How Prevalent is Informed Trade by Corporate Insiders?

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Abstract

Corporate insiders have access to private information about their firms. We use mixture model methods designed to account for noise in trading performance to assess the prevalence of informed trade by insiders required to disclose stock trades in US corporations. 30% of insiders make informed trades. Out-of-sample tests show that trades made by insiders most likely to have traded on information are predictive of future stock returns. Informed insider trade is most prevalent in chief financial officers and insider blockholders and varies across industries. For individual trades, we estimate about 10% of insider purchases and 4% of sales are informed, and these fractions vary systematically with ex ante measures of an insider's propensity to trade on information. Our method allows classification of all trades disclosed in the US. We discuss regulatory and enforcement implications of various approaches to detecting informed trade by corporate insiders.

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1. Introduction

Managers, directors, and other firm insiders are, by definition, endowed with private information about their firms. Concerns about insiders' ability to profit from trade on this information go back to the first public company, when the Dutch East India Company banned directors from trading in the stock (Koppell, 2011). Since that time, the costs, benefits, and appropriate regulations of insiders' trades have been extensively debated, not only by policymakers and market participants, but also in the academic fields of economics, finance, accounting, and law. Insider trading has been argued to benefit, for example, production decisions, information provision, and even efficient compensation design through better price efficiency. On the other hand, insider trades adversely select outside investors, which may hinder market liquidity and even market participation.

The costs, benefits, and regulation of trading by corporate insiders hinge on the extent to which insiders make informed trades. Despite the importance of this, scant evidence exists concerning the prevalence of informed trading by firm insiders. This is perhaps not surprising; by its very nature, private information is unobservable to outsiders. Directly observing whether an insider uses their private information to trade is costly and imperfect, even for enforcement agencies with subpoena power.[1] Direct observation of the use of private information is virtually impossible for researchers.

Yet, for publicly traded firms in the U.S., we do observe the *performance* of insiders' trades. Prior work has established that certain types of these trades outperform (e.g., Cohen, Malloy, and Pomorski, 2012, find that non-routine trades outperform), suggesting some trades contain private information. But what is still unclear from this large literature is the prevalence of informed trade by corporate insiders. Are privately informed trades confined to a small subset of insiders, or do a large fraction of insiders engage in such activity? Among the insiders most likely to trade on private information, what fraction of their trades are privately informed? The answers to these questions are key for understanding the welfare implications of insider trading as well as the policy debates on the legality, regulation, and enforcement of insider trading.

The answers to such questions are challenging for two reasons: First, a given insider is likely to trade for a variety of reasons, so establishing whether they ever trade on private information is made difficult by the fact that they may also trade for liquidity reasons. The second challenge is

[1] DeMarzo et al. (1998), for example, assume regulators can only observe trading volumes and prices prior to a formal investigation.

that individual stock returns are noisy. Therefore, when looking at the performance of a specific trade or individual, we are likely to observe many that outperform (or underperform) by chance. In other words, extreme performance can result from luck as well as from trading on an information advantage.

To address these challenges, we use disclosed stock trades by corporate insiders from 1985 to 2022 and examine each insider's overall return history. We use mixture-model methods specifically designed to reduce the effect of noise on inference about the extent of information embedded in financial performance.[2] About 30% of all insiders fall into the distribution of those trading on private information. On average, the insiders in this distribution earn 3.6% abnormal returns over the next month compared to those not trading on private information, who earn 0% on average (by construction).

Using the estimated mixture model parameters and a realized average abnormal return and standard error for each individual insider, we estimate a conditional probability that a given insider makes informed trades as well as a conditional expected average abnormal return. The mixture model essentially functions as a noise reduction method, and there are multiple ways for an insider to receive the same estimated conditional probability of informed trading. Intuitively, the econometrician should update more strongly that an insider trades on information if the insider's average return is higher. But estimation noise should affect this inference. Consider two insiders who both have average abnormal returns of 1%, but the standard error of the first insider's average is 1% while the second insider's standard error is 5%. It is much more likely that the first insider trades on information than the second insider. Put differently, it is more likely that the second insider's 1% average return occurred by chance than for the first insider. The conditional probability in the mixture model formally quantifies this intuition.

Our estimates have economic content out-of-sample. At any point in time, we can estimate each insider's probability of trading on information using their full trade history up until that point. We conduct out-of-sample exercises testing whether buys and sells of insiders with different ex ante conditional expectations predict differences in stock returns. The difference in future returns for

[2]Mixture models have been used to assess the extent of repeatable performance of various financial market participants, including mutual funds (Harvey and Liu, 2018), hedge funds (Chen, Cliff, and Zhao, 2017), security analysts (Crane and Crotty, 2020), and social media influencers (Dim, 2023; Kakhbod et al., 2023).

stocks with buying activity by top-quintile insiders relative to bottom-quintile insiders is 82 basis points per month, or almost 10% per year. Future returns for stocks with selling activity by top-quintile insiders are 46 basis points lower per month (i.e., 5.5% annually) than returns of stocks sold by bottom-quintile insiders. Our results are therefore broadly consistent with prior literature, which finds that insider purchases are more likely to be informed than insider sales. We find that both buys and sells of the most informed traders predict future returns, though the magnitude of the return predictability is substantially larger for insider purchases.

