relevant treatment variable. We present event study plots and test the hypothesis that the pretreatment interaction coefficients are jointly insignificant. Table IA.III shows that we fail to reject the latter hypothesis for all outcomes variables in the Newman test and all but one variable in the Bharara test.

We conclude that, even though our experiments do not allow for perfectly random assignment of traders to treatment, the estimation results in the following section are unlikely to be an artifact of obvious significant imbalances in the selection of firms on observables or preexisting trends in the outcomes variables.

IV. Empirical Results

Table IV presents the test results regarding Predictions 1 and 2. Panels A and B correspond to the Newman and the Bharara tests, respectively. Columns (1) to (4) display results for a specification without the variables in Controls. In columns (5) to (8), we consider the full specification models (9) and (10). We concentrate the discussion on the latter set of estimates of the coefficients δ_1 and δ_2.

The results of the Newman test show that, given a *reduction* in legal risk, insiders trade relatively later, and their trade quantities increase. The effects are also economically relevant, as graphically shown in Panel A of Figure 7 for the ratio between the full-model interaction coefficients and the corresponding standard deviation of each outcome variable. The relevant interaction coefficients for $\widehat{Bet}$ and $\widehat{BetNorm}$ are positive, with statistical significance at the 10% level, and show a relative increase of 30.83% and 72.98%. In turn, similar coefficients for $\widehat{Duration}$ and $\widehat{DurNorm}$ increase by 95.1% and 92.95% relative to their respective standard deviations and are statistically significant at the 1% and 5% levels.

The Bharara test results are qualitatively consistent with the model's prediction under an *increase* in legal risk. We observe a pronounced decrease in

Table IV

Impact of Legal-Risk Shocks on Illegal Insiders' Strategic Outcomes

This table shows the estimation results for the regression models (9) and (10) in Panels A and B, respectively. The dependent variables are $\hat{Bet}$, $\hat{BetNorm}$, $\hat{Duration}$, and $\hat{DurNorm}$ as defined in Appendix. The variable *InteracNewman* is given by the product between the variables *Newman* and *NewmanAgent*, as follows. *Newman* is an indicator variable equal to one for 2015 to 2016, and zero for 2013 to 2014, and *NewmanAgent* is an indicator variable equal to one if the trader received the private information from another individual (see Section III.B). The variable *InteracBharara* is given by the product between the variables *Bharara* and *SDNY*, as follows. *Bharara* is an indicator variable equal to one for the period 2009:08 to 2013:12 and zero for 2006:1 to 2009:7 and 2014 to 2015, and *SDNY* is an indicator variable equal to one for traders convicted by SDNY, and zero for traders convicted in other courts (see Section III.B). The regression specifications (1) to (8) include *Event*, *Trader*, and *Year* fixed effects as defined in Appendix. All additional control variables used in specifications (5) to (8) are as in Appendix. Standard errors (in parentheses) are clustered by the date of trading. ***, **, and * denote the 1%, 5%, and 10% levels of statistical significance, respectively

	$\hat{Bet}$ (1)	$\hat{BetNorm}$ (2)	$\hat{Duration}$ (3)	$\hat{DurNorm}$ (4)	$\hat{Bet}$ (5)	$\hat{BetNorm}$ (6)	$\hat{Duration}$ (7)	$\hat{DurNorm}$ (8)
Panel A: Newman Shock								
InteracNewman	3,765.346*	0.068	0.327***	0.139	3,828.661*	0.181*	0.262***	0.224**
	(2,163.359)	(0.084)	(0.080)	(0.091)	(2,065.028)	(0.097)	(0.074)	(0.113)
Strength					677.041	0.024	−0.030	0.016
					(412.163)	(0.026)	(0.027)	(0.062)
Volatility					2,264.216	−0.174	−0.126	0.467***
					(1,477.867)	(0.138)	(0.109)	(0.147)
VolumeVol					−65.318	−0.061**	0.017	−0.084**
					(417.940)	(0.031)	(0.024)	(0.033)
Ln(MktCap)					381.308	−0.018	0.010	0.054***
					(270.513)	(0.015)	(0.010)	(0.012)
Observations	616	700	518	479	556	679	467	434

Continued

Table IV—*Continued*

	$\hat{Bet}$ (1)	$\hat{BetNorm}$ (2)	$\hat{Duration}$ (3)	$\hat{DurNorm}$ (4)	$\hat{Bet}$ (5)	$\hat{BetNorm}$ (6)	$\hat{Duration}$ (7)	$\hat{DurNorm}$ (8)
Panel B: Bharara Shock								
InteracBharara	−729.976	−0.181***	−0.064	0.021	−1,303.607*	−0.166***	−0.050	−0.003
	(518.741)	(0.040)	(0.054)	(0.060)	(695.866)	(0.040)	(0.057)	(0.059)
Bharara	−265.420	0.098***	−0.072*	0.106**	783.586	0.063*	−0.101**	0.188***
	(1,013.077)	(0.034)	(0.043)	(0.052)	(1,137.583)	(0.034)	(0.048)	(0.056)
Strength					417.807*	−0.006	−0.021***	0.017*
					(242.019)	(0.010)	(0.008)	(0.010)
Volatility					−4,538.320***	−0.191***	−0.052	0.108*
					(1,668.646)	(0.048)	(0.040)	(0.060)
VolumeVol					1,027.562***	0.000	0.000	−0.012
					(340.459)	(0.004)	(0.005)	(0.008)
Ln(MktCap)					486.304	−0.014	−0.007	0.013
					(391.054)	(0.010)	(0.007)	(0.011)
Observations	3,059	3,359	2,682	2,486	2,853	3,276	2,502	2,338

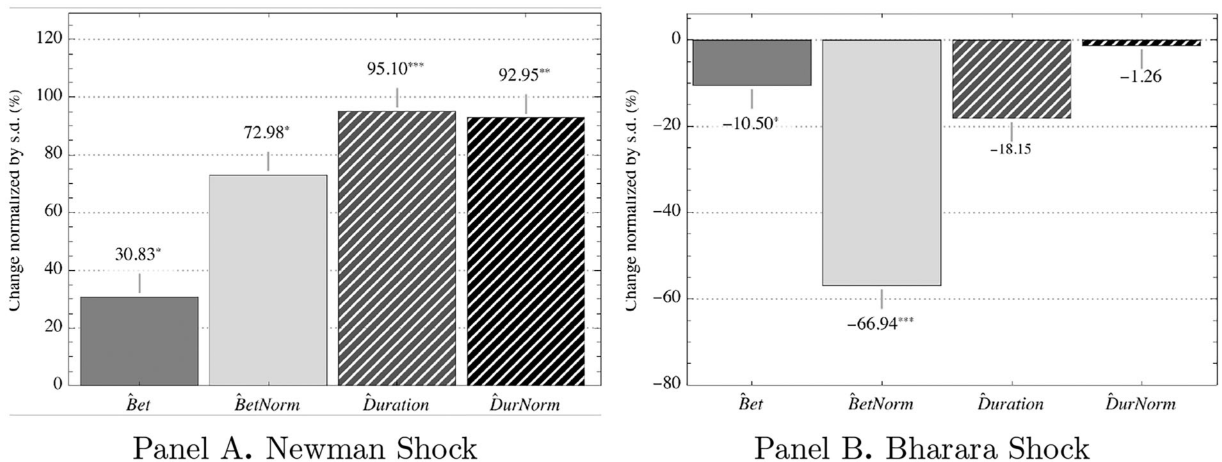


Figure 7. Summary of empirical results. Each bar displays the percentage ratio between the estimated values of δ_1 and δ_2 in the full model specifications (9) and (10) (see Table IV) and the corresponding strategic outcome's standard deviation (see Table III). Panels A and B correspond to the Newman and the Bharara tests, respectively. ***, **, and * denote the 1%, 5%, and 10% levels of statistical significance, respectively.

