Becker Meets Kyle: Legal Risk and Insider Trading*

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Abstract

Do illegal insiders internalize legal risk? We address this question with hand-collected data from 530 SEC 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 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.

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A vast literature in economics and finance has argued that private information is transmitted into asset prices through the trading activity of 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)? 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 et al. (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 deterring power, 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

[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 McCrary (2017). The evidence discussed therein indicates that, in several criminal environments, crime does not clearly respond to the severity of sanctions.

penalties on trading strategies. Third, we exploit two plausibly exogenous sources of variation in legal risk exposure to test the models' predictions. Controlling for a host of behavioral predictors, we provide 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 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 between receiving a tip and its public announcement is 44.26% for mergers and acquisitions (M&As) and 17.78% 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 $757,127 and $44,318, respectively. For pecuniary penalties, the corresponding values are $2.85 million and $200,000.

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 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's comparative statics yield 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 volumes. 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 model, the insider trades more intensely as the information deadline nears.

To test these 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 redeem several allegedly guilty individuals. Further, 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 of the District Court of the Southern District of New York (SDNY), who earned the reputation of a "crusader" prosecutor. His reign affected insiders subject to SDNY based on their residence. 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 versus prosecutors).

Our tests are based on a regression design in which the dependent variable captures either the volume or timing of the insider trades. Our goal is to identify whether the most affected group 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, court, and unobserved time-invariant trader heterogeneity.

The results in Section IV indicate that, first, volume and timing measures display economically significant abnormal values in response to the legal shocks. Second, their qualitative responses correspond well to the theoretical predictions. Specifically, following the Newman shock, traders acting on second-hand information behave relatively *less* cautiously, increasing trading quantities and trading closer to the public release time: dollar volume increases by 39.8% relative to its standard deviation, and the relative increase in a time-weighted measure of volume is of 79.3%. Conversely, traders *within* the SDNY jurisdiction reduce their trade aggressiveness during Bharara's reign, as reflected by a normalized decrease in the proportion of informed trading of 41.5%. The statistical significance of dollar volume changes across all corporate events is lower relative to that in the Newman test. However, it is economically and statistically robust for M&A events, the most frequent event type in the sample. We argue that economic motives could make insiders more sensitive to legal risk when trading on M&A information relative to earnings announcements.

In Section V, we further assess the impact of legal risk from the perspective of engagement in criminal activity. Following Becker's reasoning, a rational trader who internalizes legal consequences should be less willing to act on a private signal of a given strength, when either the probability of enforcement or the conditional penalty increases. Put differently, as a result of a positive (negative) risk shock, the insider should act on private signals of higher (lower) expected returns. We test this hypothesis by comparing the average value of a private tip under low– and high–legal risk regimes. Consistent with insiders internalizing the expected cost of their crime, we find a substantial increase in that average for the Bharara shock, 112.68% relative to its standard deviation, and a similarly marked normalized decrease for the Newman shock of 46.45%.

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 in investigations. 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 their 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.[2] One stream of the literature is 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 et al. (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 micro-level results on price aggregation are qualitatively consistent with these time-series relations.

Also related are the studies of Kallunki et al. (2018) on how insiders' wealth and income affect the decision to engage in insider trading, of Cornell and Sirri (1992) and Akey et al. (2020) on stock liquidity, of Kacperczyk and Pagnotta (2019) on asymmetric information proxies, of Ahern (2017) on insider traders' networks, and of Patel and Putnins (2021) on the structural estimation of the detection rate.

[2] Bhattacharya (2014) and Rauterberg et al. (2018) provide excellent recent reviews of the illegal insider trading literature in economic and legal studies. An important but less directly related literature examines the characteristics of legal trades by corporate insiders (e.g., Cohen et al. (2012); Klein et al. (2017)).

While the above studies consider insider trading investigations in some capacity, they do not investigate the relation between insider trading 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.[3] A notable exception is DeMarzo et al. (1998), who pioneered the analysis of optimal insider trading enforcement rules.[4] While their focus is on the normative regulation design, we focus on the positive effects of the prevailing regulations and provide empirical support to their otherwise assumed deterring power. Carre et al. (2020) 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 reflect the institutional framework by linking penalties to profits and prosecution probabilities to how the insider trades.

We also contribute to the micro-founded 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 in that we link 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

[3]See Foucault et al. (2013) for a recent and comprehensive survey of models of trading with asymmetric information.

[4]Also related is the model by Huddart et al. (2001). Due to regulatory disclosure requirements, the insider is therein forced to disclose his/her 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.

others, Dyck et al. (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. Kedia and Rajgopal (2011) study the role of constraints in the SEC budget for the commission of fraud by corporate managers. Egan et al. (2018) analyze a sample of financial advisers and analyze the ex-post penalties imposed on such advisers. To the best of our knowledge, our paper is the first to focus on the ex ante implications of legal risk for both trading behavior and private information transmission.

I Insider Trading 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.

I.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 until December 2018.[5] 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 episodes between 1995 and 2018. The average number of investigations per year is 26.4, with a maximum number of cases (47) filed in 2012.

The case contents are 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. It is also important to note that our complete data set is not a balanced

[5] 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) have used similar types of files (with releases until 2015) to study the relation between informed trading and empirical proxies of asymmetric information.

panel; hence, the number of observations could differ across various tests. 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.

Manual data extractions from these investigations yield 6,553 unique trades involving 957 firms and 1,303 traders. 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 two, 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 two, respectively, with a maximum of 115 trades. The mean and median numbers of trades per firm are 6.83 and three, respectively.

I.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 more than 40% of all trades (Panel D). However, we note that the 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 on date T_{info}, when the trader receives a private signal about a given firm's fundamentals. Such an advantage disappears on 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 $T_{\text{last}} \leq T_{\text{public}}$. We consider T_{info} and T_{public} as exogenous from the trader's perspective, while trading days are endogenous. This allows us to benchmark individual trading decisions. Accordingly, we define the *information horizon* as $T_{\text{public}} - T_{\text{info}}$ and the *trading horizon* as $T_{\text{last}} - T_{\text{first}}$, both measured in days. The trading horizon is

Figure 1. Timeline of an insider trading case

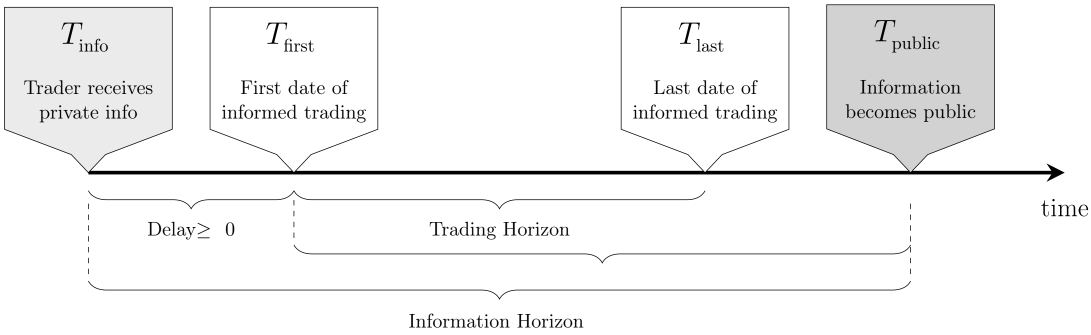
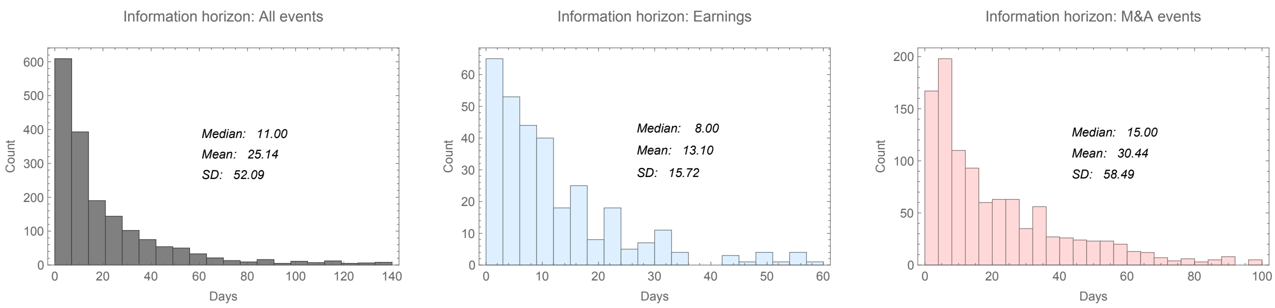


Figure 2. Distribution of private information horizons

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



trivially exogenous in the limit case in which $T_{\text{info}} = T_{\text{public}}$, that is, when the trader receives the signal just before the public announcement.

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, of 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.

I.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.

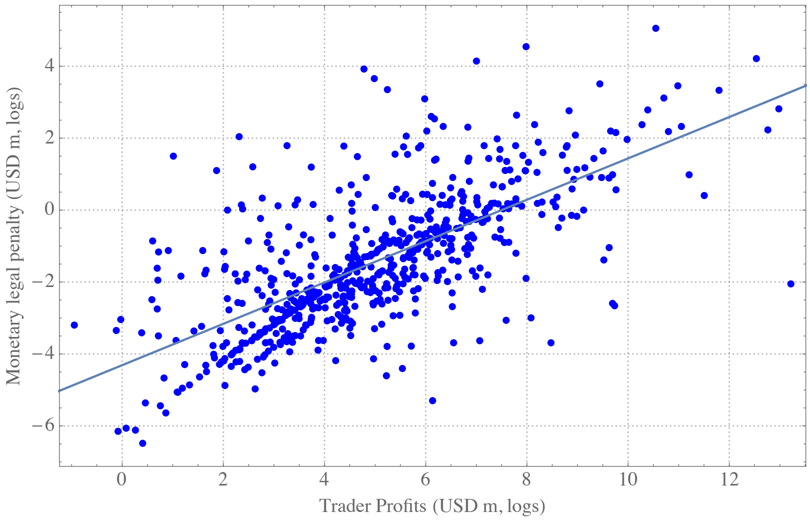
I.D Civil and Criminal Penalties

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. Non-pecuniary penalties result from a criminal investigation and usually take the form of prison time or probation. Criminal penalties amount 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 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 generally 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 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 type of penalty for each defendant in the sample. The SEC complaint files report some of the relevant information. However, since many files miss critical

Figure 3. Insiders' trade profits and monetary penalties



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 trades, 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, which motivates an analogous theoretical connection 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.[6]

[6] 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.

II Model

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

II.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.[7]

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 et al. (1998), the investigation process is based on an abnormal total volume rule that is common knowledge. We represent the investigation trigger event with $\delta_t := 1_{\{|y_t| > \overline{y}\}}$, where $y_t = x_t + u_t$ and $\overline{y} > 0$ 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

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

[7] 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 in incorporating legal risk into the insider's optimization problem.

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

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

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

where $\pi_t := x_t(v - p_t)$. The penalty in (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 (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[8] but not δ_1.[9] Thus, $p_t = \mathbb{E}\left[\tilde{v} | \sum_{s \leq t} y_s\right]$.

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

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

[8]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 $\{y_1, y_2\}$. Since 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.

[9]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.

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 $D \times q\left(x_2\right)^{1-\delta_1}$.

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

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

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 (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 (1) and enforces penalties as in (2).

II.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.[10] To facilitate interpretation, we also display the equilibrium outcomes of the particular case of the model without legal risk (that is, $c = 0$ or $D = 0$).[11]

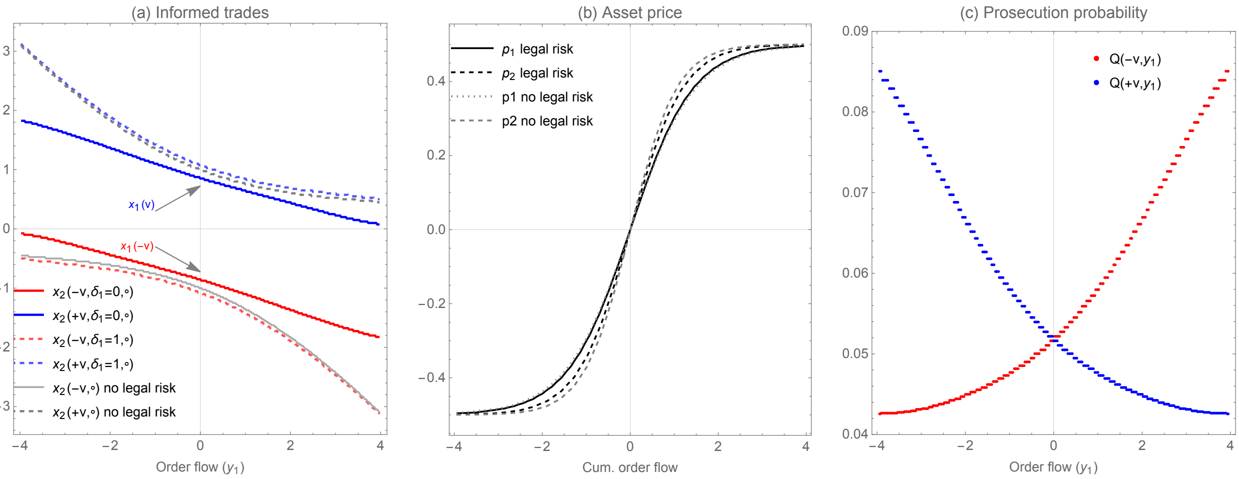
The left panel of Figure 4 displays insider's trades in each period. To illustrate, consider the case of positive news on the top side. In the first period, the trade size is entirely determined by the asset value v. In the second period, trade size also depends on y_1 and δ_1. For a given δ_1 value, the informed trader places a less aggressive trade when prices have moved upwards 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

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

[11] 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.

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) line represents 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 (1) for a given realization of $\tilde{v}$ and y_1 value. Parameter values are as follows: σ and the length of the asset value support $(2v)$ are equal to one, $\overline{y} = 2$, $D = 0.35$, and $c = 2$.



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. 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 that, we define two *strategic outcomes*:

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

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 (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 85 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, $\lim_{c \to 0} |x_2| - |x_1| > 0$ ($\lim_{c \to 0} Duration > \frac{1}{2}$). 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.

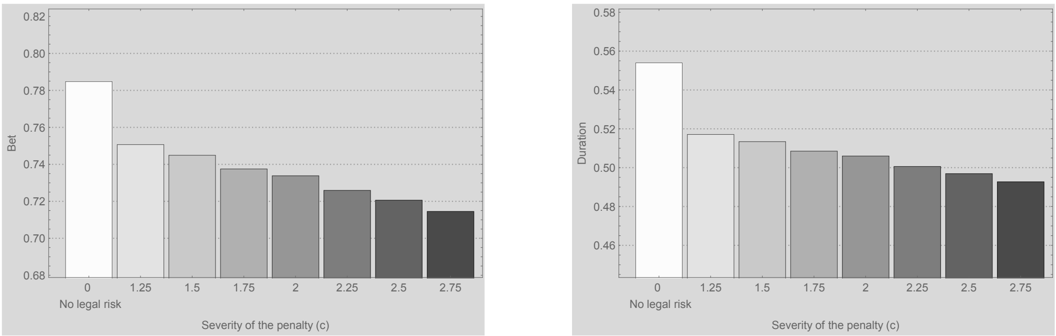
III Empirical Methodology

To test the model's predictions, we require empirical measures of legal risk. Finding such measures is generally unfeasible; 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 reign 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 macro-level 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.

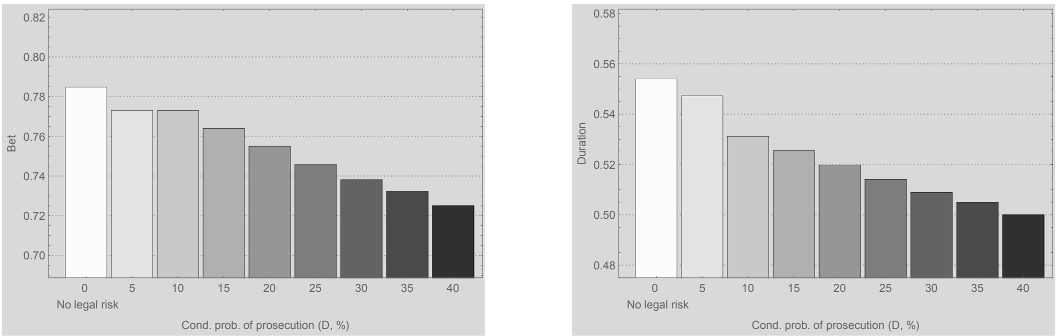
Figure 5. Legal risk parameters and strategic outcomes: Empirical Predictions

This figure shows the impact of changes in the legal risk parameters c and D on the values of Bet and $Duration$ as given by (5). Other parameter values are as in Figure 4.

(a) Severity of the penalty: c



(b) Conditional probability of prosecution: D



III.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 sentence 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 of the wrongful acquisition of that information.[12] Because the

[12]In the Newman–Chiasson decision (Nos. 13-1837-cr and 13-1917-cr), the court of appeals' judges write, "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 the tipper seemingly contradicted the Supreme Court's 1983

defendants 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 insider trading prosecution cases. Several cases were abandoned for which prosecutors had already obtained guilty pleas. 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."[13] Consistent with these views, other pundits argue that this ruling significantly reduced the expected legal hazard of insider traders.[14]

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 weakened in December of 2016, when another decision, the Supreme Court's ruling in *United States v. Salman*,[15] reversed some, but not all, conditions specified in the Newman ruling.[16] Therefore, we argue that the two-year period December 2014 to December 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,[17] for identification purposes, we consider

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."

[13]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/.