A number of important papers document that some insiders are more likely to make informed trades than others. For instance, Cohen, Malloy, and Pomorski (2012) identify insiders that engage in non-routine trades, which earn abnormal returns. Other proxies include insiders with short investment horizons (Akbas, Jiang, and Koch, 2020) and insiders who trade profitably ahead of earnings announcements (Ali and Hirshleifer, 2017). Interestingly, we find that the conditional probability of trading on private information is positively correlated with these measures, but is distinct. Controlling for whether the insider is a non-routine trader, a short-horizon trader, or makes more profitable trades ahead of earnings announcements does not impact the out-of-sample return predictability. Perhaps most interestingly, we document that some insiders most likely to be trading on private information are not in the samples of prior work because they often have insufficient trading histories to survive necessary sample screens. Therefore, while our paper is related to these prior studies, we are the first to be able to estimate an aggregate fraction of insiders engaging in privately informed trades.

The extent to which a particular insider engages in informed trade (as measured by mixture model conditional probabilities or expected abnormal return) is systematically related to their role within the company. In particular, C-suite executives are 10% more likely than the unconditional mean to engage in informed trade, while other firm officers are less likely. Disaggregating the C-suite result reveals it is driven by CFOs, and there is no relation between being a CEO and the probability of trading on information. Inside owners, but not officers or directors, are more likely to engage in informed trade. The inside owner relation is driven by inside owners holding block ownership exceeding 10% of the firm.[3] Block owner trades also earn higher average abnormal

[3]This only includes blockholders that are insiders and required to file a Form 4 with the SEC; it does not include outside blockholders.

returns than trades made by other insiders. Finally, firm directors are significantly less likely to trade using private information and are expected to earn significantly lower alpha on their trades.

Our ex ante classification of insiders into groups more or less likely to engage in informed trade allows improved classification of whether a given trade is informed or not. To do this, we estimate trade-level mixture models in which the probability of an informed trade is a function of the insider's ex ante estimated propensity to make informed trades. The estimation yields three empirical facts about informed insider trade. First, buys are two to three times more likely to be informed than sells. Second, the ex ante classifications of insiders using the insider-level mixture model are strongly associated with future differences in informed trade. For purchases, the unconditional probability a particular trade is informed ranges from 6.6% for the lowest quintile insiders to 14% for the highest quintile insiders. Finally, insiders not classified by the insider-level mixture model (due to sample filters requiring past trades) should not be interpreted as insiders that do not engage in informed trade. The probability that purchases made by these unclassified insiders are informed is almost 11%, which is comparable to that of the second-highest quintile of classified insiders. On the other hand, sells by unclassified insiders are among the least likely trades to be informed.

Our work is most closely related to the literature that attempts to identify cross-sectional differences in which insiders engage in informed trading by conditioning on ex-ante trading patterns predicted to be correlated with using private information. Several of these (Cohen et al., 2012; Akbas et al., 2020; Ali and Hirshleifer, 2017) are described above. Other examples in this vein include Cline et al. (2017), Biggerstaff et al. (2020), and Goldie et al. (2023).

Our work builds on this literature but focuses on a different economic question. These papers establish that the trades of insiders that behave in ways the authors conjecture are related to opportunistic trading do, in fact, contain information on average. However, it is quite possible that other trading patterns would also identify informed trading. So, while these papers convincingly show that some trades have information, they are less able to speak to the overall prevalence of informed trading, either in terms of the fraction of insiders that take advantage of private information or in terms of the fraction of overall trades that are informed. Indeed, we show that some of the trades (and insiders) most likely to be informed are not included in the samples of prior work because of the data requirements for identifying the past trading patterns. A primary contribution of our paper is our ability to estimate a conditional probability that a given trade is informed for *all* trades disclosed by US corporate insiders in securities with publicly observable prices, regardless of the length of the insider's trading history. While prior literature shows the presence of privately informed trades, we quantify the overall prevalence of traders using private information (how often trades contain private information) as well as the probability that any trade or insider is trading on private information. This distinction is particularly important when it comes to questions of optimal regulation and enforcement.

Our paper also contributes to the large literature on the optimal design and enforcement of insider trading regulations. For example, our results shed light on what fraction of trades are informed and what fraction are uninformed liquidity trades, potentially allowing regulators to evaluate the efficacy of disclosure rules in the context of Huddart et al. (2001), which provides theoretical predictions for the impact of insider disclosure on their trading behavior. DeMarzo et al. (1998) discuss optimal enforcement of insider trading and develop optimal investigation policies that depend on the number of shares bought/sold and the return to the stock, which are assumed to be the only observable information prior to a formal investigation. Our results suggest there is substantial information about the likelihood that an insider used private information in both the history (or lack thereof) of the insider's average trading performance and its noisiness as well as the cross-section of performance across insiders and trades. This could impact the theoretically optimal enforcement policy, improving enforcement efficiency.

Finally, another large literature discusses the costs and benefits of insider trading more generally. Going back to at least Hirshleifer (1971), many papers have identified tradeoffs that can arise from allowing insiders to trade on their information. For example, Dye (1984) points out that firm managers are often encouraged to buy stock in their firms and therefore suggests insider trading may allow for the efficient provision of incentives that outweigh adverse selection effects. Leland (1992) discusses how price efficiency resulting from privately informed insider trades may allow for better resource allocation in the firm, with value improvements that again may outweigh the costs of insider trading. Theoretical work in this area is traditionally challenging to test because informed trading by insiders is largely unobservable. Our results take a step in this direction by providing a methodology for identifying and quantifying privately informed trades by insiders.