$\hat{Bet}$ and $\hat{BetNorm}$, equivalent to 10.5% and 66.94% of their standard deviation, as shown in Panel B of Figure 7. These coefficients are statistically significant at the 10% and 1% levels. Also as predicted, the interaction coefficients for $\hat{Duration}$ and $\hat{DurNorm}$ are negative, although these two coefficients display low t-test values compared to the Newman shock.

Overall, the evidence suggests that rogue insiders internalize legal-risk exposure changes, as shown by the mostly economically significant changes in the strategic outcomes. We also observe that the impact on strategic outcomes is fairly consistent with that captured in Predictions 1 and 2. Individuals who benefit from a decrease in legal risk from the Newman ruling trade relatively heavier volumes closer to the event announcement. Those who suffer an increase in legal risk from the Bharara shock trade lighter volumes[30] and relatively earlier, although the evidence from duration measures is not as strong as that based on Newman's shock.

V. Ex Ante Benefits and Private Signal Value

Thus far, we have analyzed the impact of expected legal costs on insiders' trading strategies. We now assess the impact of legal risk from the perspective of the ex ante benefits of crime engagement.

A. Insiders' Engagement Decisions

Following the seminal ideas of Becker (1968), we consider an extension of the model decision that incorporates crime engagement. Assume that the agent who observes the private signal decides whether to act on that signal at time T_{info}. Doing so requires paying an amount $k > 0$ representing factors such as the moral stigma of infringing on the law, a bribe to the tipper, and/or the opportunity cost of due diligence to verify the information quality and set up a brokerage account. As before, the liquidation value $\tilde{v}$ equals $v > 0$ with probability one-half, and equals $-v$ otherwise. To introduce richer heterogeneity in the value of private signals, assume that the value $|v| \sim G$ is publicly observed

[30] In separate analyses, we inquire whether insiders' responses to the legal shocks are similar across corporate events. We consider the two main event types, M&As and earnings announcements, and split the sample accordingly to compute separate estimates of the interaction effects. Notably, for the Bharara test, the coefficient δ_2 associated with $\hat{Bet}$ displays a more robust and sizable decline in response to the legal shock for M&A events than for earnings. Such heterogeneity could be intuitive for several reasons. First, unlike M&As, earnings announcements are fully anticipated and likely attract additional speculators besides genuine insiders. Provided that such speculators can influence the trading process, it is plausible that the speculators' actions would distort insiders' strategies. Second, there could be different perceptions of legal-risk exposure: if M&As occur at times of relatively normal trading activity, insiders could be warier that any abnormal trading activity would leave traces that regulators could more easily detect. Third, one could also expect differences at the prosecution stage of a potential trial. Insiders could anticipate a lower risk of successful prosecution when trading on earnings news due to the plausible deniability of misappropriated knowledge; for example, by citing sentiment-based trading motives.

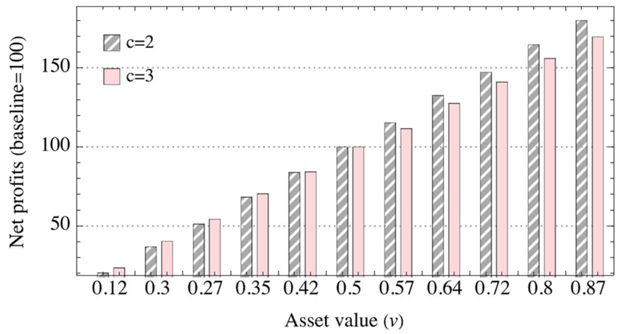


Figure 8. Insider's value function: Variation in the private signal value and the severity of the penalty. This figure shows the value of $V_1(|v|;c)$ (see equation (3)) for various v values and $c \in \{2, 3\}$, using the normalization $V_1(0.5; 2) = 100$. Other parameter values are as in Figure 4. (Color figure can be viewed at wileyonlinelibrary.com)

at time T_{info}, where G is a continuous cumulative distribution function with support $[0, \overline{v}]$. Only the insider observes the sign of the value, though.

Upon observing $|v|$, the insider anticipates (gross) profits given by $V_1(|v|; c, D)$, where V_1 follows equation (3). Consider parameter c. Everything else being equal, Figure 8 shows that V_1 increases with the extent of mispricing, v, and decreases with c. Given the expected benefits and costs, a rational agent who internalizes legal risk would be willing to act on the private signal if the net payoff is positive, which requires $V_1(|v|; c) - k > 0$. If $\hat{v}(c)$ satisfies $V_1(\hat{v}(c); c) = k$ and $c_H > c_L$, then $\int_0^{\overline{v}} |v| dG(|v|\,||v| > \hat{v}(c_H)) > \int_0^{\overline{v}} |v| dG(|v|\,||v| > \hat{v}(c_L))$.

Therefore, in response to increased expected legal costs, insiders will become more selective and, thus, act only upon private signals of sufficiently high value. The fact that private signals of low values are dropped because they are not worth the risk, leads to the following empirical prediction.

PREDICTION 3: *The average value of insiders' private signals increases with legal risk.*

B. Empirical Test and Results

The empirical assessment of this prediction requires measuring the value of insiders' private signals. While the SEC verifies the material and nonpublic nature of information in insider trading investigations, the agency does not report *how material* the received information is. To shed light on this aspect, we exploit an attractive feature of our sample: the ability to observe when traders receive information. Accordingly, for each corporate event, we compute the percentage change in the corresponding stock price from the opening price on date 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 a return as the *private signal value* (*PSV*):

$$PSV := \left| \frac{Opening\ Price(T_{\text{public}} + 1) - Opening\ Price(T_{\text{info}})}{Opening\ Price(T_{\text{info}})} \right|. \tag{11}$$

The left panel of Figure 9 displays the distribution of *PSV* for the entire sample. The mean and median values are 44.62% and 30.10%, respectively. The middle and right panels show that the distributions for earnings and M&A events are quite different: the median *PSV* for earnings is merely 13.06%, while the median value for M&A events is 36.49%. For a small fraction of M&A cases, the value of *PSV* exceeds 100%.

Next, we test Prediction 3 by relating the conditional means of *PSV* to the legal-risk shocks in Section III.A. Specifically, we estimate the following models:

$$PSV_{ij} = a_3 \times Newman_i + b_3 \times Trader_j + c_3 \times Year_i + \delta_3 \times InteracNewman_{ij} + d_3 \times \textbf{Controls}_{ij} + \varepsilon_{3,ij}, \tag{12}$$

$$PSV_{ij} = a_4 \times Bharara_i + b_4 \times Trader_j + c_4 \times Year_i + \delta_4 \times InteracBharara_{ij} + d_4 \times \textbf{Controls}_{ij} + \varepsilon_{4,ij}, \tag{13}$$

where the interaction terms and **Controls** are as defined in Section III.C except for *Strength*. We also include trader and year fixed effects to account for cross-trader variation in the choice of signals as well as market conditions. Given the opposite signs of the legal shocks, we expect the coefficients of interest δ_3 and δ_4 to be negative and positive under Prediction 3.