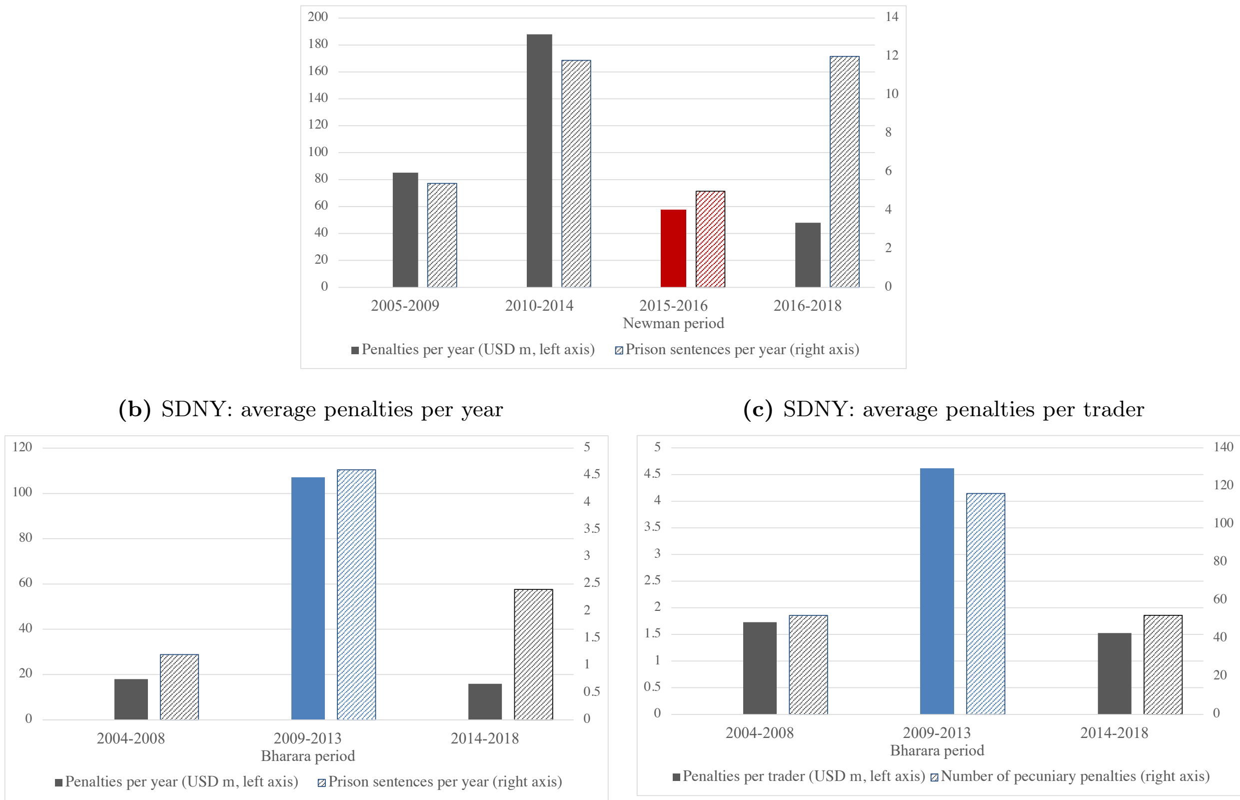
[14]See, for example, https://www.nytimes.com/2016/08/02/business/dealbook/supreme-court-could-rewrite-insider-trading-law.html.

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

[16]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.

[17]First, we cannot observe a whole detailed relationship between the tipper and the trader 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 makes a gift of confidential information to a trading relative or friend. There is ambiguity in applying this view in practice, e.g., what is the precise definition of "friend"? Is, say, a Facebook or LinkedIn contact a friend?

Figure 6. Monetary penalties and prison sentences 2004-2018: All districts and SDNY



(a) All districts

(b) SDNY: average penalties per year

(c) SDNY: average penalties per trader

This figure displays the monetary insider trading penalties and the number of prison sentences. Panel (a) corresponds to all the districts and highlights the Newman ruling period in red. The solid columns display the average value of monetary penalties per year; the dashed columns the yearly average number of prison sentences. Panel (b) presents the same information corresponding to SDNY and highlights 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). Sources: SEC, district courts, LexisNexis, and Securities Law360.

that the decline in legal risk must have been relatively stronger for those traders who received a tip from another party. Conversely, those who traded on self-acquired information were essentially unaffected. Accordingly, we hand-collect records regarding the type 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 Reign at the SDNY. Not all insider trading prosecutors act with the same conviction or possess the same ability to prove financial crime in court. SDNY became renowned as a tough court under the reign 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.'[18]

Since his appointment in 2009, Bharara enjoyed a flawless five-year trial record in insider trading cases. 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 prisoned his sibling, Raj Rajaratnman, and brought the most insider trading defendants in recent years.[19] The judicial setbacks continued in 2014 with the Newman ruling, as discussed above, which substantially weakened Bharara's power[20] (his tenure ended in 2017). Hence, for identification purposes, we argue that illegal traders prosecuted by the SDNY faced exceptionally high legal risk from 2009 to 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 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 onwards.[21] 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 in 2004-2008.[22]

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 reign is also associated with the greater severity of the penalties

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

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

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

[21] We note that, from 2011 on, the considered Bharara period is contemporaneous with the implementation of the SEC's Whistleblower Reward Program (WRP) as part of the Dodd–Frank Act. The underlying idea of this program is to use monetary payments to incentivize whistleblowers to provide regulators with original information on insider trading activity. 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.IV.

[22] 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.

assessed, as captured by c. Hence, we can assess whether insiders respond to these specific factors.

III.B Insider Trading Strategies: Empirical Proxies

In this section, we construct empirical counterparts to the strategic outcomes in (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:

$$\hat{Bet}Norm := \max_a \left\{ \frac{\text{Informed vol}_a}{\text{Normalvol}_a} \right\}, \tag{6}$$

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. We include the max operator because some traders simultaneously use both stocks and options. For options, we compute the normal volume across all contracts with the same underlying stock.[23] To allow for comparability across contracts, which could have distributions of volumes of different magnitudes, we standardize the values in (6) in the regression analyses that follow (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:

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

where 1_{split} is an indicator function that equals one if the insider trades on more than one date; otherwise, the measure is not well defined. We note that the 7-day threshold is below the mean and median values

[23] Since the trading activity in options and stocks may be generated by a different stochastic process, in our regressions, we apply the maximum operator to the standardized ratios.

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:

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

This normalization has the advantage of facilitating comparisons across information corporate 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 (7) and (8) separately for stock and option trades. Figure IA.9 characterizes the empirical distributions of these proxies.

III.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:

$$StratOutcome_{ijk} = a_1 \times Newman_i + b_1 \times NewmanAgent_j + \delta_1 \times \underbrace{Newman_i \times NewmanAgent_j}_{\text{InteracNewman}} \tag{9}$$
$$+c_1 \times \mathbf{Controls}_{ij} + d_1 \times Court_k + e_1 \times Trader_j + f_1 \times EventType_i + \varepsilon_{1,ijk},$$

where each unit of observation is associated with a trade i by insider j prosecuted by court k; *Newman* is an indicator variable equal to one for the period December 2014 to December 2016, and zero for the period January 2013 to November 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.

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.*[24] 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.*[25] To mitigate the impact of outliers on our estimates, we winsorize these variables at the 1% level.

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.

We include several fixed effects. *EventType* absorbs possible differences in the way insiders trade around corporate events, such as M&As or earnings announcements. The inclusion of court fixed effects, $Court$, accounts for the possibility that the legal jurisdiction affects insiders' perceived legal risks. We also include trader fixed effects, $Trader$, which captures any unobserved time-invariant insider-level characteristics that could affect trading behavior. Note that for a given insider, his/her trades could fall both in the periods before and after the shock because the insider could exploit information from multiple corporate events. In our sample, the average number of assets traded by insiders is 1.83.[26] Further, even if the insider traded on a single firm, the insider's trades could still span the periods before and after the legal shock.[27] Therefore, the addition of trader fixed effects brings the regression

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

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

[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]In the Newman test, there are 12 traders who span both before and after the shock (corresponding to 298 observations)

specification closer to an idealized setting where the set of insider traders is unaltered across time.

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:

$$StratOutcome_{ijk} = a_2 \times Bharara_i + \delta_2 \times \underbrace{Bharara_i \times SDNY_j}_{\text{InteracBharara}} + c_2 \times \mathbf{Controls}_{ij} \tag{10}$$
$$+ d_2 \times Court_k + e_2 \times Trader_j + f_2 \times EventType_i + \varepsilon_{2,ijk},$$

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 2009–2013, and zero for the periods 2006–2008 and 2014–2015.[28] Our coefficient of interest is δ_2. All the other regressors are as defined above. To allow for the correlation of residuals across individual traders, we cluster standard errors by the date of trading in the estimation of regression models (9) and (10). Table III provides descriptive statistics for the dependent and control variables.

To validate our empirical results, we begin with two standard tests assessing balancedness and parallel trends. First, we present in Table IA.V separate summary statistics for the regressors corresponding to observational units affected and unaffected by the Newman and the Bharara shocks. The respective subsamples do not differ significantly along most dimensions. The only notable difference is that, on average, traders outside SDNY trade stocks with higher volume volatility. Next, we estimate time-series regressions using quarterly indicator variables to detect any pre-trends in the dependent variables before the legal shocks. Table IA.VI shows that most coefficients do not differ markedly over time. We note that they are quite stable in the exceptional instances in which coefficients are statistically different from zero. We conclude that the estimation results for δ_1 and δ_2 are unlikely to be an artifact of significant imbalances in the selection of firms on observables or pre-existing trends in the outcomes variables.

and 161 traders who trade only in one period (1,271 observations). In the Bharara test, 57 traders span both periods (1,148 observations), and 657 traders span one period (3,469 observations).

[28]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 on Bharara's weakening power due to the Newman ruling.

IV Empirical Results

This section presents the test results regarding Predictions 1 and 2.

IV.A Main Results

Table IV displays the Newman and the Bharara results in Panels A and B, respectively. Columns 1 to 4 display results for a specification without control variables or fixed effects. In columns 5 to 8, we consider specifications with controls and the event and court fixed effects. Finally, in columns 9-12, we additionally include trader fixed effects. We mostly concentrate the discussion on the estimates of the coefficients δ_1 and δ_2 in the full specification models (9) and (10).

The results of the Newman test show that, given a *reduction* in legal risk, trade quantities increase, and insiders trade relatively later. The coefficients of $\hat{B}et$ and $\hat{B}etNorm$ are positive, with statistical significance at the 10% and 5% levels, respectively. The effects are also economically relevant, as summarized in the top panel of Figure 7, with increases of 39.8% and 73.8% relative to the standard deviations of these measures. In turn, the coefficients of $\hat{D}uration$ and $\hat{D}urNorm$ increase by 79.3% and 124.6% relative to their respective standard deviations. Both of these estimated coefficients are statistically significant at the 1% level.

The Bharara test results are qualitatively consistent with the model's prediction under an *increase* in legal risk, albeit their statistical significance is lower than that in the former test. We observe a pronounced decrease in $\hat{B}etNorm$, equivalent to 41.5% of its standard deviation (see the middle panel of Figure 7). The coefficient of $\hat{D}urNorm$ is negative and significant at the 5% level, displaying a nonnegligible reduction of 36.6% relative to its standard deviation. The coefficients of $\hat{B}et$ and $\hat{D}uration$ are both negative and economically sizable in the full specification, but they are statistically insignificant.

Contrasting the results across specifications, we find that the use of control variables and various fixed effects does not materially affect the results for trade quantities. However, they are important to identify the effect on trade timing, captured by the duration measures. This is particularly evident in the case of specification that includes trader-fixed effects.

Overall, the evidence suggests that, first and foremost, insiders do internalize changes in legal risk exposure, as shown by the economically significant changes in the strategic outcomes. Second, we observe that the impact on strategic outcomes is fairly consistent with the model's predictions, holding true for both negative and positive shocks to legal risk.

IV.B Trade Quantities and Event Types

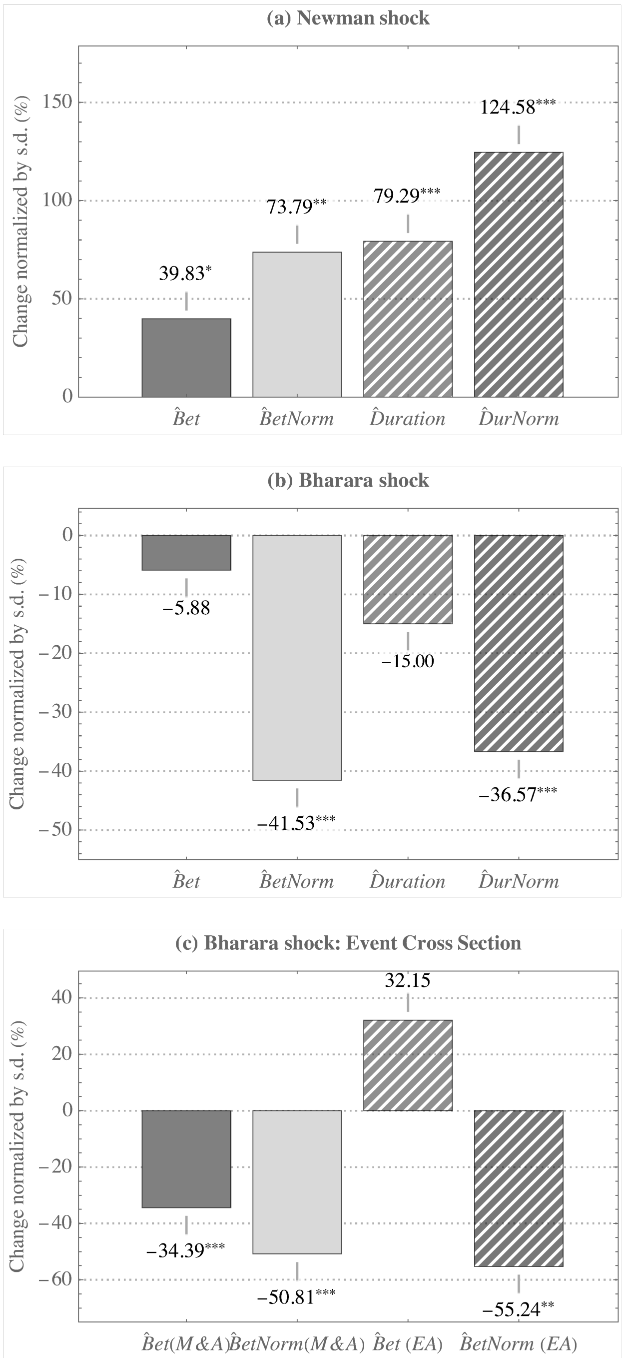
Unlike the Newman test, the Bharara test result for dollar trade quantities, $\hat{B}et$, lacks statistical significance. Next, we inquire whether insiders' response to the latter legal shock across corporate events can help explain why. We consider two main event types, M&As and earnings announcements, and split the sample accordingly to compute separate estimates of δ_2 in model (10). Table IA.VII presents the results together with those on the complementary metric $\hat{B}etNorm$.

The value of δ_2 associated with $\hat{B}etNorm$ displays a statistically significant decline in response to the legal shock for both M&A and earnings events. Regarding $\hat{B}et$, we find that the M&A sample displays patterns that are more consistent with our theoretical prediction. As shown in the bottom panel of Figure 7, there is a sharply negative response to the legal shock, equivalent to a 34.39% decrease relative to its standard deviation, which is statistically significant at the 1% level. The estimated coefficient is not statistically significant for earnings events.

These results suggest that our stylized model, which is silent on the characteristics of the private tip beyond mispricing, more clearly captures the interactions among market participants around M&A events. Such a conclusion might indeed be intuitive for at least a few reasons. First, in contrast to 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 easier for the regulator to detect. Third, one could also expect differences at the prosecution stage of a potential trial. In particular, 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 7. Summary of empirical results

The number displayed in each bar corresponds to the percentage ratio between the estimated interaction coefficient δ_1 and δ_2 in (9) and (10) and the corresponding standard deviation of the corresponding strategic outcome. Panel (a) corresponds to the Newman test. Panels (b) and (c) correspond to the Bharara test results using the full sample and by corporate event type, respectively. The interaction coefficients used in Panels (a) and (b) are from Table IV, and those in Panel (c) are from Table IA.VII. M&A and EA denote mergers and acquisitions and earnings announcements, respectively. ***, **, * denote the 1%, 5%, and 10% levels of statistical significance, respectively.



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.

V.A Insiders' Engagement Decision

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 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 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 (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.

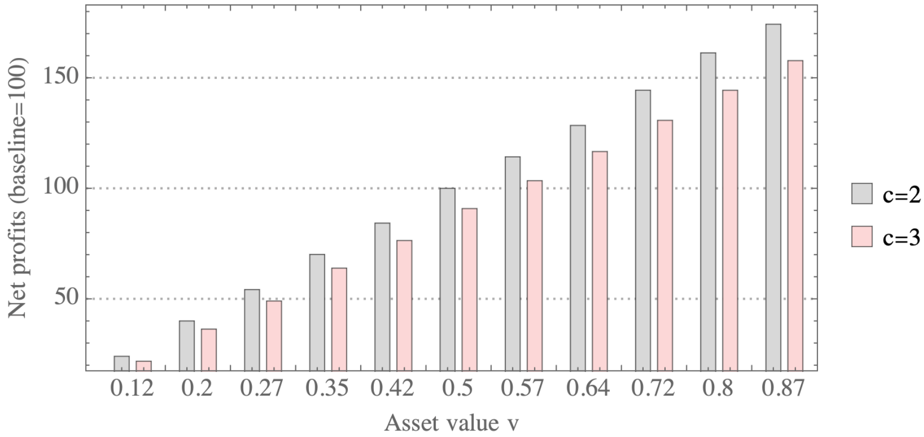
Prediction 3 The average value of insiders' private signals increases with legal risk.