2. Modeling Informed Insider Trading as a Mixture Distribution

2.1. Methodology and Likelihood

We model the distribution of insider abnormal returns as a mixture of two distributions: an uninformed distribution and an informed distribution. A fraction π of insiders make trades that are informed. The remaining $1-\pi$ fraction of insiders make trades that are not informed. Empirically, the econometrician is able to estimate average abnormal returns for a given insider, denoted $\bar{r}_i$. The dispersion in estimated average abnormal return across insiders belonging to either group is driven by two components: true variation in informed trading and estimation error. Denote the true abnormal return of insider i by α_i. We assume that the (unobservable) true abnormal return of uninformed insiders is a point mass at zero ($\alpha = 0$) and that the true abnormal return of informed insiders is distributed exponentially with mean μ ($\alpha_i \sim \text{Exp}(1/\mu)$). The estimated abnormal return $\bar{r}$ is measured with estimation error, e_i, which is assumed independent of α_i and normally distributed around zero with a standard deviation of s_i, the standard error of insider i's abnormal performance. Thus, the estimated abnormal performance is $\bar{r}_i = \alpha_i + e_i$.

Figure 1 provides an illustration of the mixture model. Panel (a) shows the relative frequencies of the unobservable true abnormal return of insiders. Insiders that do not make informed trades comprise the grey bin located at zero, while the remaining π insiders make informed trades with magnitudes of varying amounts (the hatched purple bins). Thus, the unconditional distribution of informed insider trading is a mixture of the uninformed and informed component distributions.

Panel (b) of Figure 1 shows the effects of estimation noise on these component distributions. With noisy measures of the true informed insider trading, the distributions of $\bar{r}$ for uninformed and informed insiders overlap. The distribution of $\bar{r}$ for uninformed insiders is normally distributed around zero; all variation is due to estimation noise. The distribution of $\bar{r}$ for informed insiders is the convolution of an exponential and normal random variables;[4] variation in this distribution is due both to variation in the degree of informed trading and variation due to estimation error. In the example, the substantial overlap in the distributions leads to an unconditional distribution that is unimodal with positive skewness.

Let $f_{\text{I}}(\bar{r}_i|\text{informed})$ denote the density of the observed average abnormal return conditional on

[4]This random variable is known as an exponentially-modified gaussian random variable.

an insider trading on information. Under the assumptions that informed trading is exponentially distributed and estimation noise is normally distributed, the conditional density of $\bar{r}$ is:

$$f_{\mathrm{I}}(\bar{r}_i|\text{informed}) = \int_{-\infty}^{\infty} g(\bar{r}_i - a; \mu) \cdot \phi(a; s_i)\ \mathrm{d}a\,, \tag{1}$$

where $\phi(\cdot; s_i)$ is the density of a mean-zero normal variable with standard deviation s_i and $g(\cdot; \mu)$ is the density of an exponential variable with mean μ. The unconditional density function for insider i's estimated average abnormal return $\bar{r}$ is:

$$f(\bar{r}_i) = (1-\pi) \cdot \phi(\bar{r}_i; s_i) + \pi \cdot f_{\mathrm{I}}(\bar{r}_i|\text{informed})\,. \tag{2}$$

The parameters of the model are π and μ. The likelihood function L for a sample of average abnormal returns of N insiders is:

$$L\left(\bar{r}_1, \bar{r}_2, ..., \bar{r}_N | s_1, s_2, ..., s_N, \pi, \mu\right) = \prod_{i=1}^{N} f(\bar{r}_i)\,. \tag{3}$$

To estimate the parameters π and μ, we maximize (3) subject to the restrictions that $\pi \in [0, 1]$ and $\mu \geq 0$.

2.2. Conditional Probabilities and Expectations

Given estimates for π and μ, the model allows calculations of the conditional probability that a particular insider i is informed, conditional on the insider's realized average abnormal return $\bar{r}_i$, its standard error s_i, and the estimated parameters. Denote the conditional probability by $\tilde{\pi}$. The conditional probability that insider i makes informed trades is:

$$\begin{aligned}\tilde{\pi}_i =& \Pr\left(\text{insider } i \text{ trades on information} | \bar{r}_i, s_i, \pi, \mu\right) \\ =& \frac{\pi_j \cdot f_{\mathrm{I}}(\bar{r}_i|\text{informed})}{(1-\pi) \cdot \phi(\bar{r}_i; s_i) + \pi \cdot f_{\mathrm{I}}(\bar{r}_i|\text{informed})}\,.\end{aligned} \tag{4}$$

Let $\tilde{\mu}_i$ denote the conditional expectation of insider i's information *conditional* on belonging to the informed component distribution (along with parameter values and realized $\bar{r}_i$ and s_i). Note that the conditional expectation of insider i's information is zero if i belongs to the no-informed-trading component. Thus, the conditional expectation of the magnitude an insider trades on information, conditional on their average abnormal return, standard error, π, and μ, which we denote $\tilde{\alpha}_i$, is:

$$\begin{aligned} \tilde{\alpha}_i =& \mathbb{E}\left[\alpha_i | \bar{r}_i, s_i, \pi, \mu\right] \\ =& \tilde{\pi}_i \tilde{\mu}_i \, . \end{aligned} \tag{5}$$

Let $f_{\alpha|\bar{r}}$ denote the density of true informed trading conditional on realized average abnormal return. The conditional expectation of insider i's information $\tilde{\mu}_i$, conditional on being in the component distribution that utilized private information, is calculated:

$$\begin{aligned} \tilde{\mu}_i =& \mathbb{E}\left[\alpha_i | \bar{r}_i, s_i, \pi, \mu, \text{informed}\right] \\ =& \int_{-\infty}^{\infty} a \cdot f_{\alpha|\bar{r}}(a|\bar{r}) \, \mathrm{d}a \, . \end{aligned} \tag{6}$$

It is straightforward to show that, under our distributional assumptions, $f_{\alpha|\bar{r}}$, is a truncated normal distribution with mean of $\bar{r} - s_i^2/\mu$ and standard deviation of s_i truncated below at zero, so $\tilde{\mu}_i$ is the mean of this truncated normal distribution.