Table V shows the estimation results of equations (12) and (13) in columns (1) and (2). In both tests, we find economically significant differences that support Prediction 3. The change in the *PSV* for the Bharara shock is −20.31% relative to its standard deviation, displaying statistical significance at the 10% level. For the Newman shock, the corresponding change is positive at 37.11% but it is not statistically significant.

Columns (3) and (4) of Table V display estimation results for otherwise identical specifications but where the dependent variable is *Strength* (measuring the value of the tip relative to T_{first} instead of T_{info}, as defined in Section III.C). These closely related tests could help establish robustness to a scenario where the trader, upon becoming informed, waits to decide on crime engagement; the firm's stock price can move as the insider evaluates the situation. The results are qualitatively similar for both shocks and display higher *t*-stat values.

In sum, the evidence on the distribution of private signals complements that on insider trading strategies in Section IV and provides further support for the notion that these traders internalize legal risk, particularly in the case of the Bharara shock.

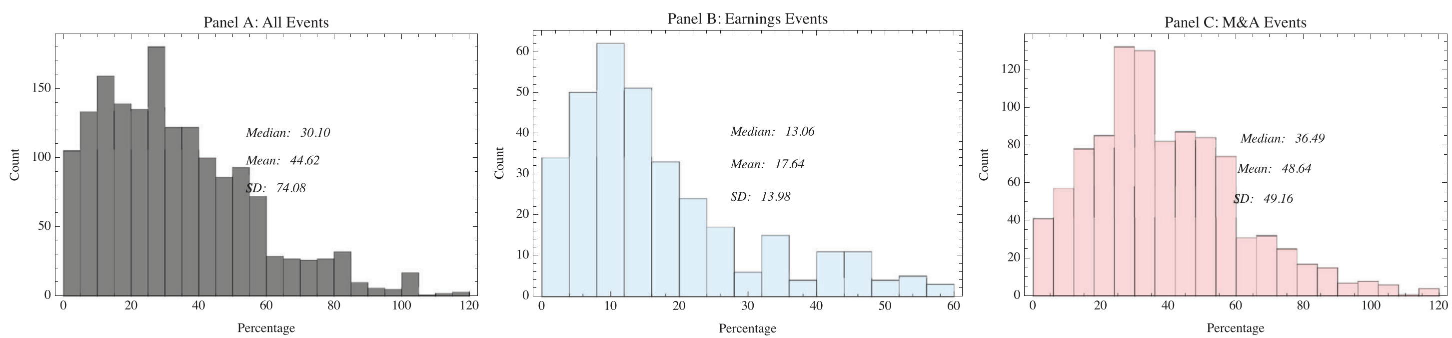


Figure 9. Distribution of private signal values. This figure displays the distribution of *PSV* (see equation (11)). Panel A corresponds to all the events. Panels B and C correspond to earnings and M&A events, respectively. (Color figure can be viewed at wileyonlinelibrary.com)

Table V

Ex Ante Engagement Decision: Evidence from Private Signal Values

This table shows the estimation results for the regression models (12) and (13). The dependent variable in columns (1) and (2) is *PSV*, defined by equation (11) as the percentage change in the corresponding stock price (its absolute value) from the opening on the day the insider receives the private tip to the opening of the day following the information disclosure. The dependent variable in columns (3) and (4) is *Strength*, defined as the percentage change in the corresponding stock price (its absolute value) from the opening on the day the insider trades first to the opening of the day following the information disclosure, adjusted by the S&P500 return. The interaction term corresponds to *InteracNewman* in columns (1) and (3), and *InteracBharara* in columns (2) and (4). The specifications include *Trader* and *Year* fixed effects. All control variables and fixed effect variables are as defined in Appendix. Standard errors (in parentheses) are clustered at the date level. ***, **, and * denote the 1%, 5%, and 10% levels of statistical significance, respectively

	PSV		*Strength*	
	Newman Shock (1)	Bharara Shock (2)	Newman Shock (3)	Bharara Shock (4)
Interaction term	−0.274	0.150*	−0.162	0.251**
	(0.245)	(0.079)	(0.129)	(0.110)
Volatility	1.023***	0.307***	0.376	0.211**
	(0.335)	(0.079)	(0.232)	(0.101)
VolumeVol	−0.040***	0.003	−0.023**	0.003
	(0.015)	(0.008)	(0.010)	(0.009)
Ln(MktCap)	−0.002	−0.036***	−0.023	−0.064***
	(0.020)	(0.012)	(0.014)	(0.012)
Observations	522	2,814	904	3,748

VI. Robustness to Selection

In this section, we inquire whether using SEC investigations allows us to extend the main empirical results to the population of illegal insiders. We provide three sets of results to this effect. First, we exploit the model to understand how sampling investigations based on unusual volume could affect our empirical estimates. Second, we adapt the model outcomes to the presence of less-than-fully-rational traders and examine the impact on legal-risk sensitivity. Third, we empirically exploit evidence from investigation sources to assess a lower bound on such sensitivity.

A. Volume-Based Sampling

Apart from using direct tips—from other government agencies, market players, or whistleblowers—a regulator could learn about the presence of insider trading through abnormal trade patterns, as in the model. Because public volume patterns reflect a random activity of uninformed traders, if all insiders equally internalize the risk of legal prosecution, such screening will sample unlucky traders. We ask whether this type of sample selection could meaningfully affect the predicted relations between legal risk and strategic outcomes.

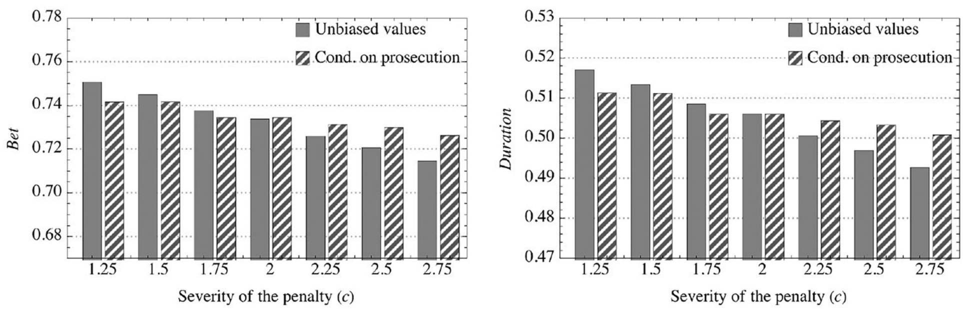


Figure 10. Volume-based detection: Potential bias on strategic outcomes. The figure presents the expected value of *Bet* and *Duration* for the universe of insiders (unbiased values) and conditional on the event of successful prosecution, for a given parameter c value. Other parameter values are as in Figure 4.