V.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,

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.



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 $T_{\text{public}} + 1$.[29] We denote the absolute value of such a return as the *private signal value* (PSV):

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

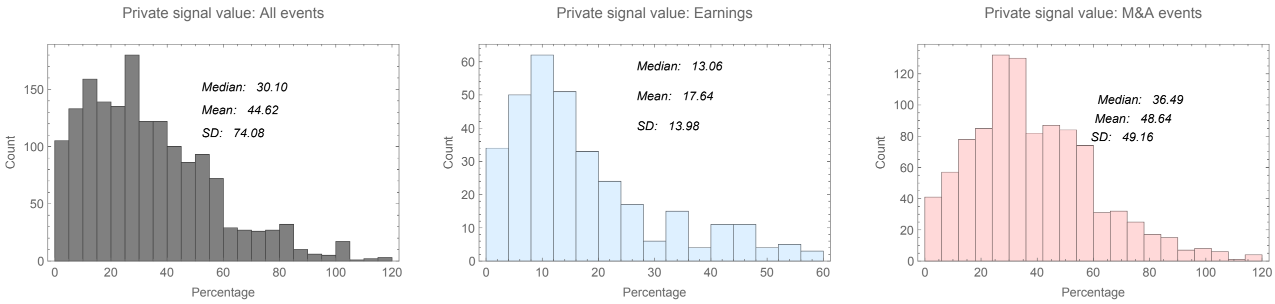
The left panel of Figure 9 displays the distribution of PSV for the entire sample. The mean and median values are 44.62% and 30.10%, respectively. The middle and right panels show that the distributions for earnings and M&A events are quite different: the median PSV value for earnings is merely 13.06%,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

[29]Using PSV instead of *Strength* is theoretically more appealing because the decision to engage in illegal trading conceptually precedes when to place the first order.

Figure 9. Distribution of private signal values

This figure displays the distribution of PSV (see equation (11)). The left panel corresponds to all the events. The middle and right panels correspond to earnings and M&A events, respectively.



Section III.A. Specifically, we estimate the following models:

$$PSV_{ij} = a_3 \times Newman_i + b_3 \times NewmanAgent_j + \delta_3 \times InteracNewman_{ij} + c_3 \times \mathbf{Controls}_{ij} + d_3 \times YM_i + e_3 \times Trader_j + \varepsilon_{3,ij}, \quad (12)$$

$$PSV_{ij} = a_4 \times Bharara_i + b_4 SDNY_j + \delta_4 \times InteracBharara_{ij} + c_4 \times \mathbf{Controls}_{ij} + d_4 \times YM_i + e_4 \times Trader_j + \varepsilon_{4,ij}, \quad (13)$$

where the interaction terms and **Controls** are as defined in Section III.C except for $Strength$. We also include trader fixed effects to account for the cross-trader variation in the choice of signals. Compared to the specifications in (9) and (10), we include year-month fixed effects, YM, to account for the possibility that asset returns could also depend on the period; e.g., during bad or good market conditions. We do not include court fixed effects because these are collinear with the trader fixed effects. 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 (12) and (13) in columns 3 and 4. We find economically significant differences that support Prediction 3 in both tests. The change in the PSV value for the Newman shock is -46.45% relative to its standard deviation. For the Bharara shock, the corresponding change is larger at 112.68%. The estimated coefficients display statistical significance at the 10% and 1% levels, respectively. The results are almost identical without the inclusion of the three firm-level controls, as shown in columns 1-2.

In sum, the evidence on the distribution of private signals complements that on insiders' strategies in Section IV and provides further support for the notion that these traders internalize legal risk.

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.

VI.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.

For that, we exploit the equilibrium connections from Section II to simulate the moments in (5) and condition the expectations on the prosecution event, for which we use the notation 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 $\delta_1 := 1_{\{|u_1+x_1|>\overline{y}\}})$ and define a no-investigation region $[\underline{u}_1, \overline{u}_1]$ with thresholds $\overline{u}_1 := \overline{y} - x_1$ and $\underline{u}_1 := -\overline{y} - x_1$, 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.

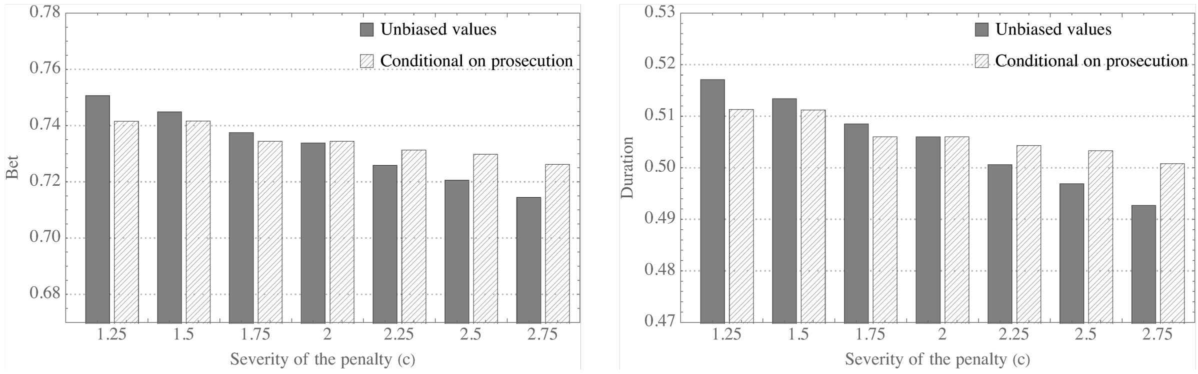
On the other hand, the value of x_2 can also *increase* moving from lower to higher values of u_1. This is because the value of x_2 is not a continuous function of u_1 due to δ_1 changing outside of the no-investigation region. For $u_{1\ell}$ and u_{1h} in a neighborhood of $\overline{u}_1$, $u_{1\ell} < \overline{u}_1 < u_{1h}$, 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^{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^{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

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 parameters values are as in Figure 4.



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.

VI.B Bounded Rationality

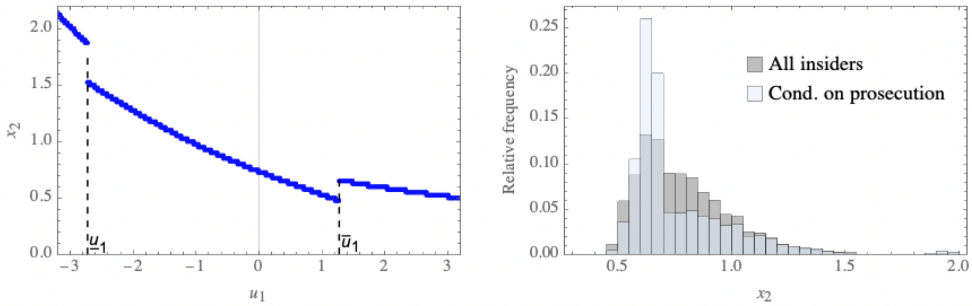
We also examine the possibility of legal risk sensitivity being heterogeneous, either because some insiders wrongly underestimate the real threat, or perhaps they completely neglect it. The model's outcomes suggest that the regulator's screening could also lead us to *underestimate* the degree to which 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 $\tilde{D} = {}^{D}\!/_{2}$ 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

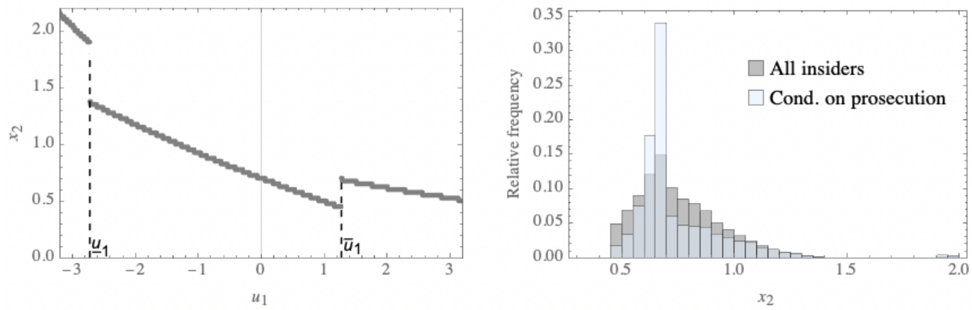
Figure 11. Effect of legal risk on potential selection bias

This figure displays simulation outcomes for the second trading period with positive private information for different values of c. The left column shows the insiders' optimal x_2 response to a given realization of $t = 1$ liquidity trading volume, 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 column shows the distribution of x_2 for all insiders and the prosecuted group. Other parameter values are as in Figure 4.

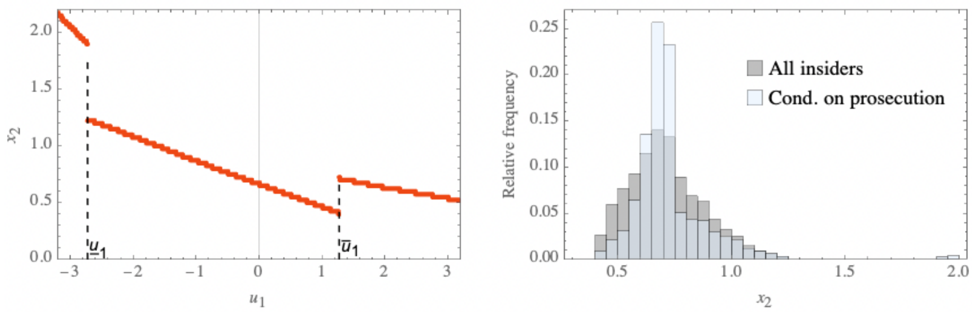
(a) Low legal risk ($c = 1.25$, mean $x_2 >$ mean x_2^{P})



(b) Medium legal risk ($c = 2$, mean $x_2 \approx$ mean x_2^{P}).



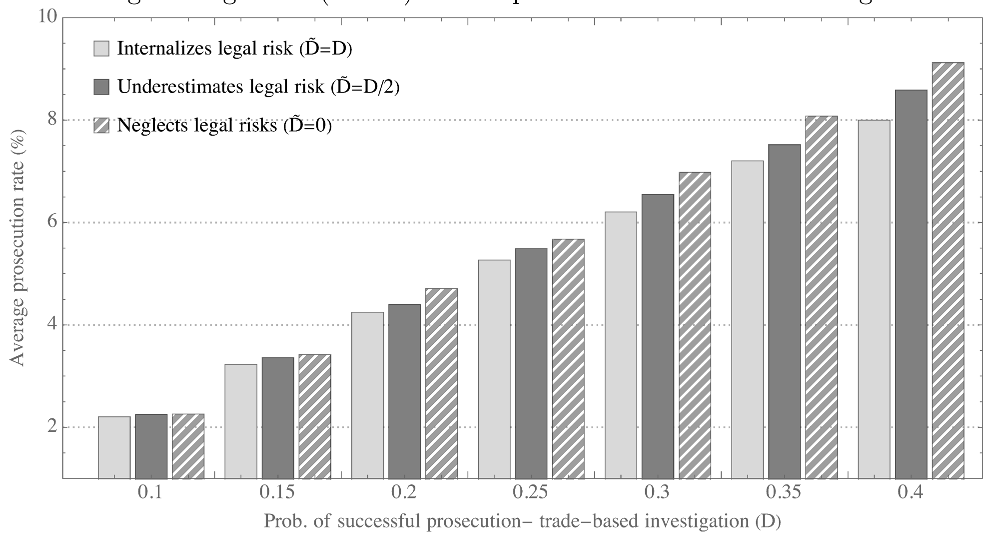
(c) High legal risk ($c = 2.75$, mean $x_2 <$ mean x_2^{P})



displayed in Figure 12 and indicate a clear pattern: the more overoptimistic insiders are, the more likely prosecution becomes successful. This is because the insiders' trade aggressiveness increases with the degree of subjective underestimation of D.

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.



Applying the same reasoning as the ex-ante engagement choice in Section V, sample selection could bias downwards 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 that underestimate or neglect legal risk, one can consider the estimates in Sections IV and V as a lower bound on the population's response.[30] 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.

VI.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

[30]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.

heterogeneity in the origins of the SEC investigations.

In particular, we focus on cases referred to the SEC from sources that are 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 first-hand 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, and they display economic and statistical significance. In the Bharara test, all coefficients are negative, consistent with the same predictions for a positive shock; $\hat{B}etNorm$ and $\hat{D}urNorm$ are also statistically significant at the 1% and 5% level, respectively. In sum, we find qualitatively similar patterns to those based on the universe of SEC investigations.

Overall, these results suggest that we 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 in 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 insiders' trades reveal their private information. For that, we evaluate price movements on insider trading days and explore how legal risk can influence the process of information transmission.[31]

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

VII.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, on average, be consistent with whether good or bad news motivated the trades. We empirically assess such a connection in two ways.

First, we compute the average daily returns for the affected stocks when insiders trade. Panel A of Table IA.VIII shows the results. In columns 1-3, we focus on positive news events, and in columns 4-6 on negative news. Further, we consider three measures of returns: raw, net of the total market return, and net of the S&P 500 index return. We observe that the average return on days with positive information is 1.1% and 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.VIII 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, we find that daily 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.

VII.B Information Transmission and Legal Risk

To take a closer look at the information aggregation process over insiders' trading horizon, we normalize such a period across investigations by considering a nonparametric time scale. Specifically, we split the period $[T_{\text{first}}, T_{\text{public}}]$ into 10 subperiods of equal length and calculate the mean cumulative stock returns across insider trading episodes over this period; accordingly, the trading horizons in this sample must be at least 10 days long.

Panel (a) of Figure 13 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 $T_{\text{public}} + 1$). We reverse the return sign of negative news events for comparability. 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 their private information. At the end of the trading period, the mean cumulative return is about 39.2% of PSV across all information events. 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.[32]

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 Section 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 ignoring legal risk always brings more information into the asset price. The gap versus a rational trader increases with the severity of the legal threat.

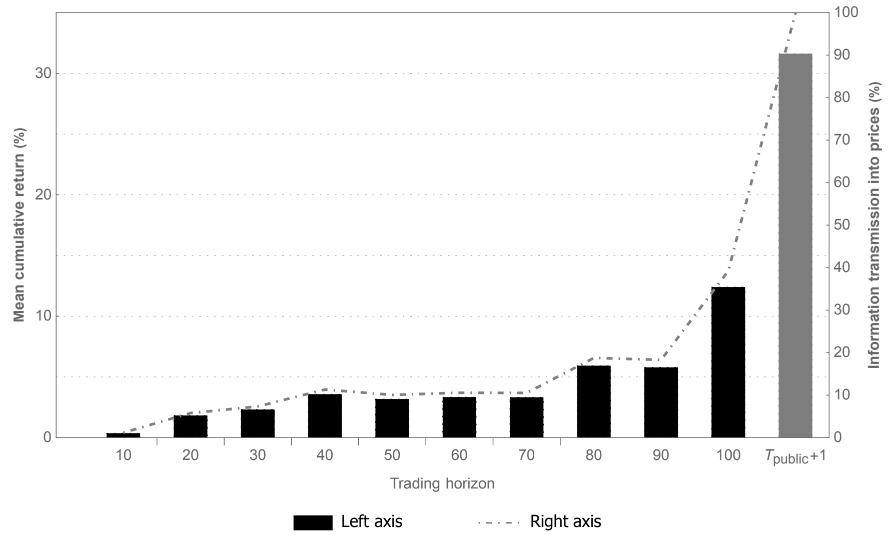
A second insight arises from contrasting price adjustment by legal risk regime. Panels (b) and (c) of Figure 13 show the fraction of private information transmitted into prices for each subperiod corresponding to a low/high legal risk regime as given by the values of $InteracNewman$ and $InteracBharara$. Heterogeneity is moderate in the case of the Bharara test. At the end of the trading horizon, events corresponding to the low-risk regime ($InteracBharara = 0$) show 37.16% information transmission versus 33.54% in the high-legal risk regime. The differences are more striking for the Newman test: in

[32] We stress that Figure 13 displays the process of price aggregation 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. Therefore, we display in Figure IA.10 the same disaggregated process of price adjustment for earnings announcements and M&A events, separately. We observe that at the end of the insiders 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 arguably lessens the concern that illegal insiders play little to no role in driving price transmission.

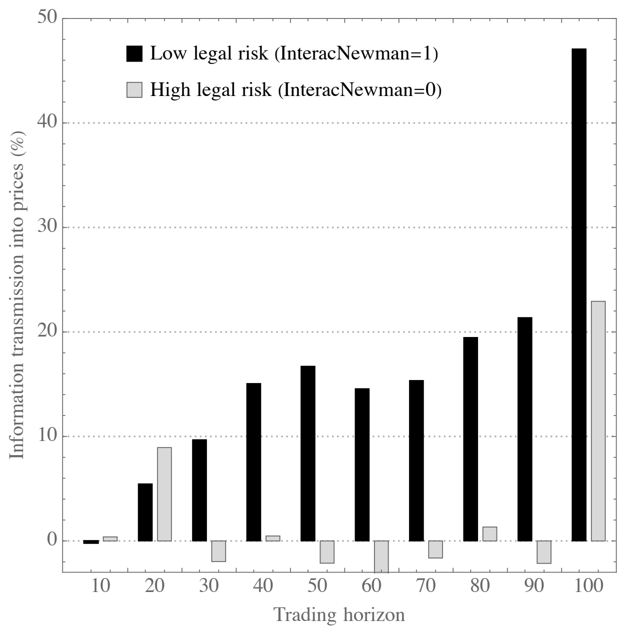
Figure 13. Trades and information transmission into prices

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 value. The dotted line corresponds to the percentage ratio between each decile column and the rightmost column, and reflects the proportion of private information in prices. Panels (b) and (c) display the mean cumulative stock return for low- and high- legal risk cases as given by the values of *InteracNewman* and *InteracBharara* defined in Section III.C. Negative values represent price movements opposite to the direction of the private signal.