Figure 2 illustrates the conditional probability (4) and conditional expectation (5) as a function of average abnormal return $\bar{r}_i$ and estimation noise s_i. Consistent with intuition, both are increasing functions of the average abnormal return.

The effect of estimation noise is more interesting. In Panel (a), see that the amount of estimation noise in the average abnormal return substantially affects inference about whether a particular insider trades on information. For low levels of estimation noise, the average abnormal return is a fair proxy for whether the insider trades on information. Negative abnormal returns are more likely to be uninformed insiders, while positive abnormal returns are more likely to be informed insiders. As estimation noise increases, however, the average abnormal return is a less reliable proxy for whether the insider trades on information. The slope of the conditional probability function is much shallower in average abnormal return, consistent with the fact that the realized average return could be high or low due to estimation error (i.e. luck) rather than true trading on information.

The effects of estimation noise for the conditional expectation are also interesting. The conditional expectation is a convex function of realized average abnormal returns, with greater convexity for insiders with less estimation noise. For low noise, the conditional expectation is not far from simply taking the maximum of $\bar{r}_i$ and zero. The shape of the conditional expectation function is flatter with greater estimation noise. This is because some insiders that truly trade on information may have been unlucky and realized a negative $\bar{r}_i$. Similarly, some insiders that do not trade on information may have been lucky and realized a positive $\bar{r}_i$. The mixture model approach essentially shrinks these realized returns as a function of the estimation noise.

3. Data

The data on stock transactions by corporate insiders is from the Thomson Reuters Insider Filing database, which captures and cleans Form 4 filings by corporate insiders. Our sample covers trades from 1985 to 2022. We also use stock returns and trading volumes from CRSP and financial reporting information from Compustat.

On a given transaction date, insiders sometimes report multiple transactions in a single stock and/or across multiple stocks. We aggregate such trades to the daily level to create an insider-stock-date panel. Index insider i's trades by $j = 1, ..., n_i$.[5] For trade j made by insider i on day t, we calculate a 21 trading day market-adjusted abnormal return

$$r_i^j = D_i^j \left(\prod_{k=1}^{21} (1 + r_{j,t+k}) - \prod_{k=1}^{21} (1 + r_{m,t+k}) \right) , \tag{7}$$

where $r_{j,t+k}$ is the day $t+k$ return of the stock purchased or sold in trade j, $r_{m,t+k}$ is the day $t+k$ CRSP-value-weighted return, and D_i^j denotes a buy sell indicator defined as:

$$D_i^j = \begin{cases} +1 & \text{for purchases} \\ -1 & \text{for sales} . \end{cases} \tag{8}$$

The mixture model described in Section 2 uses an average abnormal return and its standard error for each insider i as inputs to estimating parameters π and μ. We calculate an average abnormal return for insider i as:

$$\bar{r}_i = \frac{1}{n_i} \sum_{j=1}^{n_i} r_i^j , \tag{9}$$

[5] In our full-sample estimation, n_i is simply the total number of distinct stock-date observations for insider i. In our out-of-sample estimation, we will estimation an annual time-series of π and μ using only past available data. For this analysis, n_i is the total number of distinct stock-date observations for insider i as of the year end of the estimation.

as well as its associated standard error s_i. To ensure sufficient data for estimation, we require an insider have at least 10 stock-day observations to be included in the mixture model estimation.

Figure 3 plots histograms of the average abnormal returns, $\bar{r}_i$, in Panel (a) and of the standard errors s_i in Panel (b), and Table 1 reports distributional statistics. While the mode of the $\bar{r}$ distribution is close to zero, the cross-sectional average $\bar{r}$ is positive 66 basis points. Just over half (55%) of the insiders have positive average abnormal returns. The $\bar{r}$ distribution exhibits slight positive skewness consistent with some insiders trading on information. Panel (b) of Figure 3 and the second column of Table 1 show there is substantial variation in the amount of estimation noise in $\bar{r}$. The cross-sectional average standard error is 2.5% and the cross-sectional standard deviation is 1.75%. This suggests value in using an informed insider classification designed to explicitly account for estimation noise like the mixture model described in Section 2.

4. Empirical Results

4.1. How Prevalent is Informed Insider Trading?

Table 2 reports estimates of the mixture model described in Section 2. To limit the effect of outliers, the sample is trimmed at the 1% and 99% levels of average abnormal returns. The empirical estimate of the fraction of insiders trading on information, π, on the trimmed sample is 28.6%. If we assume that insiders with average abnormal returns above the 99th percentile also trade on information, our estimate of the overall number of insiders trading on information is about 30%. The average magnitude of information for this set of insiders, μ, is 3.6%.

In addition to the full-sample estimation, we also estimate the model on expanding windows. Specifically, the mixture model is estimated each year using the latest average abnormal return and standard error for each insider with at least ten trades prior that year end. The time-series of π and μ are plotted in Figure 4. The parameter estimates are fairly stable over time. Aside from the first few years of the sample, the fraction of insiders utilizing information has consistently been around the 30% range. The average magnitude of the utilized information is more variable, dropping from above 5% in the late 1980's to below 4% in the mid-1990s before rising to almost 5% again in the early 2000s. After that, there has been a fairly steady decline in the magnitude of utilized information.