For that, we exploit the equilibrium connections from Section II to simulate the moments in equation (5) and condition the expectations on the prosecution event, for which we use the notations Bet^{P} and $Duration^{\mathrm{P}}$. From the perspective of selection bias, the baseline model delivers a *worst-case* scenario: 100% of insider trading detection is based on the regulator's active trade screening. Figure 10 displays the value of these conditional outcomes for different penalty-severity values c (similar patterns hold for parameter D). We highlight below two helpful insights from these results.

First, Predictions 1 and 2 hold in the selected sample: the qualitative impact of legal risk on outcomes is unchanged relative to the unbiased population values. This is important since, provided insider traders are sensitive to changes in legal risk, we can expect $Bet^{\mathrm{P}}(c) - Bet^{\mathrm{P}}(c')$ to empirically identify the same directional response from c to c' relative to the population counterpart.

Second, the analysis clarifies how volume-based sampling affects the gap between unconditional and conditional values for a given legal risk level. To gain useful intuition, assume that the private signal is positive. Consider the uninformed volume in each period, u_1 and u_2. The realization of u_2 affects the likelihood of prosecution, but it is unrelated to the insider trades; therefore, it does not generate bias. Instead, the realization of u_1 can affect x_2 outcomes in two ways. Recall that $\delta_1 := 1_{\{|u_1+x_1|>\bar{y}\}})$ and define a no-investigation region $[\underline{u}_1, \overline{u}_1]$ with thresholds $\overline{u}_1 := \bar{y} - x_1$ and $\underline{u}_1 := -\bar{y} - x_1$, as illustrated by the left column of Figure 11.

On the one hand, extreme realizations of liquidity trading lead to a more frequent sampling for positive values $u_1 > \overline{u}_1$; prosecution following $u_1 < \underline{u}_1$ is less likely, since $x_1 > 0$ when $v > 0$. Such adverse positive realizations lead to p_1 increases that diminish the informational advantage in the second period. Everything else being constant, the detection rule thus reduces the average value of x_2 in the detected sample.

On the other hand, the value of x_2 can also *increase*, moving from lower to higher values of u_1. This is because the value of x_2 is not a continuous function

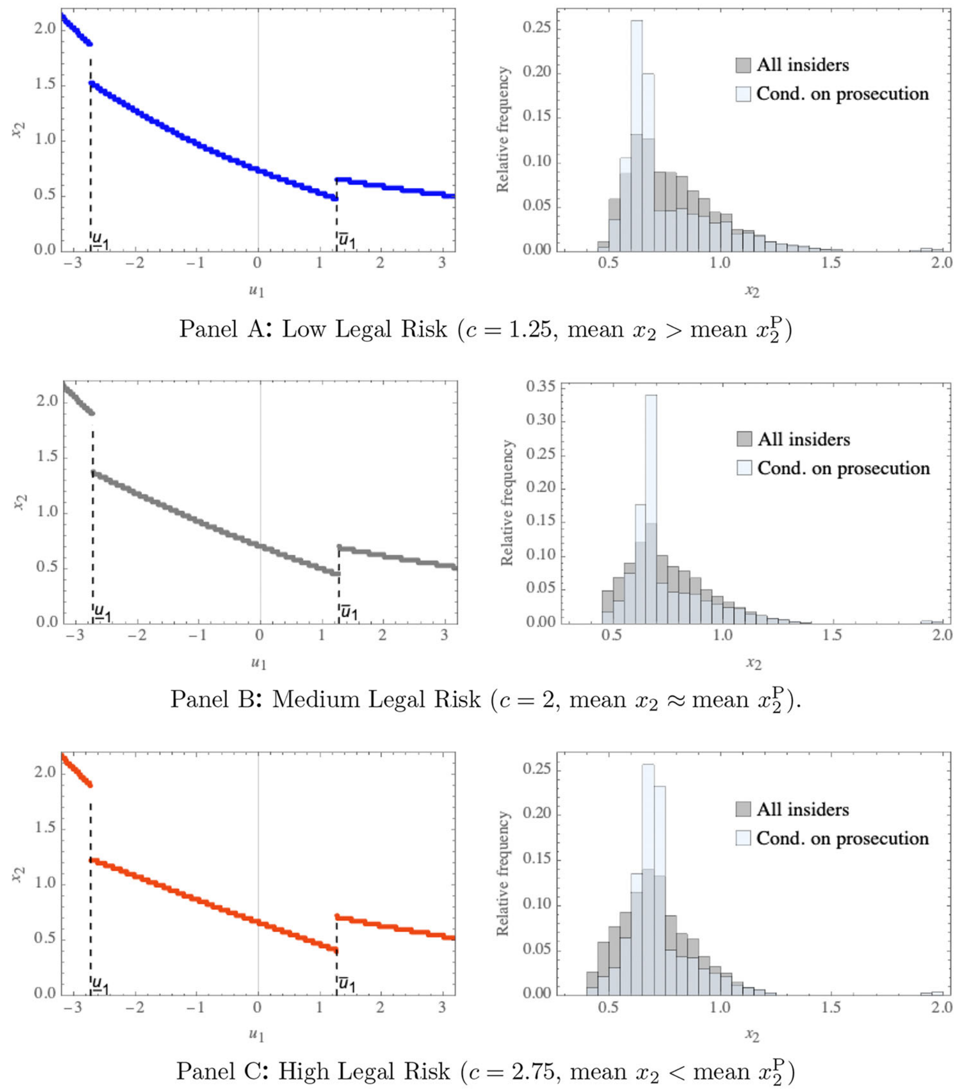


Figure 11. Effect of legal risk on potential selection bias. This figure displays simulation outcomes for the second trading period with positive private information for different c values. The left columns in all three panels show the insiders' optimal x_2 response to a given realization of liquidity trading volume at $t = 1$, u_1. The investigation-triggering thresholds values are $\overline{u}_1 := \overline{y} - x_1$ and $\underline{u}_1 := -\overline{y} - x_1$. The right columns in all three panels show the distribution of x_2 for all insiders and the prosecuted group. Other parameter values are as in Figure 4. (Color figure can be viewed at wileyonlinelibrary.com)

of u_1 due to δ_1 changing outside of the no-investigation region. For $u_{1\ell}$ and u_{1h} in a neighborhood of $\overline{u}_1$, $u_{1\ell} < \overline{u}_1 < u_{1h}$, we generally have $x_2(v, u_{1\ell}, 0) < x_2(v, u_{1h}, 1)$. Since u_1 values greater than $\overline{u}_1$ are sampled more frequently due to the detection rule—recall that screening at $t = 2$ can still detect an insider benefitting from $\delta_1 = 0$—the impact of u_1 on x_2 through δ_1 can create an upward bias in the conditional distribution of x_2.

The interaction of these two effects implies that the bias can be negative, zero, or positive. What is most interesting for our purposes is that the sign of the bias is related to legal risk. As we consider diminishing levels of legal risk, the discontinuous jump $x_2(v, y_1, \delta_1 = 1) - x_2(v, y_1, \delta_1 = 0)$ becomes arbitrarily small. Therefore, the first effect is likely to dominate for low-risk environments, imposing a negative bias on detected outcomes. Conversely, high legal-risk levels are more likely to impose a positive bias due to the strength of the second effect. This is graphically illustrated in the right column of Figure 11 by the change in the conditional distribution of x_2 as c increases. The implied biases for *Bet*$^{\mathrm{P}}$ and *Duration*$^{\mathrm{P}}$ are negative for $c = 1.25$, null for $c = 2$, and positive for $c = 2.75$.