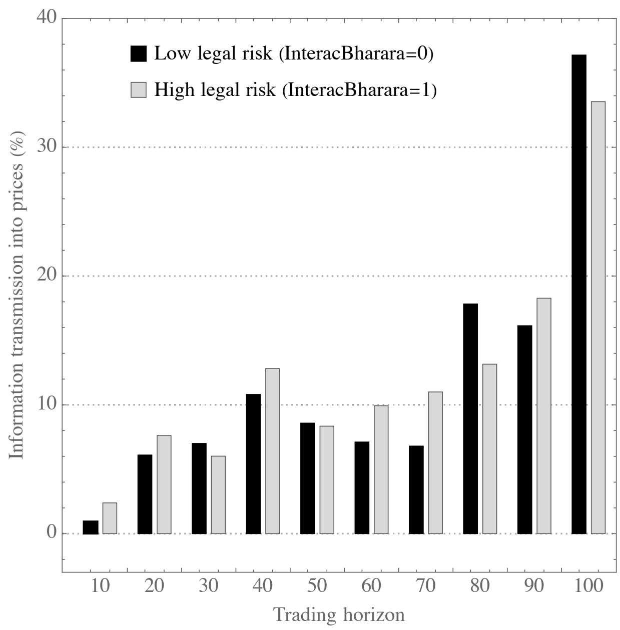
(a) All events



(b) Newman shock



(c) Bharara shock



the low-risk regime ($InteracNewman = 1$), information transmission occurs faster and to a much fuller extent. Before the public announcement, the low-risk regime shows that 47.09% of the information is reflected in the price versus 22.93% in the high-risk regime.

Overall, our finding that insider traders internalize legal risk is a natural explanation of the seemingly weak amount of information aggregation prior to 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 et al. (1995), among others.[33]

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 model to (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 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.

[33]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 et al. (2020), who show that, in general equilibrium, the shift of holdings from informed to uninformed investors reduces price informativeness.

Trading Opportunity Costs. Upon receiving a confidential tip, most insiders do not trade on each day before the public announcement. It is difficult to rationalize such sparse trading behavior within a conventional Kyle setting since inaction usually stems from fixed costs (Stokey (2008)). For that reason, in Section IA.3, we consider an extension that features such costs, capturing unobservable factors, such as the opportunity and/or monitoring costs of agents. We use the model to characterize the impact of legal risk on the frequency of market trading activity and develop an empirical test.

Exogenous Detection and Whistleblower Reward Program. 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 in the case of whistleblowers. Section IA.4 considers an extension of the model with this additional source of detection, and it exploits the SEC's adoption of a whistleblower reward program to evaluate the impact of a shock to the whistleblowing probability on insider traders' strategies. The results are consistent with those described in Section IV.

Dismissed Investigations. Section IA.5.A considers a cross-sectional legal risk test based on individuals who, according to the SEC, traded on superior information but, according to a judge, cannot be proven to have committed a crime. To the extent that such traders did not fully internalize the prosecution threat, a comparison with similar convicted insiders can be regarded as a cross-sectional test of the strategic behavior of insiders facing different legal risk. The main result is that these traders act less cautiously on average, which fits well with the hypothesis that they face lower legal risk.

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.B the theoretical impact of threshold changes and then contrast such changes against the considered legal risk shocks. We argue therein that changes in detection thresholds are unlikely to explain our empirical findings.

IX Conclusion

The debate on whether and under what circumstances insider trading should be illegal has a long tradition. As Rauterberg et al. (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, such desirable social goals can only be achieved if insider trading regulations provide meaningful criminal deterrence.

In this paper, we address whether illegal insiders internalize the legal consequences of their actions. By developing and testing the predictions of a model in which an insider rationally responds to legal risks in the Beckerian tradition, we provide empirical support to the effectiveness of U.S. insider trading regulations. Using plausibly exogenous shocks to legal risk exposure, we show that illegal insiders: (i) trade more (less) cautiously when the legal threat is high (low), (ii) act strategically regarding crime engagement, by concentrating on private tips of higher value when the expected legal cost increases. (iii) Their responses to legal risk are reflected in asset prices.

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.

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Appendix A: Definitions 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 regression tests
$\hat{D}uration$	The proportion of informed trade volume executed after seven days from the moment in which the insider received the private tip
$\hat{D}urNorm$	Proportion of informed trade over the second half of the trading horizon. The trading horizon is the period between the first and the last date of insider trading
PSV	Stock price return 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 public disclosure of information
	Panel B: Control variables
$Strength$	Stock price return for a given firm from the opening of the day when the insider trades until the opening of the day following the public disclosure of information, 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 12:2014 to 12:2016, and zero for 2013:1–2014:11
$NewmanAgent$	Indicator variable equal to one if the trader received the private information from another individual
$InteracNewman$	The product between $Newman$ and $NewmanAgent$
$Bharara$	Indicator variable equal to one for the period 2009–2013, and zero for 2006–2008 and 2014–2015
$SDNY$	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
Court FE	Fixed effect variable capturing the specific U.S. federal district court
Trader FE	Trader-specific fixed effect variable

Table I

Corporate Events, Industries, and Trading Instruments: Summary Statistics

This table provides general characteristics of the sample of SEC insider trading investigations. The sample period covers from 1995 to 2018. In Panel A: 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. 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 & Acquisitions	702	53.22
Earnings announcements	289	21.91
General business events (patents, trials)	134	10.16
Shares offerings & tenders	94	7.13
Dividend changes & 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
Non-Classifiable Establishments (99)	173	2.91
Food & Kindred Products (20)	172	2.89
Communications (48)	168	2.82
Panel E: Trading instrument		
Stocks	4,109	66.42
Options	2,025	32.74
ADS	37	0.60
Bonds	15	0.24

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 from 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 used 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 prisoned traders within a case, the percentage of traders who received probation and whose cases were 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 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	-	-	-	-

Table III
Dependent and Control Variables: Summary Statistics

The definition of the variables in this table is as in Appendix A. The construction of the dependent variables and controls is discussed in Sections III.B and III.C.

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
$\hat{D}uration$	0.72	0.54	0.75	1	0.28
$\hat{D}urNorm$	0.45	0.28	0.47	0.55	0.24
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	-	-	-	-

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 A. The variable *Newman* is an indicator variable equal to one for 12:2014–12:2016, and zero for 2013:1–2014:11; *Bharara* is an indicator variable equal to one for the period 2009–2013 and zero for 2006–2008 and 2014–2015; and *SDNY* is an indicator variable equal to one for traders convicted by SDNY, and zero for traders convicted in other courts. The control and fixed effect variables are as in Appendix A. Standard errors (in parentheses) are clustered by the date of trading. ***, **, * denote the 1%, 5%, and 10% levels of statistical significance, respectively.

	$\hat{Bet}$	$\hat{BetNorm}$	$\hat{Duration}$	$\hat{DurNorm}$	$\hat{Bet}$	$\hat{BetNorm}$	$\hat{Duration}$	$\hat{DurNorm}$	$\hat{Bet}$	$\hat{BetNorm}$	$\hat{Duration}$	$\hat{DurNorm}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Newman shock												
Newman	-1,973.688***	-0.190***	-0.020	-0.070**	-582.500**	-0.138***	-0.060	-0.119**	-389.961	-0.160**	-0.180***	-0.039
	(461.028)	(0.052)	(0.044)	(0.033)	(267.586)	(0.050)	(0.043)	(0.046)	(486.202)	(0.079)	(0.060)	(0.063)
NewmanAgent	-1,578.308***	-0.192***	0.043	0.189***	312.855	-0.135**	-0.065	0.116				
	(575.814)	(0.058)	(0.046)	(0.054)	(384.766)	(0.057)	(0.053)	(0.071)				
InteracNewman	2,715.688***	0.199***	0.136**	-0.113**	1,730.630**	0.147***	0.198***	-0.072	4,946.552*	0.183**	0.222***	0.299***
	(864.812)	(0.056)	(0.058)	(0.053)	(801.545)	(0.056)	(0.063)	(0.062)	(2,842.019)	(0.090)	(0.066)	(0.110)
Strength					-41.692	-0.027**	0.034	0.053	730.550*	0.026	-0.035	0.028
					(201.517)	(0.013)	(0.026)	(0.036)	(419.063)	(0.026)	(0.024)	(0.062)
Volatility					-35.959	-0.103	-0.088	0.096	1,619.550	-0.171	-0.132	0.447***
					(646.861)	(0.079)	(0.101)	(0.101)	(1,246.490)	(0.138)	(0.109)	(0.145)
VolumeVol					-154.466	0.005	0.028***	-0.007	-325.229	-0.059*	0.017	-0.091***
					(212.605)	(0.006)	(0.010)	(0.009)	(550.584)	(0.030)	(0.023)	(0.034)
Ln(MktCap)					104.227	-0.042***	-0.008	0.055***	381.372	-0.015	0.004	0.055***
					(167.861)	(0.010)	(0.012)	(0.012)	(248.295)	(0.014)	(0.009)	(0.013)
Court FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
EventType FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trader FE	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Observations	653	733	521	484	593	712	473	442	556	679	467	434

TABLE IV

Impact of Legal Risk Shocks on Illegal Insiders' Strategic Outcomes

	$\hat{Bet}$	$\hat{BetNorm}$	$\hat{Duration}$	$\hat{DurNorm}$	$\hat{Bet}$	$\hat{BetNorm}$	$\hat{Duration}$	$\hat{DurNorm}$	$\hat{Bet}$	$\hat{BetNorm}$	$\hat{Duration}$	$\hat{DurNorm}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel B: Bharara shock												
Bharara	-1,211.211*	0.069***	-0.072***	-0.020	-880.681	0.055***	-0.084***	-0.046**	1,798.198***	0.117***	0.006	-0.023
	(623.684)	(0.015)	(0.018)	(0.021)	(636.222)	(0.016)	(0.022)	(0.023)	(508.125)	(0.024)	(0.025)	(0.026)
InteracBharara	-2,683.647**	-0.077***	0.053*	0.061*	-1,891.786	-0.057**	0.069**	0.077**	-730.667	-0.103***	-0.042	-0.088**
	(1,288.707)	(0.024)	(0.027)	(0.035)	(1,217.167)	(0.024)	(0.029)	(0.037)	(1,012.053)	(0.027)	(0.035)	(0.044)
Strength					-1,347.557**	-0.022***	-0.007	0.018	467.263**	-0.006	-0.011	0.012
					(534.408)	(0.008)	(0.011)	(0.012)	(218.656)	(0.009)	(0.008)	(0.010)
Volatility					-2,259.626**	-0.113***	0.060	0.049	-2,984.012**	-0.134***	0.053	0.066
					(1,031.110)	(0.032)	(0.038)	(0.049)	(1,295.755)	(0.040)	(0.037)	(0.045)
VolumeVol					1,663.608***	0.007***	-0.002	0.004	1,027.137***	-0.004	-0.004	-0.017**
					(306.848)	(0.003)	(0.005)	(0.005)	(352.961)	(0.004)	(0.005)	(0.008)
Ln(MktCap)					346.745	-0.049***	-0.008	0.008	704.222*	-0.011	-0.006	0.015
					(316.184)	(0.006)	(0.006)	(0.007)	(368.502)	(0.009)	(0.007)	(0.010)
Court FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
EventType FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trader FE	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Observations	3,251	3,536	2,698	2,506	3,040	3,447	2,521	2,360	2,853	3,276	2,502	2,338

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 is PSV defined by equation (11) as the percentage change in the corresponding stock price from the opening price on the date the insider receives the private tip to the opening price immediately after the information becomes public. The interaction terms correspond to $InteracNewman$ in columns (1) and (3) and $InteracBharara$ in columns (2) and (4). The interaction terms and control variables are defined in Appendix A. We note that the regression results do not feature the independently estimated coefficients of $Newman/\ Bharara$, and $NewmanAgent/SDNY$. The former are subsumed by the inclusion of time fixed effects and the latter are subsumed by trader fixed effects. Standard errors (in parentheses) are clustered at the date level. ***, **, * denote the 1%, 5%, and 10% levels of statistical significance, respectively.

	Newman shock	Bharara shock	Newman shock	Bharara shock
	(1)	(2)	(3)	(4)
Interaction term	-0.313*	0.827***	-0.343*	0.832***
	(0.183)	(0.297)	(0.187)	(0.302)
$Volatility$			1.131***	-0.100
			(0.364)	(0.350)
$VolumeVol$			-0.041***	0.038***
			(0.016)	(0.018)
$Ln(MktCap)$			-0.002	-0.043
			(0.020)	(0.029)
Constant	0.475***	0.358***	0.039	0.962**
	(0.109)	(0.034)	(0.384)	(0.463)
Year-month FE	Yes	Yes	Yes	Yes
Trader FE	Yes	Yes	Yes	Yes
Observations	522	2,834	522	2,807

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 patters, as described in Section VI.B. The dependent variables are $\hat{B}et$, $\hat{B}etNorm$, $\hat{D}uration$, and $\hat{D}urNorm$ as defined in Appendix *A*. The variable *Newman* is an indicator variable equal to one for 12:2014–12:2016, and zero for 2013:1–2014:11; *Bharara* is an indicator variable equal to one for the period 2009–2013 and zero for 2006–2008 and 2014–2015. The variables $InteracNewman$ and $InteracBharara$ are defined in Appendix A. All regressions include the control and fixed effect variables as in Table IV. Standard errors (in parentheses) are clustered by the date of trading. ***, **, * denote the 1%, 5%, and 10% levels of statistical significance, respectively.

	$\hat{B}et$	$\hat{B}etNorm$	$\hat{D}uration$	$\hat{D}urNorm$
Panel A: Newman shock				
$Newman$	-681.221	-0.213**	-0.173***	-0.020
	(972.761)	(0.089)	(0.065)	(0.073)
$InteracNewman$	6,570.520*	0.242**	0.205**	0.234*
	(3,800.733)	(0.110)	(0.080)	(0.129)
Controls	Yes	Yes	Yes	Yes
Court FE	Yes	Yes	Yes	Yes
EventType FE	Yes	Yes	Yes	Yes
Trader FE	Yes	Yes	Yes	Yes
Observations	445	555	377	359
Panel B: Bharara shock				
$Bharara$	15.175	0.127***	-0.004	-0.046**
	(151.530)	(0.027)	(0.028)	(0.022)
$InteracBharara$	-505.521	-0.119***	-0.019	-0.084**
	(311.966)	(0.032)	(0.040)	(0.040)
Controls	Yes	Yes	Yes	Yes
Court FE	Yes	Yes	Yes	Yes
EventType FE	Yes	Yes	Yes	Yes
Trader FE	Yes	Yes	Yes	Yes
Observations	2,227	2,590	1,987	1,861

Internet Appendix for

"Becker Meets Kyle: Legal Risk and Insider Trading"

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Abstract

This document contains supplementary information and analyses. The first section provides further background on the legal process of insider trading investigations. Section 1.A illustrates the main elements of an insider trading case by considering Matthew Martoma's trades in Elan and Wyeth. Section 2 supplements Section II in the main body of the paper and presents additional model specifications. Section 2.A provides more details on the equilibrium computation algorithm. Section 2.B considers an alternative specification for the conditional penalty function, and Section 2.C addresses the possibility of a reversal in the trade direction. Sections 3 and 4 provide two additional model extensions coupled with dedicated empirical tests. The former considers fixed trading costs, and the latter the possibility of insider trading detection through whistleblowers. Section 5 provides a legal risk test based on dismissed investigations, and identification robustness analyses supplementary to Section VI. Section 6 contains supplemental tables and figures.

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1 Background on Insider Trading

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

The illegal variety is not defined homogeneously around the world. In the United States, the legal framework prohibiting insider trading was established by Rule 10b-5 of the Securities Exchange Act of 1934, which specifies that illegal insider trading refers to "buying or selling a security in breach of a fiduciary duty or other relationship of trust and confidence, while in possession of material, nonpublic information about the security." Under the classical view of insider trading, a trader violates Rule 10b-5 if trading on material, nonpublic information about a firm to which the trader owes a fiduciary duty. Information is deemed *material* if a reasonable investor would consider it important in deciding whether to buy or sell securities. In recent decades, the scope of what constitutes illegal insider trading has increased. In particular, the 1997 Supreme Court case of *United States v. O'Hagan* upheld the SEC's authority to enforce insider trading under the so-called misappropriation theory. Under this theory, it is a violation of Rule 10b-5 to intentionally misappropriate and trade on confidential information in "breach of a duty owed to the source of the information." What constitutes such a violation of duty is a controversial legal issue.[1]

The consequences of being found liable for insider trading can be severe. Individuals convicted of criminal insider trading can face up to 20 years of imprisonment per violation, criminal forfeiture, and fines of up to $5,000,000 or twice the gain from the offense. A successful civil action by the SEC could lead to the disgorgement of profits and a penalty not to exceed the greater of $1,000,000, or

[1] Despite the aforementioned increased scope, finding a trader guilty of insider trading is not easy. The legal practice of insider trading asserts that to find a tippee criminally liable for insider trading, federal prosecutors must prove all of the following elements: (i) the insider had a fiduciary duty; (ii) the insider breached that duty by disclosing confidential information to a tippee; (iii) the tip was made in exchange for a personal benefit, meaning a benefit of some consequence; (iv) the tippee knew of the tipper's breach (that is, the tippee knew the information was confidential and divulged it for a personal benefit); and (v) the tippee nevertheless used that information to make a trade. Bhattacharya (2014) provides an insightful overview of the legal arguments.

three times the amount of the profit gained or loss avoided. The common rule is that the penalty is equal to the size of the profits realized in the case, in addition to the forfeiture of the profits realized in the case. In addition, the court requires the insiders to pay interest on the profit amounts and typically bars convicts from trading activities for a substantial period. Moreover, individuals can be barred from serving as officers or directors of a public company or, in the case of licensed professionals, such as attorneys and accountants, from serving in their professional capacity before the SEC.