4.2. Trades by More Informed Insiders Predict Returns

In this section, we consider the out-of-sample performance of our mixture model estimates. To do so, we use the annual π and μ time series estimated using expanding windows described above to calculate a conditional expectation (5) of insider informed trade for each insider with at least 10 distinct trading days prior to a given year end. Insiders are sorted into quintiles on the basis of the conditional expectation each year.

To test the model out-of-sample, we consider whether buys and sells by insiders with different lagged conditional expectations predict future stock performance. Specifically, we create a stock-month panel with indicator variables for whether there were any purchases or sales by an insider classified in a particular quintile as of the prior year-end. For instance, Buy Quintile 4 (Sell Quintile 4) is an indicator variable for whether any insider in the top quintile of conditional expectation bought (sold) shares in month t. We regress month $t+1$ stock returns on buy and sell indicator variables for each quintile of conditional expectation. Note that this is an out-of-sample exercise of our ability to rank insiders' propensity to use information because the quintile is formed using information known as of the beginning of month t.

Table 3 reports the estimates of the regression of future monthly returns on buy and sell indicators for each quintile of insider conditional expectation. As is standard, we control for a stock's market capitalization, book-to-market ratio, and lagged monthly and annual return. We consider specifications both with (even numbered columns) and without (odd numbered columns) month fixed effects

There is substantial cross-sectional spread in future returns as a function of buying activity by insiders across conditional expectation quintiles. Without month fixed effects, the difference in future returns for stocks with buying activity by top-quintile insiders relative to bottom-quintile insiders is 82 basis points per month, or almost 10% per year. The predictability remains strong with the inclusion of month fixed effects. The Hi-Lo spread is 69 bps per month, or 8.3% annually. The differences are statistically significant at the 1% level.

Selling activity also results in cross-sectional spread in future returns as a function of an insiders ex-ante conditional expectation quintile (columns (3) and (4)). The Lo-Hi spread is about 46 bps per month without monthly fixed effects and 31 bps per month with fixed effects. The differences are again statistically significant.

The spreads in future stock returns resulting from both buying and selling activities remain practically unchanged and strongly significant if we include buying and selling indicators in the same regression (columns (5) and (6)). Overall, the results of Table 3 provide strong support for the mixture model's ability to differentiate between insiders with higher propensities to profit from their private information.

4.3. Characteristics of Informed Insiders

Insiders are not homogeneous. There is the potential for insiders to differ in terms of incentives, ability, or even information sets. For example, the CEO likely has a different information set than the board chair, despite both clearly having access to important non-public information about the firm. It is therefore natural to ask whether the prevalence of informed trading by insiders varies as a function of the insider's role in the firm. Using the roles in the firm as disclosed on Form 4s, we test whether the insider's conditional probability of being informed ($\tilde{\pi}$) and their conditional expected alpha ($\tilde{\alpha}$) are a function of their role.

To do this, we regress $\tilde{\pi}$ and $\tilde{\alpha}$ on indicators for each of the 54 possible roles indicated in the Thomson Reuters Insider Filing database. Thomson reports up to four roles that can be indicated on a given filing. It is therefore possible that for any given filing, more than one indicator is turned on. An indicator is set to one if the insider reported that role on any filing in a calendar year, and zero otherwise.

We conduct two analyses and report the results in Table 4. The first aggregates these dummy variables into broader groups: C-suite, directors, owners, non-C-suite officers, and non-officer managers, and others. The results from this analysis are reported in Columns (1) and (3) of Table 4. The second analysis disaggregates these into indicator variables for each of the individual roles. We report these results in Columns (2) and (4). For brevity, we only report results for the roles that appear in at least 5% of the observations. All other role indicators are included as controls, but the coefficients are suppressed for space.

C-suite executives are more likely to make informed trades and their expected alpha is substantially higher. Specifically, insiders from the C-suite are 3 percentage points more likely than than those not in the C-suite to be drawn from the distribution of investors trading on private information. This is roughly 10% greater than the unconditional π estimate of approximately 30%. These investors have an expected monthly alpha ($\tilde{\pi}$) roughly 23 bps larger than insiders not in the C-suite. Inside owners have the largest probability of making informed trades and the largest expected performance (7% and 83 bps, respectively), while non-C-suite executives are actually less likely to make informed trades.

When we disaggregate these roles, it is clear that the C-suite result is driven almost entirely by CFOs and the ownership result stems from large insider blockholders. On the other hand, the lower probabilities and performance expected from non-C-suite officers is prevalent across most of those roles. Finally, while the aggregate director category is insignificant, this includes directors that may take on other roles as well. When we look at directors that serve no other roles, the results suggest a lower propensity to engage in informed trades.

Table 5 reports the average $\tilde{\pi}$ and $\tilde{\alpha}$ for across all insider-years in that industry. There is significant dispersion in both the probability of informed trading and the expected performance. Utilities, Finance, and Chemicals, on average, have insiders that are least likely to be trading on private information.The industries where informed trade and expected alpha are highest are Healthcare (including pharmaceuticals), Business equipment (including tech-related industries), and Telecommunications.