Such pattern results in the *flatter* slope of *Bet*$^{\mathrm{P}}$ and *Duration*$^{\mathrm{P}}$ relative to the unbiased graph shown in Figure 10. The critical empirical consequence is that using the selected outcomes from investigations should work *against* the econometrician to identify changes in strategic outcomes caused by a legal-risk shock; the quantitative changes will appear smaller irrespective of the shock's sign.

In sum, while the selected outcomes are not identical to the population values for a fixed legal-risk level, our identification approach should lead to the correct answer regarding whether insiders internalize legal risk. Simultaneously, the empirical estimates could *underestimate* the impact of legal risk on strategies due to volume-based sampling.

B. Bounded Rationality

We also examine the possibility of legal-risk sensitivity being heterogeneous, either because some insiders wrongly underestimate the real threat, or perhaps they completely neglect it. The model's outcomes suggest that the regulator's screening could also lead us to *underestimate* the degree to which insiders internalize legal risks. If the regulator actively searches for abnormal trading patterns, traders who do not internalize legal risks will be overrepresented in the sample of investigations.

To see this, we consider a model similar to that in Section II, but with boundedly rational insiders acting on the subjective assessment $\tilde{D} < D$. We compute the equilibrium outcomes using $\tilde{D} = \frac{D}{2}$ and $\tilde{D} = 0$; the trading function for the latter coincides with the no-legal-risk case displayed in Figure 4, in which the insiders ignore the early abnormal volume flag δ_1. Next, we use these equilibrium outcomes to compute the relative frequency of prosecution under different legal-risk scenarios. The results are displayed in Figure 12 and indicate a clear pattern: the more overoptimistic insiders are, the more likely prosecution be-

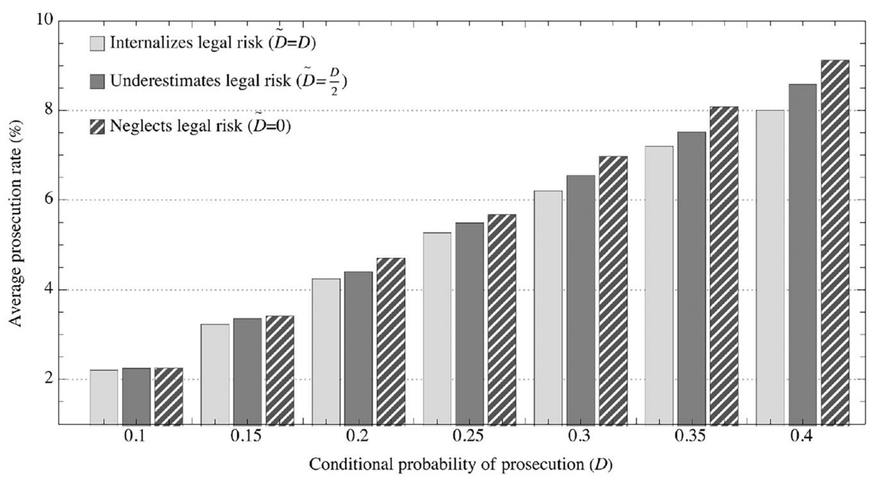


Figure 12. Legal risk and prosecution probabilities with overoptimistic insiders. This figure contrasts the equilibrium prosecution frequency of an insider who internalizes legal risk against overoptimistic alternatives for several D values. The first alternative corresponds to an insider that underestimates legal risk, acting on the subjective perception $\tilde{D} = \frac{D}{2}$. The second one corresponds to an insider that neglects legal risk ($\tilde{D} = 0$). Other parameter values are as in Figure 4.

comes successful. This is because the insiders' trade aggressiveness increases with the degree of subjective underestimation of D.

Applying the same reasoning as the ex ante engagement choice in Section V, sample selection could bias downward the gap between the average value of the private signals that we identify.

In sum, if the population of insiders contains a fraction of individuals who underestimate or neglect legal risk, one can consider the estimates in Sections IV and V as a lower bound on the population's response.[31] In this regard, our empirical finding that insiders in SEC investigations *do internalize* legal risks reassures us that the same conclusion would hold for the population of illegal insiders.

C. Evidence from the Investigation Sources

The analysis above suggests that the investigation selection could deliver a lower bound on the true impact of legal risk. We now seek to empirically assess such a lower bound, for which we exploit heterogeneity in the origins of the SEC investigations.

[31] Consistent with Predictions 1 and 2, the estimated coefficients of δ_1 and δ_2 in Table IV suggest that insiders display the opposite behavior to a negative and a positive shock to legal risk. However, comparing the absolute value of the responses to the Newman and the Bharara shocks is difficult. For the reasons explained in this section, one cannot rule out the possibility that, in either case, the population responses are larger than the ones we identify.

In particular, we focus on cases referred to the SEC from sources likely to indicate unusual trading patterns, including stock and options exchanges, brokers, and industry regulating agencies, such as FINRA and ORSA. The number of trades associated with these sources is 4,569, representing slightly more than 60% of our sample. Following the model's insights, we hypothesize that the individuals in these specific investigations should be *less likely* to internalize legal risks relative to those detected through other means (e.g., whistleblowers with firsthand knowledge) and those who went undetected. Next, we perform the same empirical tests for this subsample as in our baseline setting.

The results in Table VI indicate that this group of insiders responds to changes in the legal environment. In the Newman test, all four interaction coefficients are positive, in line with Predictions 1 and 2 following a negative shock to legal risk. Turning to the Bharara test, all coefficients are negative, consistent with the predictions for a positive shock. As graphically summarized in Figure 13, the impact of legal risk is economically meaningful, and the interaction coefficients are statistically significant at 10% or higher levels in all but one case.

In sum, we find qualitatively similar patterns to those based on the universe of SEC investigations. These results suggest that one can bound illegal insiders' legal-risk sensitivity away from zero, further supporting the hypothesis that rogue insiders' decisions internalize legal risk.

VII. Informativeness of Asset Prices

The main focus of the previous sections was on the relation between legal risk and illegal insiders' trading strategies. This approach is new to the literature, which has traditionally examined insiders' impact on prices (e.g., Meulbroek (1992)). Our focus has a solid conceptual appeal since, unlike prices, trading decisions fall under insiders' discretion; it also allows for nuanced tests exploiting the features of insider-level strategies. In this section, we provide a complementary perspective on the extent to which insider trades reveal their private information.[32] For that, we evaluate price movements on insider trading days, assess the information transmission process of over insiders' trading horizons, and explore how legal risk can influence the extent of such price adjustments.

A. Returns on Insider Trading Days

Because illegal insiders act on material private information, one expects prices to respond to their trades. Specifically, price movements should be consistent, on average, with whether good or bad news motivated the trades. We empirically assess such a connection in two ways.

[32] Vives (2008, Ch. 9) reviews the theoretical analyses of the speed of information aggregation in models with long-lived private information.