1.A A Tale of an Insider Trader

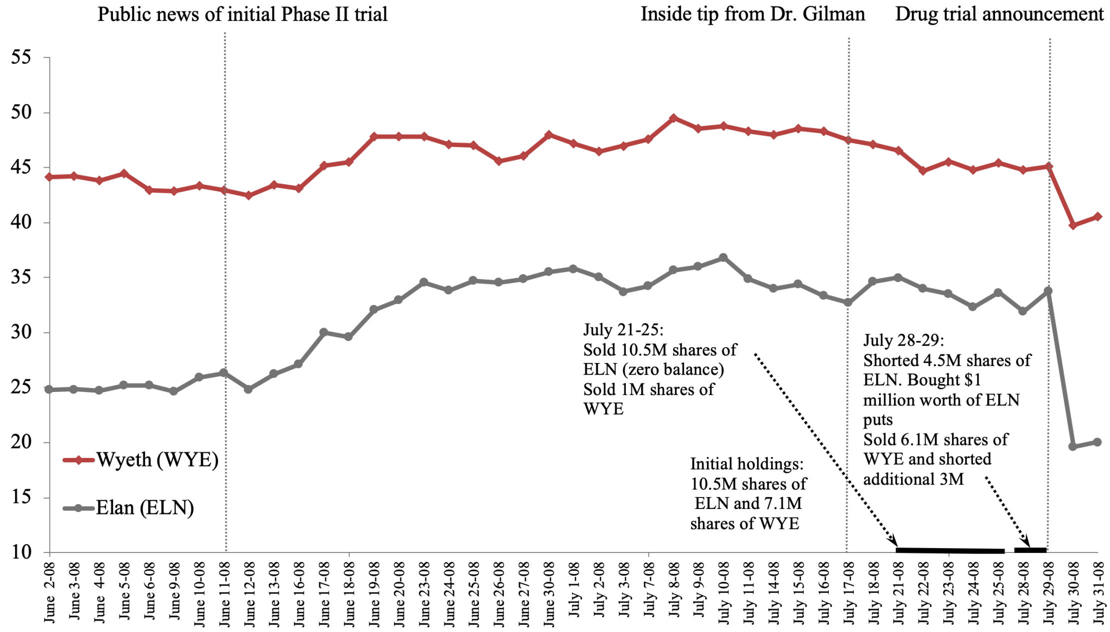
Between 2006 and 2010, Matthew Martoma worked at CR Intrinsic, an unregistered investment adviser, serving as a portfolio manager from 2008 until his departure. Martoma perpetrated the insider trading scheme with Sidney Gilman, a professor of neurology at the University of Michigan.[2]

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

Gilman first met Martoma through paid consultations arranged by the expert network firm. Gilman provided Martoma with nonpublic information concerning the Phase II trial starting in at least 2007. In the weeks leading up to the July announcement, Gilman held several calls with

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

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



Martoma during which he provided information regarding the safety and efficacy results for the trial. On July 17–18, 2008, Gilman and Martoma had a lengthy phone call during which Gilman suggested that the drug had potential serious negative side effects.

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

Although the investment advisers' portfolios achieved a zero balance in Elan securities by July 25, 2008, they continued to sell short Elan securities on July 28 and 29, until the public announcement. By the close of the market on July 29, 2008, both companies had a combined short position of approximately 4.5 million securities. The gross sales proceeds of Elan shares exceeded $500 million and constituted over 20% of the reported trading volume in the seven days prior to the announcement. In addition, on July 28 and July 29, Martoma and the portfolio manager purchased over $1 million worth of Elan put options with strike prices below the Elan share price on those three trading days.

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

On July 29, 2008, after the close of the U.S. markets, Gilman presented the results of the Phase II trial at the aforementioned conference. The market reacted negatively. On July 30, 2008, Elan's shares opening price was $19.63, declining nearly 42% relative to the previous close price of $33.75. In turn, Wyeth's stock price fell from to $39.74 from $45.11, a decrease of nearly 12%. Figure IA.1 presents the time series of Elan and Wyeth stock prices and summarizes Martoma's trades.

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

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

2 Supplement to Section II

This appendix provides supplementary material to Section II. Section 2.A describes the algorithm used to compute the model's equilibrium. Section 2.B considers a model specification with a fixed penalty. Section 2.C shows an equilibrium case in which the insider reverses trade direction.

2.A Equilibrium Computation

To compute the model's equilibrium, we employ an algorithm that consists of the following steps:

Step 0. We guess the value of the informed trader policy $x_1^0(v)$ and $x_2^0(v, p_1, \delta_1)$, the pricing functions $p_1^0(y_1)$ and $p_2^0(\sum_t y_t)$, and the informed trader value functions $V_1^0(v)$ and $V_2^0(v, y_1, \delta_1)$.

At each iteration $i \geq 1$:

Step 1. Taking all other equilibrium objects as a given, we find the optimal value $x_1^i(v)$ to maximize the right-hand side of equation (3).

Step 2. Given the distributions of $\tilde{v}$ and u, we simulate the realization of the joint process $\left\{v, y_1 = x_1^i(v) + u_1\right\}$ and use a nonparametric kernel to compute $p_1^i(y_1) = \mathbb{E}(\tilde{v}|y_1)$.[3]

Step 3. We find the optimal value $x_2^i(v, p_1, \delta_1)$ to maximize the right-hand side of equation (4).

Step 4. We simulate the realization of the joint process $\{v, \sum y_t\}$ by drawing, first, v, $x_1^i(v)$, and $\delta_1\left(x_1^i(v) + u_1\right)$; second, $x_2^i(v, p_1, \delta_1)$ and y_2. Similarly to Step 2, we then estimate $p_2^i(\sum_t y_t) = \mathbb{E}(\tilde{v}|\sum_t y_t)$.

Step 5. We compute $V_1^i(v)$ and $V_2^i(v, y_1, \delta_1)$ according to equations (3) and (4).

Step 6. We check for numerical convergence of the policy functions: $\left\|x_1^i - x_1^{i-1}\right\| + \left\|x_2^i - x_2^{i-1}\right\| < \epsilon$. If convergence has not been achieved, we return to Step 1.

Finally, we check the robustness of the equilibrium outcomes to arbitrary alternative guesses in Step 0.

[3] The probability density function for a value P is given by a linearly interpolated version of $\frac{1}{nh}\sum_{i=1}^{n} k\left(\frac{P-P_i}{h}\right)$ for a kernel k and bandwidth h. We compute the equilibrium outputs using a Gaussian kernel.

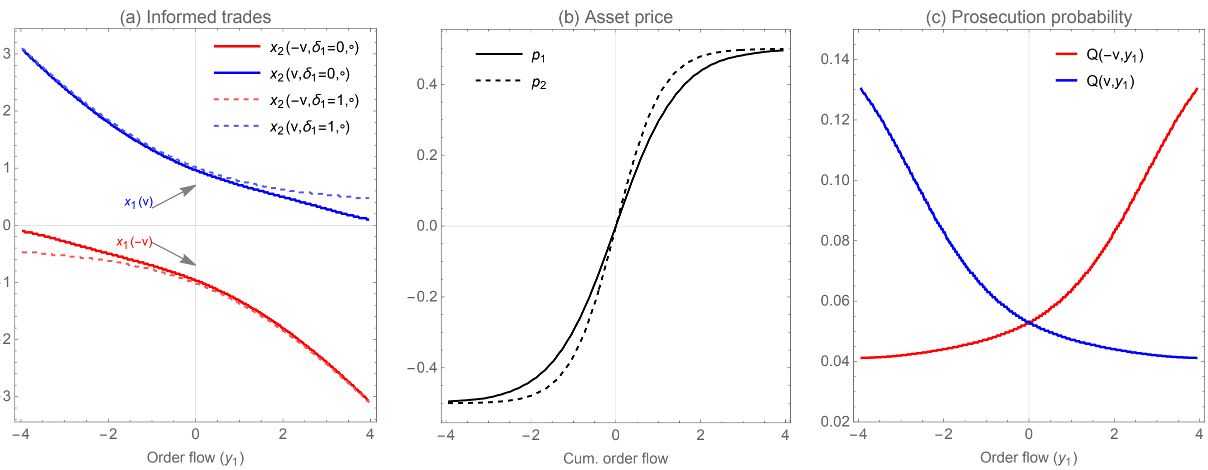
2.B Alternative Penalty Specification

We consider the following alternative to the legal penalty function in (2):

$$P(\pi_1, \pi_2) = F \times 1_{\{\sum \pi_t > 0\}}, F > 0. \tag{2.1}$$

The penalty in (2.1) is fixed rather than proportional to trade profits. The indicator function in (2.1) implies that the penalty is only enforced when the insider realizes positive trade profits. The term $F > 0$ can represent non-pecuniary costs, such as prison time, or subjective costs, such as public shaming for being a criminal. Under the latter interpretation, a reckless individual would display $F = 0$, and an individual with incorruptible morals or lexicographic preferences for a good reputation, $F \to +\infty$. The latter individual would never trade on misappropriated private information.

Figure IA.2
Equilibrium objects: Fixed penalty
This figure displays the equilibrium outcomes of the model with a fixed penalty given by (2.1), and $F = 0.2$ and $c = 0$. Other parameter values are as in Figure 4.



Despite being amenable to alternative interpretations, the main equilibrium predictions of the model are not significantly affected if (2.1) substitutes for (2). Figure IA.2 displays the equilibrium relations corresponding to the parameter values in Section II but with $c = 0$ and $F = 0.2$. One can see that a fixed penalty makes the graph of x_2 steeper than the counterpart in Figure 4. Intuitively, advantageous realizations of u_1 lead to high expected profits in the second period, without making the potential penalty larger. Conversely, adverse realizations of u_1 make the insider relatively more concerned about the invariant legal penalty and induce more cautious behavior. Needless to say, if F is sufficiently high, a rational insider refrains from trading altogether.

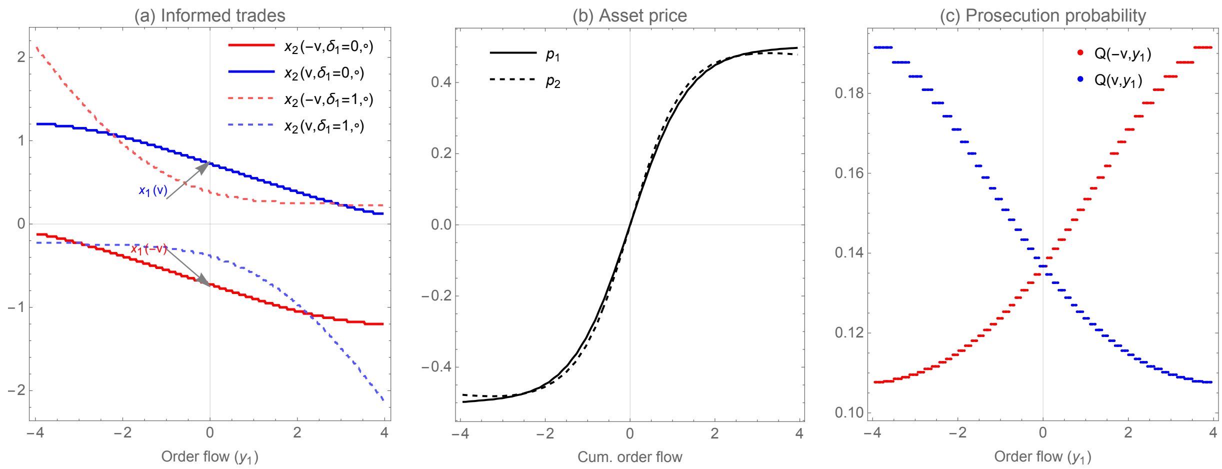
2.C Trade Direction Reversals

Since the insider internalizes the regulator's screening process, the insider could find it optimal to revert the direction of trades for sufficiently extreme parameter values. Figure IA.3 illustrates one such scenario for a high probability of prosecution success, $D = 0.75$. Take the second-period decision of the insider with positive news. We can see that if $\delta_1 = 0$, the insider adds a positive amount to the last period's position, provided the realization of u_1 is not too large; otherwise, the insider does not trade. However, if $\delta_1 = 1$, the near-certainty of enforcement calls for the insider to sell to undo the accumulated position. Hence, $x_2(v, y_1, \delta_1 = 1)$ takes on negative values and $x_2(-v, y_1, \delta_1 = 1)$ takes on positive values. Since the conditional penalty is in all cases greater than trade profits—recall that $c > 1$—it could be optimal to experience trade losses in the second period to approximate zero expected total profits and thereby minimize the legal penalty.[4]

The threat of hefty legal penalties drives the optimality of trading against one's information in this setting. Such a mechanism contrasts with that in previous studies. Under special conditions, the insider trader in Back and Baruch (2004) can find it optimal to submit money-losing orders to bluff the market makers. In Chakraborty and Yilmaz (2004), trading against one's information is part of many equilibria provided the presence of the insider is uncertain to the market maker. The model by Huddart et al. (2001) incorporates a regulatory disclosure requirement forcing to disclose the insider trades after each trading period. The disclosure regulation induces the insider to add noise to its demand. This feature can result in trades that are inconsistent with the insider's private information.

[4]For the considered parametrization, the equilibrium frequency of such trade reversals is 11.72%.

Figure IA.3
Equilibrium objects: Trade direction reversals
This figure displays an instance of trade direction reversals. The equilibrium outcomes correspond to the model presented in Section II, with the same parameter values as in Figure 4, except $D = 0.75$.



3 Trading Opportunity Costs and Multi-date Trading

We have documented in Section I that most insiders trade on more than one day; the median number is 2. Simultaneously, upon receiving the confidential tip, most insiders do not trade on every day before the corresponding public announcement. It is difficult to rationalize such sparse trading behavior within a conventional Kyle setting since inaction usually stems from fixed costs (Stokey (2008)). For that reason, we consider an extension of the baseline legal risk model in Section II that features such costs, intuitively capturing unobservable factors, such as the opportunity costs and/or monitoring costs of agents (e.g., Peng and Xiong (2006)) and/or fixed transaction costs (e.g., Lo et al. (2004)). We use the model to characterize the impact of legal risk on the frequency of market trading activity. Then, we develop an empirical test using the sources of legal risk variation described in Section III.

3.A Model Extension

The information and trading environments are like in Section II, except that active participation in the market is subject to a fixed opportunity cost. The latter is normalized to zero for the first date and equals $f \geq 0$ for the second date; therefore, f represents the additional cost of returning to the market. We focus on the case in which fixed costs are relatively low: in equilibrium, a private tip is sufficient for an insider to open a position.[5] Having opened a position, depending on what the insider learns after the first period, the insider decides whether to incur the cost to trade again. Therefore, we will see that equilibria can display either single-period or two-period insider trades.

Accordingly, the insider's value function is identical to that in equation (3) in the first period, and in the second period it is as follows:

$$V_2(v, y_1, \delta_1) = \max_{x_2 \in \mathbb{R}} \mathbb{E}_{u_2, \delta_2 | \{v, y_1, \delta_1\}} \left\{ \pi_2(x_2) - 1_{\{x_2 \neq 0\}} f - P(\pi_2; \pi_1) \right\}, \tag{3.1}$$

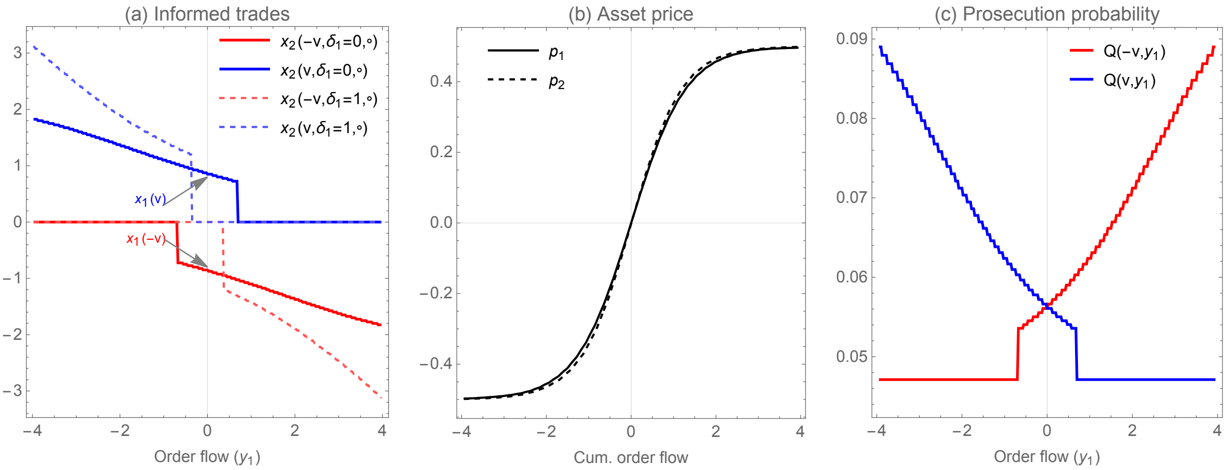
where the functions π and P are as in Section II.

We use the algorithm in Section 2.A to compute an equilibrium numerically. Figure IA.4 displays the strategic outcomes. Consider the trading strategy following positive private information in Panel (a). We can see that, as before, the insider places a less aggressive order x_2 when prices have moved upwards due to a high y_1 realization. For a given δ_1, if the value of y_1 is sufficiently large, the expected profit associated with any $x_2 > 0$ falls below f. In such case, the informed trader does not return to the market and we obtain a single date of insider trading ($x_2 = 0$).