5. Comparison to Existing Proxies of Informed Corporate Insiders

As discussed in the introduction, the existing literature has produced proxies for which insiders are more or less likely to trade on private information. In this section, we compare our conditional expectation measure to several of the most prominent of these proxies: non-routine traders (Cohen, Malloy, and Pomorski, 2012), short horizon insiders (Akbas, Jiang, and Koch, 2020), and profitability of trades ahead of quarterly earnings announcements (Ali and Hirshleifer, 2017). Non-routine traders are insiders who have made at least one trade in each of the past three years, but who do not have trades in a particular calendar month in each of the three years. Short horizon insiders are those whose trade direction is not consistently in the same direction over the prior ten years. An insider who always buys or always sells is classified as a long-horizon insider, Insider with some buying and selling activity within the year are classified as either medium- or short-term insiders. High QEA profitability insiders are those that trade ahead of quarterly earnings announcements and whose pre-QEA trades are associated with the highest quintile of QEA-window profitability.

We first consider how the mixture model conditional probability (4) estimates correlate with these measures. The results are reported in Panel A of Table 6. Consistent with the conclusions of the prior literature, we find positive correlations between each proxy and the conditional probability $\tilde{\pi}$. Non-routine insiders have 4% higher $\tilde{\pi}$, compared to an average of 22% for routine insiders. Long-horizon insiders have a 22% conditional probability. With increasing levels of short-termism, the conditional probability rises, consistent with Akbas et al. (2020). Medium horizon insiders have 4% higher $\tilde{\pi}$, and short-horizon insiders have 9% higher $\tilde{\pi}$. Finally, insiders in the top quintile of QEA profitability exhibit $\tilde{\pi}$s that are on average 5% higher than the remaining four quintiles.

Each of the proxies is also associated with higher mixture model conditional expectations ($\tilde{\alpha}$ s) as well (Panel B of Table 6). The average conditional expectation of non-routine insiders is about 50% higher than that of routine insiders. In terms of abnormal returns, non-routine insiders' average $\tilde{\alpha}$ is 29 bps higher than the 60 bps average $\tilde{\alpha}$ of routine insiders. The wedge is even larger for long- versus short-horizon insiders. Long-horizon insiders have average $\tilde{\alpha}$ of 57 bps; short-horizon insiders' average $\tilde{\alpha}$ is twice as much, with medium-horizon insiders falling in between. Top quintile QEA profitability insiders exhibit conditional expectations that are 33 bps higher than those of the remaining four quintiles.

It is important to note that, while these proxies are positively related to our insider-level measure of informed trading as expected, they actually explain very little of the cross-sectional variation in informed trading as measured by $\tilde{\pi}$ and $\tilde{\alpha}$. This suggests that our measure is capturing different information than prior work.

5.1. Predictability controlling for existing measures

Given the positive correlations with existing proxies of informed trade and the conditional probabilities, it is important to ask whether the mixture model provides incremental information about the informativeness of insider informed trading. To assess this, we add indicators to our stock-month return panel for buying and selling activity by insiders classified as informed by the alternative approaches. The results are presented in Table 7. We include time fixed effects and standard control variables, but suppress their coefficient estimates for space considerations.

Columns (1), (3), and (5) confirm the results in the existing literature that trading activity by insiders classified as informed by existing measures predicts future stock returns. Consistent with Cohen et al. (2012), stock returns are about 50 bps higher in months following a non-routine purchase and 17 bps lower following a non-routine sell, while buys and sells by routine insiders do not predict returns. Consistent with Akbas et al. (2020), stock returns are higher (lower) following purchases (sales) by shorter horizon investors than long-horizon investors. Purchases by short-horizon investors result in an 83 bps higher stock return in the next month than purchases by long-horizon investors. Similarly, sales by short-horizon investors result in a 36 bps lower stock return in the next month than sales by long-horizon investors. Finally, purchases by insiders in the top quintile of QEA profitability are 66 bps higher than those of the remaining quintiles.

In Columns (2), (4), and (6) of Table 7, we assess whether the predictability of the mixture model classification documented in Table 3 controlling for these measures. The cross-sectional differences in future monthly returns following purchases or sales by high and low conditional expectation quintiles remains statistically and economically significant. For purchases, the Hi-Lo spread ranges between 62 and 69 bps per month, or 7.4 to 8.3% annually. For sales, the Lo-Hi spread ranges from 26 to 30 bps per month, or 3.1 to 3.6% annually. These differences are of a similar magnitude to those reported in the last column of Table 3, indicating that controlling for existing proxies does not much affect the predictability of the mixture model. On the other hand, inclusion of trading indicators for the mixture model estimates substantially reduces the predictability of non-routine buys and sells as well as the high QEA profitability quintile trading indicators. The horizon measure of Akbas et al. (2020) continues to provide incremental information to the mixture model estimates, particularly for purchases.

Overall, the results of Tables 3 and 7 show that the ex ante conditional expectation quintiles for insiders from the mixture model contain economically and statistically significant information about which insiders are more likely to trade on private information.

5.2. Effects of sample filters

Various methods, including the mixture model described in Section 2, require filtering choices by the econometrician that may reduce the ultimate set of insiders that are classified as informed or not. For example, Cohen et al. (2012) require an insider has traded in at least once in each of the last three years in order to be classified as routine or non-routine. This choice is necessary for their classification scheme, and of course, the authors provide robustness analyses concerning the choice of three years. In assessing the prevalence of informed trade, it is important to assess the effects of such filtering requirements on the resulting analysis sample. Armed with the conditional probability and expectation estimates, we now consider whether passing the sample filters is itself correlated with the propensity to trade on private information.