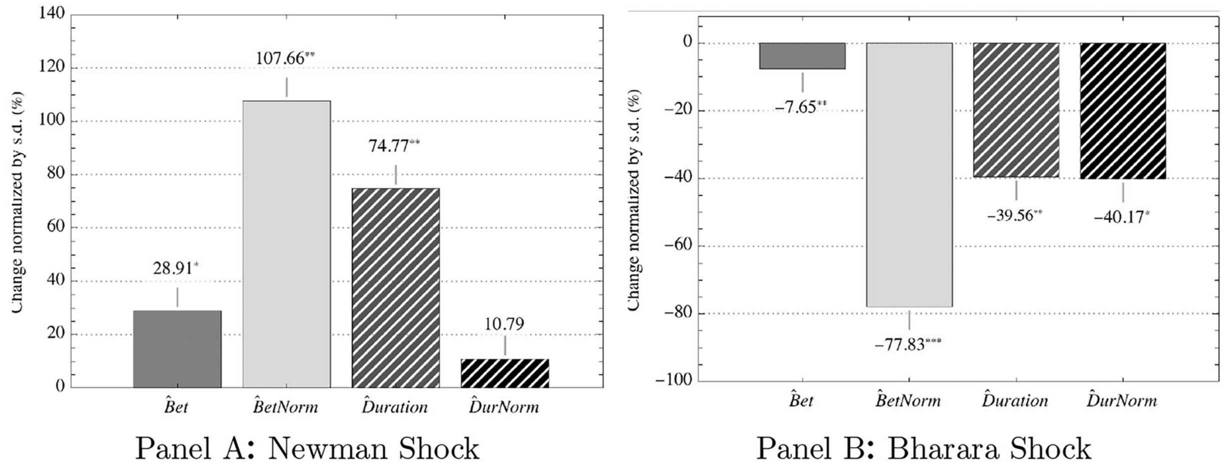


Figure 13. Evidence from investigation source: Results summary. Each bar displays the percentage ratio between (i) the estimated values of δ_1 and δ_2 in the full model specifications (9) and (10), for the sample of cases referred to the SEC from sources likely to indicate unusual trading patterns (see Table VI), and (ii) the corresponding strategic outcome's standard deviation (see Table III). Panels A and B correspond to the Newman and the Bharara tests, respectively. ***, **, and * denote the 1%, 5%, and 10% levels of statistical significance, respectively.

Table VI

Impact of Legal-Risk Shocks on Illegal Insiders' Strategic Outcomes: Evidence from the Investigation Source

This table shows the estimation results for the regression models (9) and (10) in Panels A and B, respectively. The sample is restricted to investigations referred to the SEC by agencies that are likely to detect insider trading based on abnormal trading patterns, as described in Section VI.B. The dependent variables are $\hat{Bet}$, $\hat{BetNorm}$, $\hat{Duration}$, and $\hat{DurNorm}$ as defined in Appendix. The variable *Newman* is an indicator variable equal to one for 2015 to 2016, and zero for 2013 to 2014; *Bharara* is an indicator variable equal to one for the period 2009:8 to 2013:12 and zero for 2006:1 to 2009:7 and 2014 to 2015. The variables *InteracNewman* and *InteracBharara* are defined in Appendix. All regressions include the control and fixed effect variables in Table IV. Standard errors (in parentheses) are clustered by the date of trading. ***, **, and * denote the 1%, 5%, and 10% levels of statistical significance, respectively

	$\hat{Bet}$	$\hat{BetNorm}$	$\hat{Duration}$	$\hat{DurNorm}$
Panel A: Newman Shock				
InteracNewman	3,589.503*	0.267**	0.206**	0.026
	(2,105.572)	(0.123)	(0.100)	(0.144)
Strength	790.112	0.010	−0.021	0.016
	(486.744)	(0.031)	(0.032)	(0.070)
Volatility	1,494.518	−0.082	−0.204	0.311*
	(2,035.081)	(0.193)	(0.149)	(0.171)
VolumeVol	549.342	−0.128**	0.043	−0.036
	(683.040)	(0.055)	(0.040)	(0.046)
Ln(MktCap)	463.651	−0.009	0.012	0.043***
	(334.782)	(0.019)	(0.012)	(0.011)
Observations	445	555	377	359
Panel B: Bharara Shock				
InteracBharara	−950.331**	−0.193***	−0.109**	−0.096*
	(468.657)	(0.046)	(0.055)	(0.056)
Strength	302.509**	−0.005	−0.032***	0.023**
	(130.601)	(0.011)	(0.008)	(0.011)
Volatility	744.246	−0.172***	−0.144***	0.106
	(579.744)	(0.060)	(0.047)	(0.071)
VolumeVol	5.919	−0.013	0.022**	−0.040***
	(115.235)	(0.010)	(0.011)	(0.011)
Ln(MktCap)	296.907	0.001	−0.017**	0.029***
	(245.729)	(0.013)	(0.009)	(0.010)
Observations	2,227	2,590	1,987	1,861

First, we compute the average daily returns for the affected stocks when insiders trade. Panel A of Table IA.VI shows the results. We consider three measures of returns: raw, net of the total market return, and net of the S&P500 index return. Columns (1) to (3) show that the average return on days with positive information is 1.1%, and columns (4) to (6) show that on days with negative information is −0.6% and –0.7% for raw and adjusted returns.

Second, we perform a simple event study analysis by regressing raw and abnormal stock returns on the binary variable *InsiderTrade*, which equals one for days when insiders trade and zero for days within a 20-day window prior to the trade event. To soak up cross-sectional variation in the returns, we include three additional variables: size, volume, and share price, all measured 20 days prior to the trade event. Panel B of Table IA.VI shows that the coefficient of *InsiderTrade* is positive and statistically significant for all specifications with positive news, and negative and statistically significant for all specifications with negative news. The coefficients of other controls are insignificant, consistent with the ample empirical literature documenting little daily return predictability from firm characteristics.

In sum, stock returns respond to the actions of informed traders and, on average, change in the direction of private information. This suggests that at least some information in insider trades gets immediately impounded into prices.