More generally, upon observing the realizations of both y_1 and δ_1, the insider decides whether to incur the cost to revisit the market. For each value of δ_1 one can identify a critical value $\hat{y}_1$ such that, for more adverse realizations of y_1, it is optimal to stop trading, even when p_1 fails to reflect the true asset value. In the case of positive private information, a high investigation likelihood reduces such threshold value: $\hat{y}_1(v, \delta_1 = 1) < \hat{y}_1(v, \delta_1 = 0)$. Since values $y_1 > \hat{y}_1(v, \delta_1 = 0)$ result in $x_2(v, y_1, \delta_1 = 0) = 0$, the endogenous detection probability (1) becomes $q(x_1) \times D$ for such y_1 values, as shown in Panel (c).

[5] In that case, incorporation of an explicit fixed cost at $t = 1$ does not affect the insider's decision; hence, we normalize such a cost to zero. If, on the other hand, fixed costs were high enough to prevent a trading profit, the insider would not open a position, and there would be no room for an insider trading investigation.

Figure IA.4
Equilibrium objects: Model with fixed trade opportunity costs
This figure displays the equilibrium outcomes of the model with fixed trading opportunity costs. Parameter values as in Figure 4 except $f = 0.1$.



Next, to capture the extent to which the informed trader is active in both periods, we define a third strategic metric:

$$Splitting := \mathbb{E}\left[\mathbf{1}_{\{x_1\neq 0, x_2\neq 0\}}\right]. \tag{3.2}$$

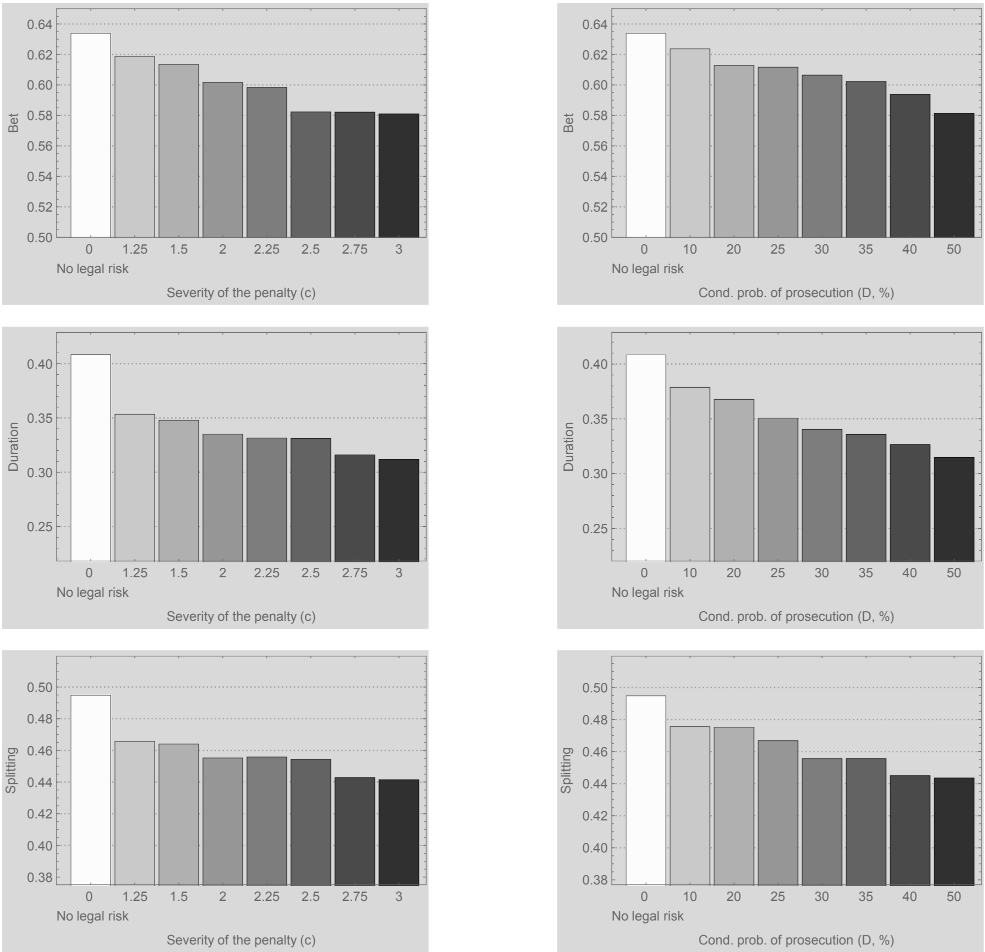
Figure IA.5 displays the full set of strategic metric simulation outcomes for the same trading environment with fixed costs but different legal risks. Panel (a) shows the impact of changes in the severity of the pecuniary penalty, c, and Panel (b) shows the impact of changes in the probability of prosecution based on internal investigation success, D. Within each panel, legal risk increases from left to right as the expected penalty increases. The top two rows show that *Bet* and *Duration* decrease with legal risk, consistent with Predictions 1 and 2. However, we note that with a trading opportunity cost $f > 0$, an increase in legal risk can exacerbate the decline in *Duration* relative to the outcomes in Section II. This is because every decision not to revisit the market in the second period implies a zero *Duration* value in the same trading session.

The bottom row shows the *Splitting* outcomes. We can see that an increase in legal risk decreases the range of scenarios that justify additional market trips. For example, for the insider with positive

Figure IA.5

Model with fixed trading costs: Legal risk changes impact on ***Bet*****,** ***Duration*****, and** ***Splitting***

This figure shows the impact of changes in the legal risk parameters c and D on the values of *Bet* and *Duration* as in (5), and *Splitting* as in (3.2). Parameter values are as in Figure 4 except $f = 0.1$.



(a) Severity of the penalty, c **(b) Cond. prob. of prosecution,** D

news, such an increase reduces the value of the threshold $\hat{y}_1(v, \delta_1)$ and increases the no-trade region $y_1 \geq \hat{y}_1(v, \delta_1)$. Therefore, a more significant legal threat corresponds to fewer market trips, reducing *Splitting*, as stated below.

Prediction 3.1 The value of *Splitting* decreases with legal risk.

Next, we test Prediction 3.1 exploiting the same shocks to legal risk found in Section III.

3.B Empirical Test

We construct two empirical counterparts to (3.2). $\hat{Splitting}$ as an indicator variable equal to one if an insider trades on more than one day, closely matching the model. A limitation of the latter is that the majority of cases span more than two dates; a binary variable cannot fully capture such an extensive margin. To account for more nuanced differences in the degree of active market presence, we define an additional empirical proxy, $\hat{SplitNorm}$, as the ratio between the trade horizon and the information horizon,

$$\hat{SplitNorm} := \frac{T_{\text{last}} - T_{\text{first}}}{T_{\text{public}} - T_{\text{info}}} \subseteq [0, 1]. \tag{3.3}$$

$\hat{SplitNorm}$ can be regarded as the analog to *Splitting* from a more granular dynamic model. To illustrate its construction, consider Martoma's trades in ELN and WYE, as described in Section I.A. The information horizon is 12 days ($T_{\text{info}} = 07/17/08$ and $T_{\text{public}} = 07/29/08$). The trading horizon is eight days ($T_{\text{first}} = 07/21/08$ and $T_{\text{last}} = 07/29/08$). Therefore, $\hat{SplitNorm} = 2/3$.

The distribution of these variables is summarized in Table IA.IV.

We test Prediction 3.1 using the regression models in equations (9) and (10). Panels A and B of Table IA.I report the Newman and Bharara test results, respectively. Consistent with the model's prediction for a negative and a positive shock to legal risk, the coefficient of $\hat{SplitNorm}$ is positive in the Newman test and negative in the Bharara test. The impacts are economically relevant since they represent changes of 57.9% and -27.6% relative to the corresponding standard deviation. The interactions coefficients associated with $\hat{Splitting}$ are not statistically different from zero.

Table IA.I
Impact of Legal Risk Shocks on Illegal Insiders' Multi-Date Trading Decisions

This table shows the estimation results for the regression models (9) and (10) in Panels A and B, respectively. The dependent variables are $\hat{S}plitting$, an indicator variable equal to one if an insider trades on more than one day, *and* $\hat{S}plitNorm$, the ratio between the trade horizon and the information horizon as defined in (3.3). All control and fixed effect variables are as defined in Appendix A. Standard errors are clustered by the date of trading. ***, **, * denote the 1%, 5%, and 10% levels of statistical significance, respectively.

	$\hat{S}plitting$	$\hat{S}plitNorm$		$\hat{S}plitting$	$\hat{S}plitNorm$
	(1)	(2)		(3)	(4)
Panel A: Newman shock			**Panel B: Bharara shock**		
$Newman$	-0.088	0.070	$Bharara$	-0.088*	-0.034
	(0.193)	(0.055)		(0.050)	(0.053)
$InteracNewman$	0.083	0.220**	$InteracBharara$	0.016	-0.105*
	(0.206)	(0.108)		(0.061)	(0.060)
$Strength$	0.035	0.089***		0.027**	0.076***
	(0.032)	(0.030)		(0.011)	(0.023)
$Volatility$	-0.094	0.056		-0.036	0.045
	(0.131)	(0.131)		(0.056)	(0.065)
$VolumeVol$	-0.017	-0.010		0.002	-0.004
	(0.015)	(0.011)		(0.007)	(0.009)
$Ln(MktCap)$	-0.003	-0.015		-0.012	-0.009
	(0.016)	(0.016)		(0.011)	(0.013)
Court FE	Yes	Yes		Yes	Yes
Event FE	Yes	Yes		Yes	Yes
Trade FE	Yes	Yes		Yes	Yes
Observations	904	585		3,747	2,982

Therefore, the sample evidence suggests that insiders internalize changes in legal risk exposure regarding the relative length of their trading horizon, as captured by $\hat{S}plitNorm$, and in an economically significant way. Such behavior corresponds well to the model prediction in the presence of trading opportunity costs. On the other hand, we do not find evidence that such changes affect the binary decision of whether to trade or not on a single date, captured by $\hat{S}plitting$. Since less than 20% of our observational units correspond to a single trading date, we conjecture that the decision to trade on a single date could respond to additional factors such as limited cognition or unfamiliarity with the trading process. A limitation of our nonlaboratory setting is that it is difficult to account for such heterogeneity without making additional assumptions. Another limitation is that, given the daily frequency of our sample, we cannot account for intraday splitting. It remains an interesting question for future research whether some insiders focus on intraday splitting while others focus on the intertemporal impact across dates.

4 Whistleblower-Based Prosecution

Besides the possibility that trade patterns reveal the presence of an insider trader to the regulator, detection could also stem from information directly provided by a third party, such as in the case of whistleblowers. This section considers, first, an extension of the model with such an additional source of detection. Second, we exploit the SEC's adoption of a whistleblower reward scheme to evaluate the impact of a shock to the whistleblower arrival probability on insider traders' strategies.

4.A Model Extension

Similar to Section II, consider a regulator who proactively screens abnormal volume to initiate internal investigations, and conditional of such observation, obtains sufficient compromising evidence with probability D. The legal penalty is given by (2). In addition, assume that a whistleblower provides first-hand and credible evidence with probability ω. The provision of such evidence is in response to private motives (e.g., an angry spouse or business partner) and bears no relation to the insider's trades. Combining prosecution sources, for any trading sequence $\{x_1, x_2\}$, the probability of a successful prosecution Q can be represented as

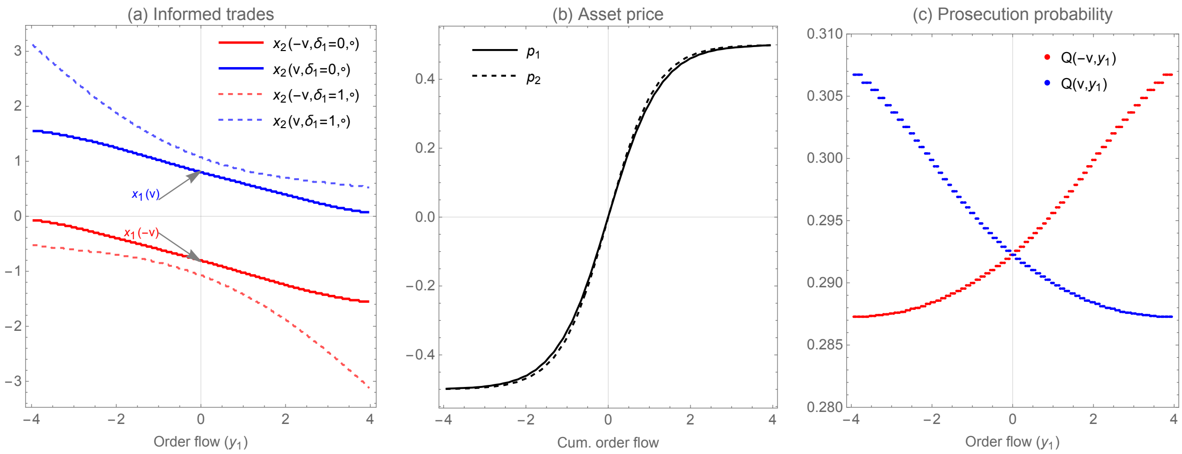
$$Q\left(x_1, x_2\right) = \left(q\left(x_1\right) + \left(1 - q\left(x_1\right)\right) q\left(x_2\right)\right) D\left(1 - \omega\right) + \omega. \tag{4.1}$$

Regardless of the detection source, analysis of the insider's trading account by regulators always reveals the trade sequence.

Figure IA.6 displays the associated equilibrium outcomes using the baseline parameter values in Figure 4 and $\omega = 0.2$. We can see that the main qualitative properties of the equilibrium are similar to those discussed in Section II; although, as expected, the insider trades relatively less aggressively.

Since we are interested in the impact of legal risk shocks on strategic outcomes, we simulate trading sessions considering multiple ω values. The results displayed in Figure IA.7 show that

Figure IA.6
Equilibrium objects: Model with whistleblowers
This figure shows the equilibrium objects of the model version that includes an exogenous probability of insider trading detection, ω, as in equation (4.1). Parameter values are as in Figure 4 except $\omega = 0.2$.



consistent with Predictions 1 and 2, an increase in legal risk regarding higher ω values is associated with lower values of *Bet* and *Duration*.

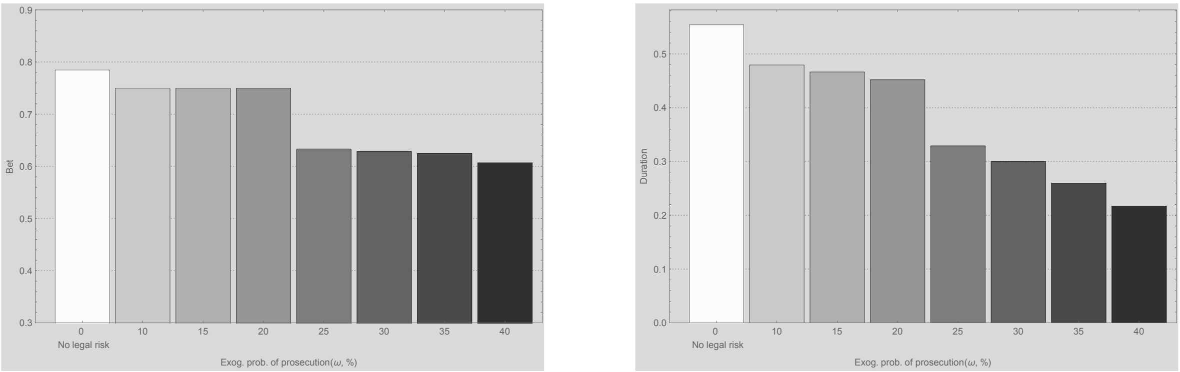
Next, we test these theoretical connections exploiting an institutional shock to the probability of whistleblower arrival.

4.B Evidence from the SEC Whistleblower Compensation Program

The Dodd-Frank Wall Street Reform and Consumer Protection Act (the Dodd-Frank Act) amended the Securities Exchange Act of 1934 by adding Section 21F,[6] entitled "Securities Whistleblower Incentives and Protection." The underlying idea of this whistleblower reward program (WRP hereafter) is to use monetary payments to incentivize whistleblowers who provide regulators with *original information* that leads to successful enforcement actions resulting in monetary penalties over $1,000,000. The program defines original information as information that is derived from the independent knowledge or analysis of a whistleblower, not known to the SEC from any other sources, and not exclusively derived from an allegation made in a judicial or administrative hearing, gov-

[6] See https://www.sec.gov/about/offices/owb/reg-21f.pdf

Figure IA.7
Model with whistleblowers: Comparative statics of changes in ω
This figure shows the impact of changes in the exogenous probability of insider trading detection, ω, on the values of *Bet* and *Duration* as given by (5). Other parameter values are as in Figure 4.



ernmental report, hearing, audit, or investigation or from the news media. Whistleblowers' awards range in the amount of 10% to 30% of the monetary penalties collected.

We exploit the adoption of the WRP as a shock to detection probabilities that are not related to the regulator's screening. While evaluating ex-ante individual risk exposure to the shock is infeasible, the program adoption is unlikely to affect all traders equally. In particular, traders subject to hefty penalties are at higher risk due to the institutional environment. First, tips on small-penalty traders are not eligible for compensation. Second, everything else being equal, blowing the whistle on large-penalty traders provides more substantial economic incentives due to the link with collected sanctions. Arguably, a trader cannot precisely anticipate legal penalties when placing trades but possibly a range in connection to expected economic profits. Accordingly, to separate traders at high risk more clearly, we define the binary variable $HighRiskWB$ as equal to 1 for traders with relatively high penalties, defined as \$2 million or higher, and zero otherwise.

Panel C of Table IA.V shows that the two sets of cases are not very different along all three considered dimensions, as is indicated by the p-values of the t-test of differences in means being all above the critical levels.