Table 8 reports the results of regressions of conditional probabilities (Panel A) and expectations (Panel B) on indicator variables for whether an insider's past trading activity satisfies the primary filter from the three alternative proxies for informed insider trading. The results using either $\tilde{\pi}$ or $\tilde{\alpha}$ show that the sample filters in each of the other measures result in samples containing insiders that are systematically less informed than the set of classified insiders from the mixture model. Conditional probabilities are three to five percent lower compared to a base of about 30% (Panel A). Similarly, conditional expectations are about 40 to 60 basis points lower, compared to a base of about 130 basis points (Panel B).

Thus, the sample filters in prior work result in samples that contain insiders that are less likely to trade on private information. Of course, the focus of these papers differs from ours. Their focus is primarily on cross-sectional differences about which insiders are informed, while our focus is on the prevalence of insider informed trade (although our model is also quite successful in generating cross-sectional differences as well).

We highlight this issue to emphasize the importance of assessing sample filters for the question of the prevalence of informed insider trading. Indeed, our analysis thus far is not immune to this issue. Recall that we require that an insider trade on at least ten distinct days in order to be included in a given mixture model estimation. This results in a set of insiders that our model does not classify. In the next section, we will conduct to a trade-level analysis and explicitly account for these "unclassified" insiders in addition to the classified insiders.

6. How many trades by corporate insiders are informed?

6.1. A Trade-Level Mixture Model

We now consider how prevalent informed trading by corporate insiders is at the trade-level. As is made clear below, we will allow the expanding window insider-level mixture conditional expectations (5) to inform a trade-level mixture model.

Let $h_{\mathrm{I}}(r_i^j|\text{informed})$ denote the density of the observed abnormal return (7) conditional on trade j by insider$i$ being informed. We again assume that informed trades are exponentially distributed and estimation noise is normally distributed. At the trade level, we estimate the standard deviation of estimation noise, s_i, as the 21-day standard deviation idiosyncratic volatility for the traded stock, estimated using the 42 days prior to the trade report. Thus, the density of r_i^j conditional on it being an informed trade is:

$$h_{\mathrm{I}}(r_i^j|\text{informed}) = \int_{-\infty}^{\infty} g(r_i^j - a; \mu) \cdot \phi(a; s_i)\ \mathrm{d}a\,. \tag{10}$$

We incorporate ex ante information about insider i by allowing the probability that a trade is informed to vary based on membership in one of six distinct groups. The first group contains insiders not classified by the insider-level mixture model (that is, those that did not have at least 10 distinct trading days as of the prior year end). The remaining five groups are the five quintiles based on the expanding window insider-level conditional probabilities. Denote indicator variables for the six groups as $x_{\mathrm{NC},i}, x_{0,i}, x_{1,i}, ...x_{4,i}$, respectively. The probability that a given trade made by insider i is informed is parameterized using the logistic function

$$\pi_i = \frac{\exp(b_{\mathrm{NC}}x_{\mathrm{NC},i} + b_0x_{0,i} + b_1x_{1,i} + b_2x_{2,i} + b_3x_{3,i} + b_4x_{4,i})}{1 + \exp(b_{\mathrm{NC}}x_{\mathrm{NC},i} + b_0x_{0,i} + b_1x_{1,i} + b_2x_{2,i} + b_3x_{3,i} + b_4x_{4,i})}\,. \tag{11}$$

The unconditional density function for abnormal return r_i^j is:

$$h\left(r_i^j\right) = (1-\pi_i) \cdot \phi(r_i^j; s_i) + \pi_i \cdot h_{\mathrm{I}}(r_i^j|\text{informed})\,. \tag{12}$$

The parameters of the model are $b_{\mathrm{NC}}, b_0, b_1, b_2, b_3, b_4$, and μ. The likelihood function $\mathcal{L}$ for a sample of abnormal returns made by N insiders, each making n_i trades, is:

$$\mathcal{L} = \prod_{i=1}^{N}\prod_{j=1}^{n_i} h(r_i^j)\,. \tag{13}$$

To estimate the parameters $b_{\mathrm{NC}}, b_0, b_1, b_2, b_3, b_4$, and μ, we maximize (13) subject to the restrictions that $\mu \geq 0$.

6.2. Empirical Prevalence of Informed Insider Trades

Figure 5 plots histograms of abnormal returns (7) for trades made by insiders (Panel A) and stock-level standard deviations (Panel B). There is considerable heterogeneity in both abnormal returns. There is a slight asymmetry toward positive abnormal returns, but the most populated bins are round zero abnormal return. There is also a lot of noise in the underlying stock returns. The trade-level mixture model will take this underlying noise, as well as the ex ante conditional expectation classifications of insider i, into account in order to estimate the extent of informed trade at the individual trade level.

We estimate the parameters separately for samples of buys and sells. Table 9 reports the results. To ease interpretation, we report probabilities π_i for each of the underlying classifications rather than the b parameters. Several interesting empirical facts stand out in Table 9.

First, consistent with the trade predictability evidence shown previously in Tables 3 and 7, the ex ante quintile classifications of insiders using the insider-level mixture model are strongly associated with future differences in informed trade. For purchases, the unconditional probability a particular trade is informed ranges from 6.6% for the Low quintile insiders to 14% for the High quintile insiders. Similarly, for sales, the unconditional probability a particular trade is informed ranges from 3.6% for the Low quintile insiders to 4.9% for the High quintile insiders.

Second, unclassified insiders should not be interpreted as uninformed insiders. For purchases, the unconditional probability a particular trade is informed for unclassified insiders is almost 11%. This is just under the 12% estimate for the second-highest quintile of insiders based on ex ante conditional expectation of informed insider trade. Regulators should not ignore purchases made by insiders with a relatively short history of trades. On the other hand, sales made by unclassified insiders are less likely to be informed than sales made by any classified insider. The unclassified π is 3.4% which is less than the lowest quintile π of 3.6%.