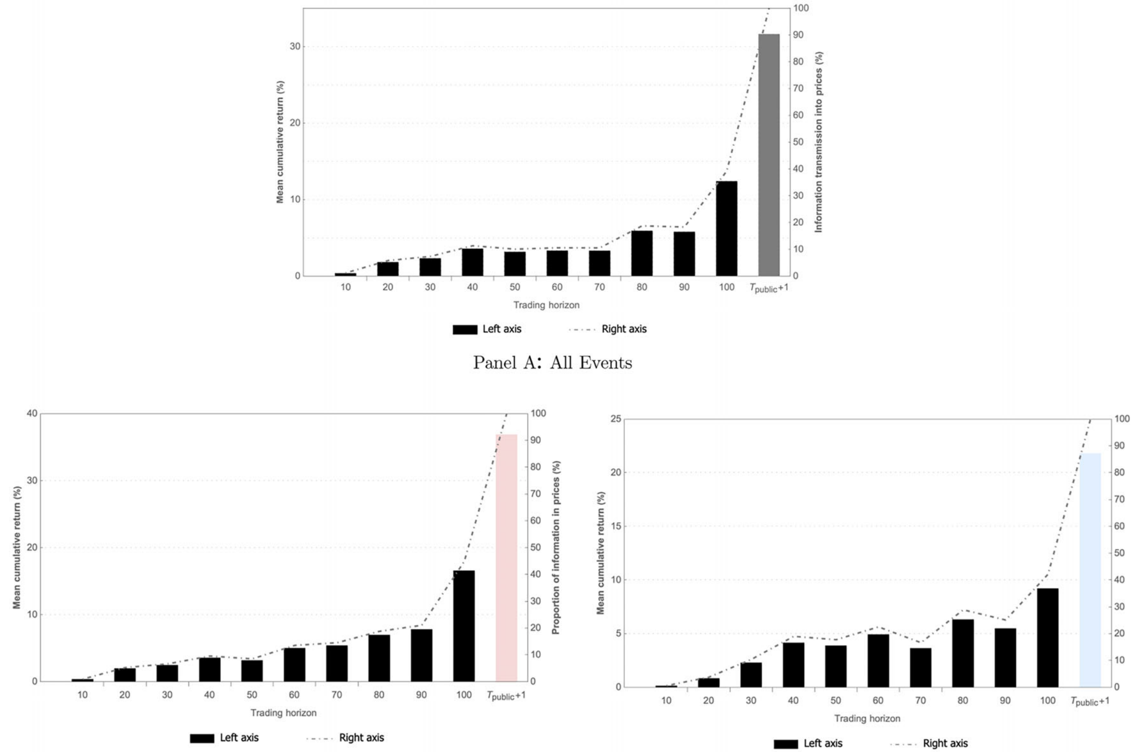
B. Information Transmission

We now look closely at the information aggregation process over insiders' trading horizon. For that, we consider a nonparametric timescale, as follows. We split the period $[T_{\text{first}}, T_{\text{public}}]$ into 10 subperiods of equal length indexed by h; accordingly, our trading horizons must be at least 10 days long. Next, we calculate the mean cumulative stock returns across insider trading episodes over this period (reversing the return sign of negative news events for comparability): $\left|\frac{\textit{Opening price}\,(T_h)-\textit{Opening price}(T_{\text{first}})}{\textit{Opening price}(T_{\text{first}})}\right|$, $h = 1:10$.

Panel A of Figure 14 shows the price adjustment process for the entire sample. Each of the first 10 bars corresponds to a trading subperiod. The rightmost bar corresponds to the average *PSV* value, representing the *total* amount of information. The dotted line corresponds to the ratio of the cumulative return to *PSV* as a percentage, expressing the relative amount of private information impounded into the price over time (100% on date $T_{\text{public}} + 1$). A negative column value means that prices move opposite to the private signal.

The resulting price pattern indicates that illegal insiders impound a significant amount but not nearly the entirety of the private information. At the end of the trading period, the mean cumulative return is about 39.2% of *PSV* across all information events.[33] We also note that, although information aggregation is noticeable since the first subperiod, nearly half of the information transmission occurs in the subperiod directly preceding the public announcement.

[33] The price adjustment pattern is similar if one considers alternative definitions of *PSV* that extend the postannouncement date to allow for potential overreactions or underreactions to the announcements. In Figure IA.10, we display the price adjustment process using the price at the opening of $T_{\text{public}} + 2$ and $T_{\text{public}} + 3$ as the postannouncement benchmark in equation (11). At the end of the trading horizon, the cumulative return using $T_{\text{public}} + 2$ is 38.63%, and using $T_{\text{public}} + 3$ is 36.54%. We note that the number of observations declines as one extends the announcement window, since many acquired firms quickly cease to trade after the announcement.



Panel A: All Events

Panel B: M&A Events

Panel C: Earnings Events

Figure 14. Trades and information transmission into prices. This figure displays the process of information aggregation into prices. The insiders' trading horizons are split into 10 equal subperiods. Panel A corresponds to all insider trading events. Each of the 10 leftmost columns represents the mean cumulative stock return up to the end of the corresponding subperiod (the return sign of negative events is reversed). The rightmost column corresponds to the mean *PSV*. 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. Panels B and C correspond to M&A events and earnings announcements, respectively. (Color figure can be viewed at wileyonlinelibrary.com)

Such partial price adjustment contrasts with the outcomes in the continuous-time analyses of insider trading by Kyle (1985) and Back (1992). In these papers, the insider is not concerned with legal risks and smoothes information transmission until the private signal is fully revealed on the announcement date. One can establish a similar contrast by considering the insider who internalizes and neglects legal risk. Using the same equilibrium outcomes as in Sections II and VI.B, Figure IA.11 displays the average information in prices before the public announcement. Due to a more aggressive trading profile, the trader neglecting legal risk always brings more information into the asset price. The information transmission gap versus a rational trader increases with the severity of the legal threat.

We stress that Panel A in Figure 14 displays the information transmission process over the trading horizon of illegal insiders specifically. Such a horizon does not necessarily coincide with the trading dates of other (unobserved) informed agents if they are present. The concern about whether other traders could be driving information aggregation is intuitively stronger for scheduled events such as earnings, and weaker for unscheduled announcements such as M&A events. Therefore, we display in Panels B and C the same price adjustment process for M&A and earnings events separately. We observe that at the end of the insider trading horizon, a similar amount of information is reflected in prices: 42.2% for earnings versus 44.92% for M&A events. Such a consistent pattern lessens the concern that illegal insiders play little to no role in driving price transmission.

C. Price Adjustment and Legal Risk

To conclude this section, we contrast the extent of price adjustment by the legal-risk regime, as given by the values of *InteracNewman* and *InteracBharara*. Figure 15 shows the mean cumulative stock return (its absolute value for negative news events) computed from T_{first} to T_{10}, the last trading subperiod before the public announcement.

Panel A corresponds to the Newman shock. For the low-risk regime, $InteracNewman = 1$, we can see that the average price change before the public announcement is more pronounced at 13.32% versus 6.22% in the high-risk regime. For the Bharara shock in Panel B, by the end of the trading horizon the average price change for events corresponding to the low-risk regime, $InteracBharara = 0$, is 11.17% versus 10.46% in the high-risk regime. For the most frequent event type, M&A, the price adjustment is also stronger in the low-legal-risk regime: 13.77% versus 9.73% for the Newman shock, and 16.17% versus 13.47% for the Bharara shock.[34] Such price patterns align well with the prediction that insiders trade less aggressively when legal risk is high.

[34] The sample size makes it infeasible to evaluate other event types regarding the Newman shock. For the Bharara shock, results are similar for earnings announcements: 7.65% versus 6.21% in the low- and high-risk regimes, respectively.