Subsequently, we assess whether $HighRiskWB = 1$ traders respond differently to changes in the prosecution environment as captured by the WRP adoption. Formally, we estimate the following model:

$$StratOutcome_{ijk} = a_5 \times WRP_i + b_5 \times HighRiskWB_j + \delta_5 \times \underbrace{WRP \times HighRiskWB_j}_{\text{InteracWRP}} \tag{4.2}$$

$$+c_5 \times \mathbf{Controls}_{ij} + d_5 \times Court_k + e_5 \times Trader_j + f_5 \times EventType_i + \varepsilon_{5,ijk},$$

where the binary variable WRP captures the shock period, as follows. WRP equals one between August 2011, the month of implementation,[7] and December 2014, to avoid an overlap with the Newman ruling; and WRP equals zero for the similar-length period Jan 2008–July 2011. The coefficient of interest is δ_5. Other variables are as described in Section III.

Columns 1 to 4 of Table IA.II present the results for the entire sample. We observe that the estimated interaction coefficients all display a negative sign, consistent with an increase in legal risk. The coefficients of $\hat{B}etNorm$ and $\hat{D}urNorm$ are statistically significant at the 1% level and display an economically meaningful change of -89.52% and -112.1% relative to their standard deviation, respectively.

In contrast to the Bharara test, the regression model in (4.2) focuses on the differential response of large-penalty traders across all legal jurisdictions. Since the WRP period partially overlaps with the *Bharara* period defined in Section III, it is conceivable that SDNY traders' response to the WRP shock could be distinct. A concerning scenario would be that large SDNY traders adjusted trading strategies sluggishly after Bharara's designation, partially driving the above results. Alternatively, SDNY insiders could display more moderate responses if they internalized a high legal risk environment following the appointment of Preet Bharara in 2009 and before the implementation of the WRP. Therefore, in Columns 5 to 8 of Table IA.II, we present estimation results that exclude traders subject to SDNY jurisdiction.

[7]See http://www.sec.gov/news/press/2011/2011-167.htm.

Table IA.II
Impact of the WRP on Illegal Insiders' Strategic Outcomes

This table shows the estimation results for the regression model (4.2). The dependent variables are $\hat{B}et$, $\hat{B}etNorm$, $\hat{D}uration$, and $\hat{D}urNorm$ as defined in Appendix A. The binary variable WRP equals 1 for the period August 2011—December 2014 and zero for January 2008—July 2011. The binary variable $HighRiskWB$ equals 1 for traders with monetary sanctions greater than or equal to \$2 million, and zero otherwise. $InteracWB$ is the product between WRP and $HighRiskWB$. All other controls and fixed effect variables are as defined in Appendix A. Standard errors are clustered by the date of trading. ***, **, * denote the 1%, 5%, and 10% levels of statistical significance, respectively.

	$\hat{B}et$	$\hat{B}etNorm$	$\hat{D}uration$	$\hat{D}urNorm$	$\hat{B}et$	$\hat{B}etNorm$	$\hat{D}uration$	$\hat{D}urNorm$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WRP	-526.862**	0.084***	-0.068**	0.149***	-326.176	0.090***	-0.025	0.046
	(266.283)	(0.030)	(0.034)	(0.047)	(364.831)	(0.034)	(0.042)	(0.048)
$HighRiskWB$	682.388*	0.014	-0.025	-0.488***				
	(403.019)	(0.010)	(0.036)	(0.139)				
$InteracWRP$	-901.266	-0.222***	-0.062	-0.269***	-1,667.330***	-0.236***	-0.107	-0.161**
	(575.535)	(0.074)	(0.079)	(0.073)	(602.333)	(0.074)	(0.082)	(0.068)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Court FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Event FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trader FE	No	No	No	No	Yes	Yes	Yes	Yes
SDNY	Yes	Yes	Yes	Yes	No	No	No	No
Observations	1,733	2,054	1,512	1,417	1,201	1,391	1,042	970

We observe a similarly robust decrease in $\hat{B}etNorm$ and $\hat{D}urNorm$, but also a significant reduction in $\hat{B}et$ at the 1% level, equivalent to 13.43% relative to its standard deviation. This suggests that, first, the impact of the WRP program is not driven by the SDNY-specific Bharara shock. Second, the response to the WRP shock is indeed more apparent for other legal jurisdictions.

The results in this section align well with the notion that insiders anticipating hefty penalties internalize a higher threat from the WRP adoption. The qualitative response patterns are generally consistent with the model predictions and the empirical findings in Section IV around the Newman and Bharara tests.

5 Additional Analyses

5.A Evidence from Dismissed Investigations

In this section, we perform robustness tests of our identification analysis that exploits the trading activity of individuals who, according to the SEC, traded on superior information but, according to a judge, cannot be proven to have committed a crime. To the extent that such traders did not fully internalize the prosecution threat, a comparison with similar convicted insiders can be regarded as a cross-sectional test of the strategic behavior of insiders facing different legal risk.

Indeed, not every insider trading prosecution proves successful. As in any legal issue, the judicial process can identify allegedly guilty traders who committed no crime, which leads to periodic dismissals of investigations initiated by the SEC.[8] While it is not feasible to establish in each case whether the lack of evidence implies a lack of crime, we posit a population-wide association between acting lawfully and the probability of not being found guilty: $\Pr(\text{no crime}|\text{dismissed}) > \Pr(\text{no crime}|\text{not dismissed})$.

Accordingly, we view dismissed cases as providing an opportunity to inquire into the strategies of individuals trading on genuine private information on a given firm's fundamentals but who are less likely to act strategically with legal risk in mind. To establish a contrast with the theoretical perspective in Section II, we do not assume that traders in dismissed investigations subjectively neglect legal risk. Instead, traders in this group act as *objectively* facing no threat or at least lower risk, in the sense that a court is likely to rule favorably if the regulator brings the trader to court.

Following this insight, we collect a set of 22 investigations brought to court by the SEC but dismissed by a judge for lack of supporting evidence.[9] If traders in dismissed cases do not internalize the prosecution threat to the same extent as convicted insiders who are otherwise similar, one should expect to observe such traders behaving in a way that is observationally equivalent to those facing

[8] In some cases, the judge is relatively explicit about the SEC's poor performance or bias. For example, in SEC v. Ladislav "Larry" Schvacho, the court in the Northern District of Georgia concluded that the SEC had attempted to portray the weak and circumstantial evidence in an "overreaching, self-serving" manner, and dismissed all claims. See *SEC v. Schvacho, Civil Action No. 1:12-cv-02557 (N.D. Ga. Decision on January 7, 2014).*

[9] We note that 98.5% of the corresponding trades occurred before 2013; therefore, this sample has almost no overlap with the post-Newman ruling period.

small legal risk. We implement such a test by estimating the following model:

$$SratOutcome_{ij} = a + b \times Dismissed_j + c \times \mathbf{Controls}_{ij} + d \times Event_i + \varepsilon_{ij}, \tag{5.1}$$

where $Dismissed$ is an indicator variable equal to one for trader j dismissed by the corresponding federal court, and zero for a trader in a control group subject to penalties. For comparability, our control group includes trades by a subset of convicted insiders with relatively low monetary penalties, corresponding to the bottom 25 percent of the unconditional distribution. Quantitatively, this restricts our sample to traders with maximum penalties below \$140,000.[10] All the control variables are as in Section III. We cluster standard errors by the time of the trade.

The estimation results are in Table IA.III. Dismissed traders exhibit higher values of $\hat{B}et$ and $\hat{D}urNorm$ with statistical significance at the 10% and 1% level, respectively. The differences are also economically sizable. For example, the dollar volume of dismissed traders displays a more aggressive stance, 53% higher relative to this variable's standard deviation in the full sample. $\hat{B}etNorm$ and $\hat{D}uration$ also display positive coefficients, consistent but statistical significance is not strong.

These results correspond fairly well to the model's predictions given the hypothesis that $Dismissed = 1$ traders face lower legal risk. Therefore, while relying on a fundamentally different empirical approach to that in Section III, we find that the evidence of this test lends further support to the notion that illegal insiders internalize exposure to legal risk.

5.B Changes in Detection Thresholds

The identification strategy in Section III exploits two sources of plausibly exogenous variation in legal risk, the Newman ruling and Preet Bharara's reign in the SDNY. These unambiguously originate in the judicial branch, not in the actions of market regulating agencies. Naturally, an underlying assumption is that the regulator that screens for illegal trading activity does not calibrate its empirical detection rule as a mechanical function of shock realizations in the judiciary. To more

[10] In the test, the number of observations does not correspond exactly to the 25th percentile cutoff, since some of the variables in the regression could be missing. In addition, the cutoff could change between 130,000 and 158,000, depending on whether we choose penalties with a zero dollar value or not. The results, however, are robust to all of the values inside the range.

Table IA.III
Strategic Decisions and Legal Risk: Evidence from Dismissed Cases

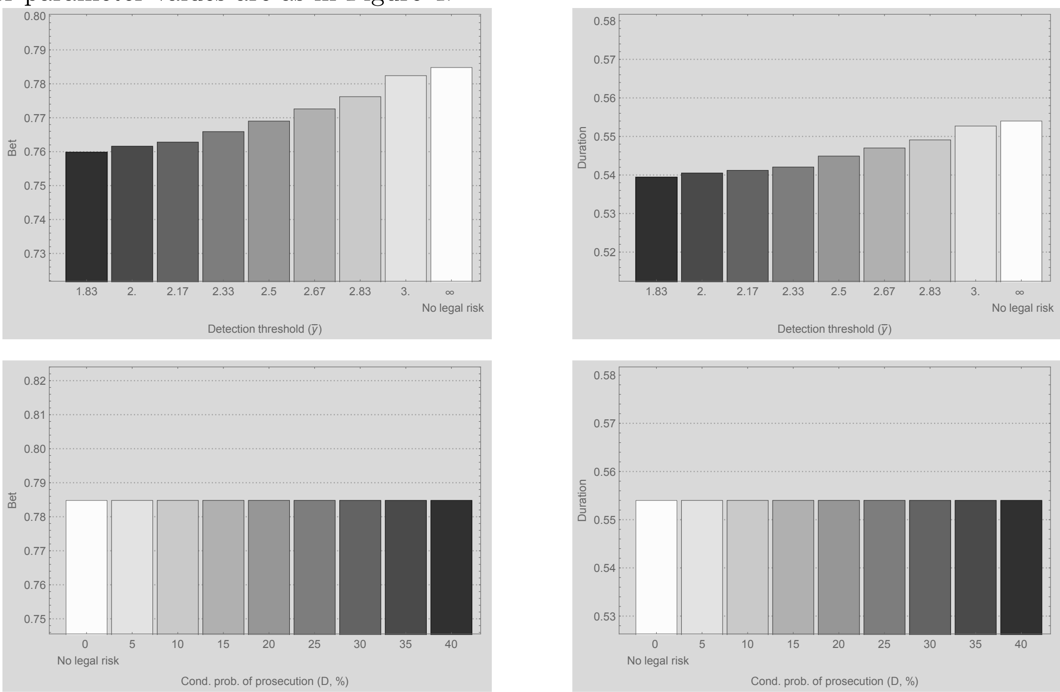
This table shows the estimation results for the regression model (5.1). The dependent variables are $\hat{Bet}$, $\hat{BetNorm}$, $\hat{Duration}$, and $\hat{DurNorm}$ as defined in Appendix A. *Dismissed* is an indicator variable equal to one for trades dismissed by the corresponding federal court and zero for those subject to penalties. The control and fixed effect variables are as described in Appendix A. Standard errors are clustered by the date of trading. ***, **, * denote the 1%, 5%, and 10% levels of statistical significance, respectively.

	$\hat{Bet}$	$\hat{BetNorm}$	$\hat{Duration}$	$\hat{DurNorm}$
	(1)	(2)	(3)	(4)
Dismissed	6,579.392*	0.082	0.010	0.174***
	(4,162.800)	(0.058)	(0.072)	(0.064)
Strength	-9,177.070	-0.183	-0.034	0.049
	(8,944.614)	(0.123)	(0.070)	(0.094)
Volatility	-8,575.867	-0.096	0.037	0.194**
	(5,606.243)	(0.065)	(0.088)	(0.087)
VolumeVol	1,681.955**	0.011	0.028**	-0.017
	(714.556)	(0.010)	(0.013)	(0.015)
MktCap	-2,438.050	-0.061**	-0.026	0.031
	(2,157.130)	(0.029)	(0.018)	(0.021)
Event FE	Yes	Yes	Yes	Yes
Observations	212	234	149	144

clearly elicit what we require of the institutional environment, we briefly discuss in this section the theoretical impact of threshold changes and then contrast such changes and the considered legal risk shocks. We argue that even if the above underlying assumption did not hold, changes in the detection threshold alone are unlikely to explain our empirical findings.

As a first step, we use the model equilibrium objects to simulate a worst-case scenario that would make our results appear spurious. Specifically, we consider the regulator changes to the detection threshold $\overline{y}$ assuming that the insider fully neglects legal risks. Figure IA.8 shows the associated average values of *Bet* and *Duration* conditional on the detection event. We can see in the top panel that if the regulator increases $\overline{y}$, a greater amount of volume is required to raise a red flag, insiders trading a large amount would be sampled more frequently, leading to higher *Bet* values. Because the insider trades an invariant amount in the first period—it only depends on the private signal—those who trade a larger amount do so by trading larger quantities in the second period. That is the reason why conditional *Duration* values appear to increase. Therefore, everything else held constant, an increase in $\overline{y}$ when the insider neglects legal risk is qualitatively analogous to a decrease in legal risk parameters D or $c$when the insider internalizes legal risk. In contrast, if the insider disregards legal risk, the expected values of *Bet* and *Duration* conditional on the detection are utterly unaffected by changes in legal risk parameters, as illustrated for the case of D on the bottom panel of Figure IA.8.

Figure IA.8
Comparative statics of changes in $\overline{y}$ and D when the insider neglects legal risk
This figure shows the impact of changes in parameters $\overline{y}$ and D on the values of *Bet* and *Duration*. Other parameter values are as in Figure 4.



While, theoretically, shocks to the regulator's detection limits can also generate changes in the distribution of *Bet* and *Duration* outcomes, we argue that they are not a plausible explanatory source for the empirical results in Section IV, due to the four reasons below.

1. We stress that the considered empirical identification shocks are specific to evolutions in the legal system, and not technical regulatory changes associated with the calibration of detection limits by organizations like the SEC or FINRA:

   (a) The Newman-Chiasson decision was made by the U.S. Court of Appeals for the Second

Circuit and affected the likelihood of prosecution of a seemingly guilty insider.

(b) The appointment of a remarkably tough SDNY prosecutor in Preet Bharara, leading to more likely convictions and a push for more severe penalties, is by the United States federal government.

2. To the best of our knowledge, there is no evidence that the SEC or other regulators set detection limits as a function of unexpected legal rulings or specific prosecutor appointments. Instead, based on our interactions with the SEC and the Financial Conduct Authority personnel, we view such limits as responding to long-term statistical patterns revealing what constitutes genuinely suspicious activity. If so, it would then require an unlikely time-series coincidence for detection limits to contemporaneously change in line both with the *Newman* and *Bharara* periods defined in Section III.

3. Even if one believed that detections limits can be a time-dependent function of the considered legal shocks, for our identification strategies to simultaneously fail, it would require very specific patterns of cross-sectional heterogeneity in detection limits, as follows.

   (a) **Newman test**. Given the empirical specification in (9), for changes in detection threshold to explain the results, it would require that at the time of the Newman ruling, the SEC increased $\overline{y}$ for traders who obtained information indirectly ($NewmanAgent = 1$ traders) while keeping $\overline{y}$ unaltered for traders who obtained information directly ($NewmanAgent = 0$ traders). Alternatively, the SEC must have kept $\overline{y}(NewmanAgent = 1)$ unaltered while decreasing $\overline{y}(NewmanAgent = 0)$. We view such scenarios as unlikely. Moreover, it isn't easy to see how the SEC would learn about the information transmission characteristics to decide on thresholds *before* an ongoing investigation, making such ex-ante heterogeneous thresholds unfeasible.

   (b) **Bharara test**. Given the empirical specification in (10), for changes in detection threshold to explain the results, it would require that at the time of Bharara's appointment, the SEC kept $\overline{y}$ unaltered for traders within the SDNY and increased it for traders located elsewhere. Alternatively, the SEC must have held the same $\overline{y}(SDNY = 1)$ while increasing $\overline{y}(SDNY = 0)$. We also view such trader-location-specific detection limit adjustment both as unlikely and arguably unfeasible.

4. Even if one assumed that the regulator adjusted the detection limits along the time-series and cross-sectional dimensions as described above, such regulatory action would not explain the findings regarding the average value of the private signals (PSV) in Table V. Intuitively, an insider that disregards legal risk would not condition taking action on the value of the private signal as a function of changes in detection limits.

Taken together, the empirical results in Tables 4 and 5 align well with insiders responding symmetrically to a negative and a positive shock to legal risk. Simultaneously, they are not easily explained by coincidental changes in the regulator's detections limits.

To conclude, the validity of our identification strategy does not depend on the regulator's detection limits never changing. Instead, it relies on the notion that such limits are reasonably stable and not driven by the considered legal-side shocks in the intricate manners outlined above.

6 Supplemental Tables and Figures

Table IA.IV
Dependent and Control Variables in the Internet Appendix: Summary Statistics

This table displays summary statistics for variables introduced in the Internet Appendix. The variable $\hat{S}plitting$ is a binary variable that equals one if the insider trades on more than one date, and zero otherwise; $\hat{S}plitNorm$ is the ratio between the number of days from the first to the last trade to the number of days from receiving the private tip to the corresponding public announcement, as defined in (3.3). $Price$ represents the average value of the stock price observed 20 days before the date of the corresponding insider trade.

	Mean	Q25	Q50	Q75	SD
Panel A: Dependent variables					
$\hat{S}plitting$	0.810	1	1	1	0.392
$\hat{S}plitNorm$	0.478	0	0.5	.857	0.380
Panel B: Control variables					
WRP	0.366	-	-	-	-
$HighRiskWB$	0.277	-	-	-	-
$Dismissed$	0.417	-	-	-	-
$InsiderTrade$	0.116	-	-	-	-
$Price$	28.11	8.64	19.06	37.64	34.55

Table IA.V
Control Variables' Balancedness: Pre-treatment Average Values

This table shows the pre-treatment average value of the control variables $Volatility$, $VolumeVol$, and $Ln(MktCap)$ as defined in Appendix A. Panels A and B show averages for each value of $NewmanAgent$ and $SDNY$, respectively, as defined in Appendix A. Panel C shows averages for each value of $HighRiskWB$, as defined in Section 4. The rightmost column shows the p-value of the test of differences in means.

Panel A: Newman shock			
Control	$NewmanAgent = 1$	$NewmanAgent = 0$	p-value
$Volatility$	0.4587	0.4995	0.435
$VolumeVol$	1.0349	0.8940	0.777
$Ln(Mkt.cap)$	14.1141	13.659	0.511
Observations	363	117	
Panel B: Bharara shock			
Control	$SDNY = 1$	$SDNY = 0$	p-value
$Volatility$	0.3807	0.3796	0.99
$VolumeVol$	0.7770	2.2791	0.021
$Ln(Mkt.Cap)$	14.1166	14.7890	0.051
Observations	865	1,326	
Panel C: WRP shock			
Control	$HighRiskWB = 1$	$HighRiskWB = 0$	p-value
$Volatility$	0.5348	0.5736	0.327
$VolumeVol$	1.5916	1.5915	0.972
$Ln(Mkt.Cap)$	13.9578	13.8511	0.768
Observations	1,121	510	

Table IA.VI
Newman and Bharara Tests: Analysis of Pre-Trends in Dependent Variables

The dependent variables are $\hat{Bet}$, $\hat{BetNorm}$, $\hat{Duration}$, and $\hat{DurNorm}$, defined in Appendix A. The controls are year/quarter indicator variables. Standard errors are clustered at the date of trading. ***, **, * denote the 1%, 5%, and 10% levels of statistical significance, respectively.

	$\hat{Bet}$	$\hat{BetNorm}$	$\hat{Duration}$	$\hat{DurNorm}$
Panel A: Newman shock				
2013 Q2	-169.284	0.133	0.118	-0.160
	(1,780.725)	(0.093)	(0.191)	(0.161)
2013 Q3	6,875.692*	0.103**	0.196	0.228
	(4,094.453)	(0.046)	(0.193)	(0.142)
2013 Q4	2,103.326*	-0.373	0.012	-0.010
	(1,137.431)	(0.312)	(0.187)	(0.121)
2014 Q1	1,275.520*	0.101*	0.120	-0.107
	(746.282)	(0.053)	(0.201)	(0.121)
2014 Q2	716.551	-0.277*	0.229	-0.097
	(780.928)	(0.147)	(0.262)	(0.143)
2014 Q3	-564.038	-0.112*	0.222	0.149
	(1,035.189)	(0.065)	(0.191)	(0.189)
Panel B: Bharara shock				
2006 Q2	-10,845.196	0.028	0.467***	0.176
	(11,837.354)	(0.062)	(0.097)	(0.228)
2006 Q3	-12,919.904	-0.006	0.447***	0.003
	(12,451.440)	(0.064)	(0.104)	(0.140)
2006 Q4	-11,825.643	-0.182*	0.248	0.231
	(12,656.584)	(0.109)	(0.163)	(0.141)
2007 Q1	-11,271.204	-0.050	0.410***	0.168
	(12,302.199)	(0.049)	(0.145)	(0.141)
2007 Q2	-8,737.101	-0.059	0.442***	0.112
	(14,530.732)	(0.044)	(0.118)	(0.134)
2007 Q3	-13,178.503	-0.007	0.448***	0.092
	(13,064.679)	(0.041)	(0.107)	(0.130)
2007 Q4	-6,826.534	-0.038	0.295**	0.176
	(12,624.326)	(0.055)	(0.128)	(0.158)
2008 Q1	-10,917.614	-0.079	0.316***	0.090
	(13,855.209)	(0.074)	(0.109)	(0.138)
2008 Q2	-17,246.359	0.064	0.504***	0.190
	(13,092.847)	(0.075)	(0.103)	(0.154)
2008 Q3	-11,196.363	0.003	0.148	-0.016
	(17,413.539)	(0.051)	(0.096)	(0.192)
2008 Q4	-11,683.590	-0.022	0.140	-0.235
	(12,864.828)	(0.075)	(0.148)	(0.172)

Table IA.VII
Impact of Legal Risk Shocks on Insiders' Trade Quantities: Cross Sectional Analyses

This table shows the estimation results for the regression model (10) restricted to specific corporate events. The dependent variables are $\hat{Bet}$ *and* $\hat{BetNorm}$ as defined in Appendix A. Panels A and B show results for M&A and earnings announcements, respectively. The variables $Bharara$, $InteracBharara$ and remaining controls and fixed effect variables are as in Appendix A. Standard errors are clustered by the date of trading. ***, **, * denote the 1%, 5%, and 10% levels of statistical significance, respectively.

	$\hat{Bet}$	$\hat{BetNorm}$	$\hat{Bet}$	$\hat{BetNorm}$
	Panel A: M&A		**Panel B: Earnings**	
$Bharara$	3,546.947***	0.152***	-377.118	0.032**
	(1,332.140)	(0.048)	(1,011.073)	(0.016)
$InteracBharara$	-4,270.337***	-0.126***	3,992.194	-0.137**
	(1,309.426)	(0.045)	(3,678.443)	(0.063)
Controls	Yes	Yes	Yes	Yes
Court FE	Yes	Yes	Yes	Yes
Event FE	Yes	Yes	Yes	Yes
Trader FE	Yes	Yes	Yes	Yes
Observations	1,840	2,150	435	516

Table IA.VIII
Returns on Days with Illegal Insider Trading

This table presents results on stock price reactions on days with illegal insider trading. Panel A reports the average returns accrued by stock investors on days when insiders trade using positive and negative private information. Market is a value-weighted portfolio of all stocks in CRSP. In Panel B, the dependent variable is the daily stock return. $InsiderTrade$ is an indicator variable equal to one for asset–day pairs with informed trading, and zero for the same asset in the 20 days prior. Additional control variables are defined in Appendix A and Table IA.IV, and their value in the regression is that observed 20 days before the date of the corresponding insider trade. ***, **, * denote 1%, 5%, and 10% level of statistical significance, respectively.

Information/ Adj. Portfolio	Positive	Positive Market	Positive S&P500	Negative	Negative Market	Negative S&P500
Panel A: Average returns on illegal insider trading days						
$Return$	0.011***	0.011***	0.011***	-0.006**	-0.007**	-0.007**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Observations	1,768	1,768	1,768	454	454	454
Panel B: Returns on illegal insider trading days - Event study						
$InsiderTrade$	0.011***	0.011***	0.011***	-0.012*	-0.013*	-0.013*
	(0.002)	(0.002)	(0.002)	(0.007)	(0.007)	(0.007)
$Ln(MktCap)$	-0.002	-0.002	-0.002	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
$Volume/100$	-0.033	-0.042	-0.042	-0.063	-0.081	-0.081
	(0.064)	(0.063)	(0.063)	(0.146)	(0.150)	(0.150)
$Price/100$	-0.004	-0.004	-0.004	-0.001	0.001	0.001
	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)
Constant	0.038	0.036	0.036	0.004	0.009	0.009
	(0.033)	(0.033)	(0.033)	(0.064)	(0.065)	(0.065)
Observations	22,405	22,405	22,405	6,972	6,972	6,972

Figure IA.9
Distribution of strategic outcomes' empirical proxies
This top panels show the unconditional distributions of $\hat{Bet}$ and $\hat{BetNorm}$. The distribution of the latter variable corresponds to nonstandardized values. The bottom panels show the distributions of $\hat{Duration}$ and $\hat{DurNorm}$ conditional on nonzero values. The definition of all variables is in Appendix A. The construction of the variables is described in Section III.B.

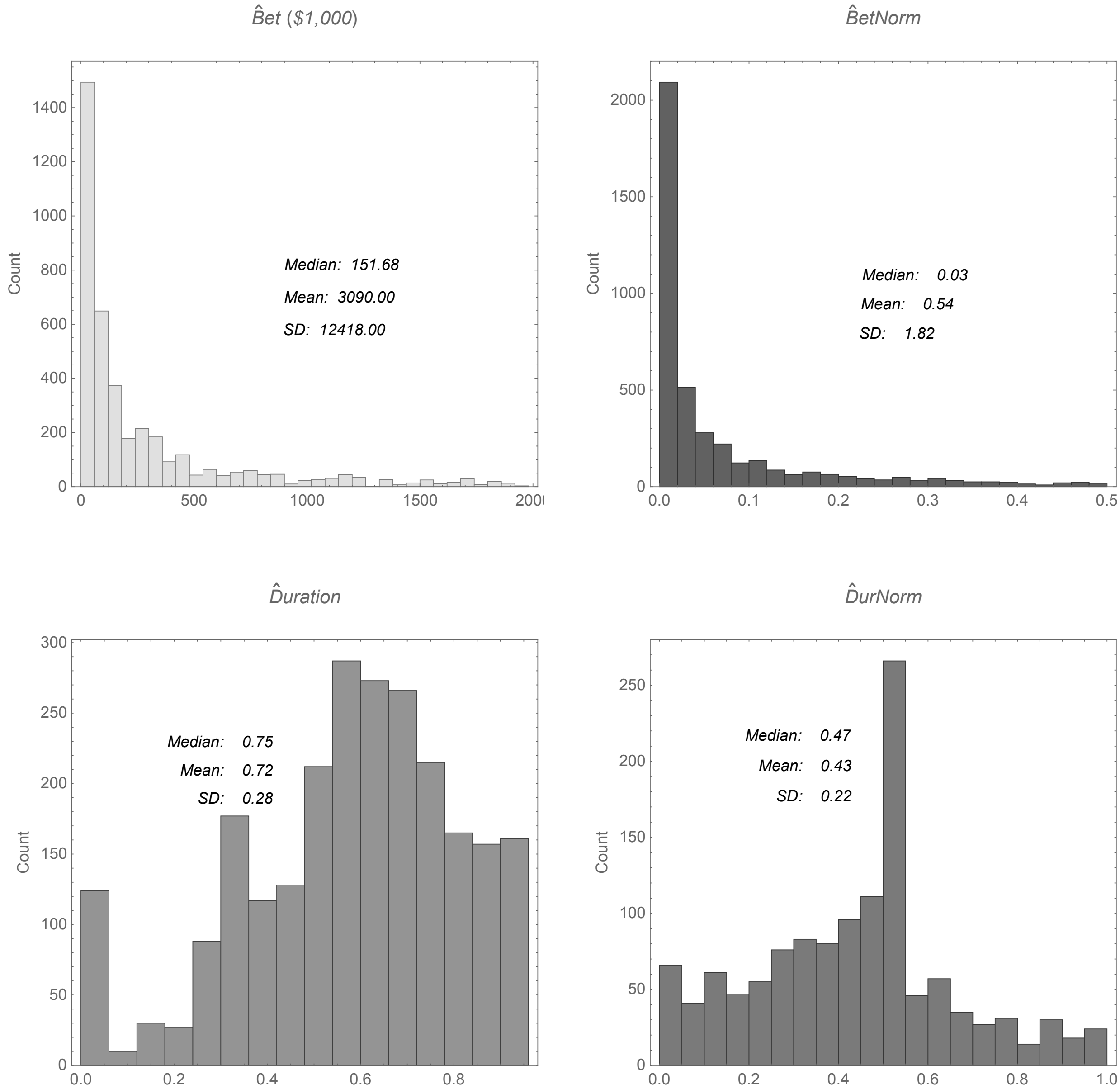
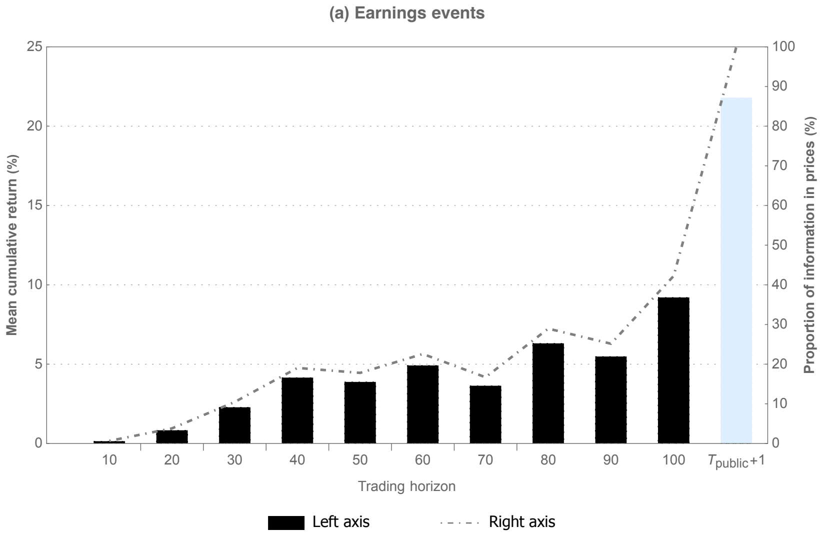


Figure IA.10
Trades and information transmission into prices: Earnings and M&A information events
This figure displays the process of information aggregation into prices. The insiders' trading horizons are split into 10 equal subperiods. Panel (a) corresponds to all insider trading events. Each of the 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 value. The dotted line corresponds to the percentage ratio between each decile column and the rightmost column, and reflects the proportion of private information in prices. Panels (a) and (b) correspond to earnings announcements and M&A events, respectively.



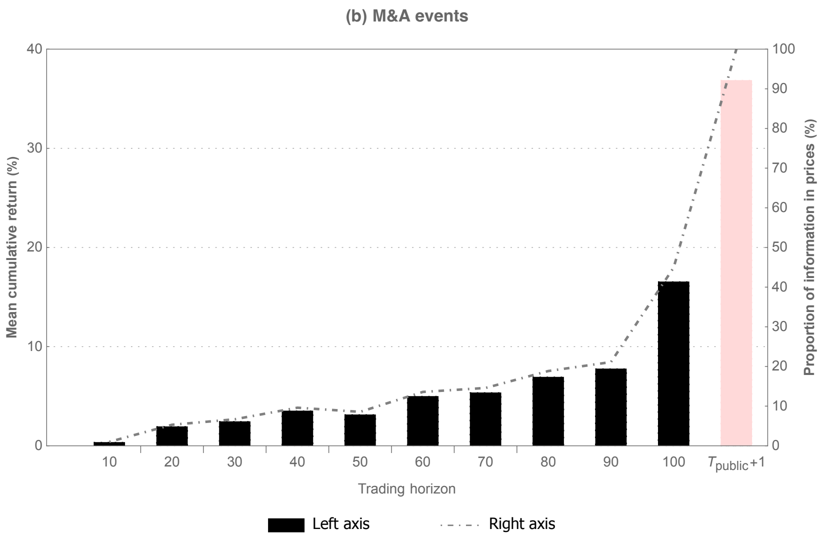
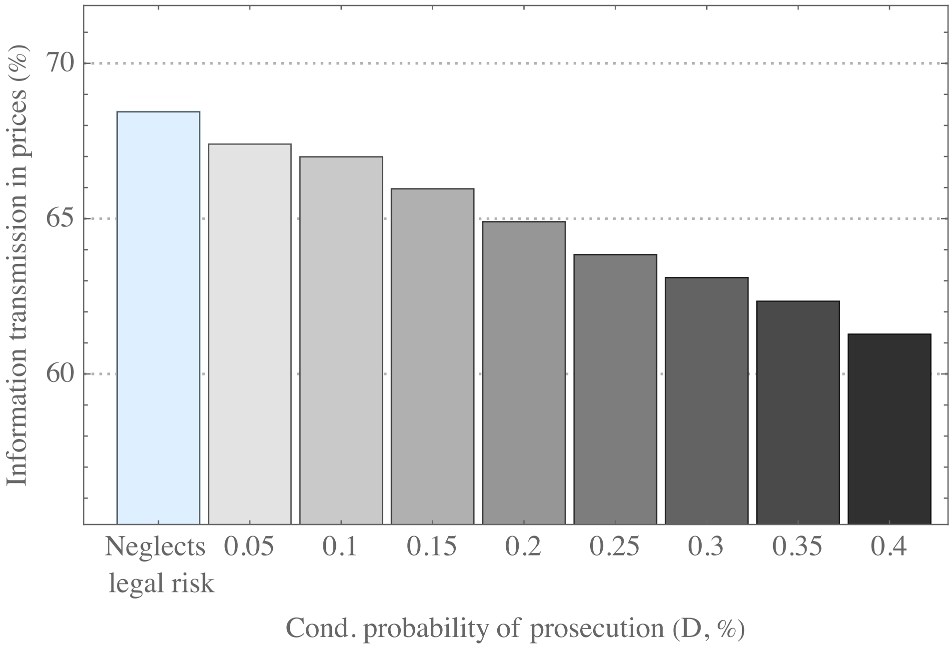


Figure IA.11
Legal risk and information transmission
This figure displays the simulated information transmission outcomes before T_{public}, $\left|\frac{p_2}{v}\right|$, for the version of the model where the insider internalizes the price impact but neglects legal risk (leftmost column) and where the insider internalizes such risk, for several values of parameter D. Other parameter values are as in Figure 4.



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