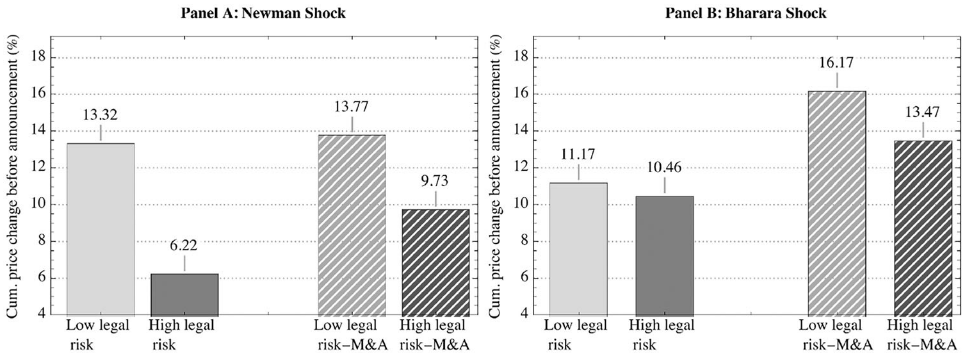


Figure 15. Cumulative price changes before announcements and legal risk. This figure displays the mean cumulative stock return (its absolute value) computed from T_{info} to T_{10}, the last trading subperiod before the public announcement. Panel A corresponds to the Newman shock. The leftmost two columns correspond to low- and high-legal-risk cases, as given by the values of *InteracNewman*. The rightmost two columns correspond to M&A events exclusively. Panel B corresponds to the Bharara shock and displays analogous prices changes for low- and high-legal-risk cases, as given by the values of *InteracBharara*. The interaction variables are defined in Appendix.

Overall, our finding that insider traders internalize legal risk is a natural explanation of the seemingly weak amount of information aggregation before public announcements. Such a finding also implies that any insider policy decisions should unequivocally factor in potential social costs resulting from the reduced informational efficiency of securities prices, as previously highlighted by Manne (1967), Leland (1992), and Bernhardt, Hollifield, and Hughson (1995), among others.[35]

VIII. Extensions and Additional Analyses

In this section, we list and briefly discuss several additional analyses, the details of which are presented in the Internet Appendix.

Fixed Penalties. The profits-linked choice of penalty function is guided by the prevailing legal framework and the evidence in Section I.D. Of course, there could be additional costs of prosecution, including prison time and subjective ones related to a loss of reputation or shame. To address this possibility, in Section IA.2.B we consider an alternative to equation (2) with a fixed penalty, which we argue is more amenable to these additional concerns. We show that the main equilibrium relations remain similar.

Trade Reversals. Rational insiders adjust their trade size according to the legal threat. For sufficiently high levels of legal risk, we show in Section IA.2.C

[35] This concern seems particularly pressing, given the recent explosion in popularity of exchange-traded funds and other passive investment vehicles that could hamper price discovery. This notion echoes the predictions of a theoretical model of Kacperczyk, Nosal, and Sundaresan (2023), who show that, in general equilibrium, the shift of holdings from informed to uninformed investors reduces price informativeness.

that the informed trader can *reverse* the trade direction at time $t = 2$ relative to $t = 1$. Such reversal does not intend to fool market makers, as is bluffing (Back and Baruch (2004), Chakraborty and Yilmaz (2004)). Instead, it is a consequence of the link between legal penalties and trade profits. Intuitively, if the insider concludes that an investigation is highly likely, given that $c > 1$, it is rational to experience losses in the second period to target zero total profits.

Exogenous Detection and WRP. Apart from the possibility that trade patterns reveal the presence of insider trading to the regulator, detection could also come from information directly provided by a third party, such as whistleblowers. Section IA.4 considers an extension of the model with this additional detection source, and it exploits the SEC's implementation of a monetary incentive program as a shock to the whistleblowing probability. The empirical results on insider traders' strategies are consistent with Predictions 1 and 2 regarding a positive shock to legal risk and with the (equal shock sign) Bharara test results in Section IV.

Changes in Detection Thresholds. An underlying assumption of our empirical identification is that the regulator who screens for illegal trading activity does not calibrate its detection rule as a mechanical function of shock realizations in the judiciary. To more clearly elicit what we require of the institutional environment, we describe in Section IA.5 the theoretical impact of threshold changes and then contrast such changes against the considered legal-risk shocks. We argue that changes in detection thresholds are unlikely to explain our empirical findings.

IX. Concluding Remarks

The debate on whether and under what circumstances insider trading should be illegal has a long tradition. As Rauterberg, Fox, and Glosten (2018, p. 821) put it, "no issue in securities law has garnered more attention from law and economics scholars and the larger public alike than insider trading." The dominant view that promotes enforcement actions highlights their potential to reduce firms' capital costs and to increase investment and welfare. However, society can only achieve such desirable goals if insider trading regulations provide meaningful criminal deterrence.

This paper provides empirical support for the effectiveness of U.S. insider trading regulations by developing and testing the predictions of a model in which an insider rationally responds to legal risks. Using plausibly exogenous sources of risk exposure, we conclude that insiders internalize the legal threat by adjusting their trading strategies. Insiders' responses also reflect on asset prices and the average values of the private signals across legal-risk regimes. While small sample sizes pose a statistical challenge to some of our tests, jointly, the qualitative responses of insiders align well with the predictions following positive *and* negative legal-risk shocks.

We cannot yet assert whether the social benefits of prevailing insider trading regulation in U.S. securities markets outweigh their social costs concerning the negative impact on the government's budget and asset prices' informativeness.

However, our results reveal the existence of a social trade-off at a fundamental level: absent deterring effects, the burden of investigative and enforcement efforts would amount to a net social loss.

We hope that the results and methods in this paper inform future studies on legal risk in financial markets subject to information asymmetries. An example of such a study is de Jong, Kooijmans, and Veld (2022), which follows our approach to address private information spillovers from syndicated loan borrowers to equity markets.

Finally, given the social importance of the addressed issues, we welcome more data cooperation from regulatory agencies to reduce sample noise and ease research costs.

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Appendix: List of Empirical Variables

Variable	Definition
	Panel A: Dependent Variables
$\hat{Bet}$	Dollar value (USD 1000s) of the trades linked to the same trader and corporate event
$\hat{Bet}Norm$	Ratio between the insider trading dollar volume and a normal volume measure for the same asset; the maximum across ratios if more than one asset is used. This regressand is standardized in the tests
$\hat{D}uration$	The proportion of informed trade volume executed after seven days from receiving the private tip
$\hat{D}urNorm$	Proportion of informed trade over the second half of the information horizon
PSV	Stock price return (its absolute value) for a given firm from the opening of the day when the insider receives the private tip until the opening of the day following the information disclosure
	Panel B: Control Variables
Strength	Stock price return (its absolute value) for a given firm from the opening of the day when the insider trades first until the opening of the day following the information disclosure, adjusted by the S&P500 index return
Volatility	Volatility of daily stock returns over the calendar year previous to the insider trading information event
VolumeVol	Volatility of the daily trading volume over the calendar year previous to the insider trading information event
$Ln(MktCap)$	The average value of the natural logarithm of the firm's monthly market capitalization over the previous calendar year
Newman	Indicator variable equal to one for the period 2015 to 2016 and zero for 2013 to 2014

NewmanAgent	Indicator variable equal to one if the trader received the firm's private information tip from a third party acting as a tipper
InteracNewman	The product between *Newman* and *NewmanAgent*
Bharara	Indicator variable equal to one for August 2009 to December 2013, and zero for January 2006 to July 2009 and 2014 to 2015
SDNY	Indicator variable equal to one if the trader is subject to the SDNY district
InteracBharara	The product between *Bharara* and *SDNY*
EventType FE	Fixed effect variable capturing the type of corporate event the insider has private information about
Trader FE	Trader-specific fixed effect
Year FE	Year-specific fixed effect

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.