Finally, consistent with prior work, the unconditional probability that a trade is informed is strongly related to whether the trade is a purchase or a sale. The estimated π_is for buys are two to three times larger than the corresponding π_i for sales. The average magnitude of information, μ, is similar between buys and sells. For both trade types, the estimate μ is around 7%.

7. Conclusion

Corporate insiders have access to private information about their firms. We use mixture model methods designed to account for noise in trading performance to assess the prevalence of informed trade by insiders required to disclose stock trades in US corporations. 30% of insiders make informed trades. Out-of-sample tests show that trades made by insiders most likely to have traded on information are predictive of future stock returns. Informed insider trade is most prevalent in chief financial officers and insider blockholders and varies across industries. For individual trades, we estimate about 10% of insider purchases and 4% of sales are informed, and these fractions vary systematically with ex ante measures of an insider's propensity to trade on information. Our method allows classification of all trades disclosed in the US. We discuss regulatory and enforcement implications of various approaches to detecting informed trade by corporate insiders.

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Table 1: Summary Statistics

This table reports cross-sectional distributional statistics of average 21-trading day abnormal returns and standard errors following trades made by corporate insiders. Average abnormal returns are defined in Equation (9) and is the average of long positions in purchased stocks and short positions in sold stocks. The sample contains all insiders who traded on at least 10 distinct days from 1985 to 2022. Because the mixture model can be sensitive to outliers, the sample is trimmed at the 1% and 99% level. The table reports fraction of insiders with sample average abnormal returns that are (1) positive, (2) significantly positive at the 5% level, (3) significantly positive at a 10% level (both in a one-sided test). The table also reports the p-value from a test of normality of the average abnormal return distribution following D'agostino and Pearson (1973).

	Average Abnormal Return	Standard Error
Mean	0.0066	0.0248
SD	0.0468	0.0175
P1	-0.1226	0.0050
P10	-0.0428	0.0094
P25	-0.0162	0.0133
P50	0.0037	0.0200
P75	0.0268	0.0309
P90	0.0604	0.0457
P99	0.1550	0.0898
Skewness	0.40	2.49
Excess Kurtosis	2.47	11.80
Fraction positive	0.55	
Significant 5%	0.18	
Significant 10%	0.24	
Normality p-value	0.0000	
N	54274	

Table 2: Mixture Model Estimates

This table reports mixture model parameter estimates. Equation (3) is numerically maximized in π and μ. To limit the effect of outliers, the sample is first trimmed at the 1 and 99% percentiles of average abnormal returns. The point estimates, negative log-likelihood, and number of observations in the trimmed sample are reported. The reported confidence interval for each parameter is bootstrapped. Specifically, the model is estimated on 1,000 bootstrapped samples (each is formed by sampling with replacement). The reported confidence intervals are the 1st and 99th percentiles of the bootstrapped parameter estimates.

	π	μ
Parameter Estimate	0.2855	0.0360
Confidence Interval:		
Lower	0.2775	0.0351
Upper	0.2943	0.0370
Negative Log-Likelihood	-84,209.61	
Observations	54,274	

Table 3: Trades by Informed Insiders Predict Future Returns

This table reports regressions of monthly stock returns as a function of insider buying and selling activity in the prior month. The mixture model is estimated each year using the latest average abnormal return and standard error for each insider with at least ten trades prior to that year end. Based on the estimated parameters and each insider's average abnormal return and standard error, the conditional expectation of insider informed trade is calculated. Insiders are sorted into quintiles on the basis of the conditional expectation. Buy Quintile 4 (Sell Quintile 4) is an indicator variable for whether any insider in the top quintile bought (sold) shares in month t. The other quintile indicators are similarly defined. Control variables include size, book-to-market, returns in month $t-1$ and months $t-12$ to $t-2$. Month fixed effects are included in even-numbered columns. Standard errors are clustered by firm and month. t-statistics are reported below coefficient estimates, and statistical significance is represented by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$). p values for tests of whether the coefficients on the High and Low quintiles differ are reported in the table footer.

	Dependent Variable: Return$_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Buy Quintile 0 (Lo)	0.13	0.19			0.08	0.11
	(0.68)	(0.92)			(0.38)	(0.57)
Buy Quintile 1	0.51**	0.41**			0.47**	0.35**
	(2.47)	(2.47)			(2.21)	(2.14)
Buy Quintile 2	0.55**	0.42***			0.51*	0.35**
	(2.15)	(2.81)			(1.87)	(2.36)
Buy Quintile 3	0.90***	0.78***			0.85***	0.72***
	(3.03)	(4.23)			(2.67)	(3.63)
Buy Quintile 4 (Hi)	0.95***	0.88***			0.90***	0.80***
	(3.64)	(5.40)			(3.25)	(5.09)
Sell Quintile 0 (Lo)			-0.08	-0.14	0.17	0.07
			(-0.54)	(-1.55)	(1.28)	(0.66)
Sell Quintile 1			-0.19	-0.17**	0.03	0.01
			(-1.56)	(-1.98)	(0.23)	(0.10)
Sell Quintile 2			-0.37***	-0.34***	-0.15	-0.16
			(-2.95)	(-3.21)	(-1.23)	(-1.60)
Sell Quintile 3			-0.38***	-0.39***	-0.15	-0.20**
			(-2.97)	(-3.55)	(-1.25)	(-2.03)
Sell Quintile 4 (Hi)			-0.54***	-0.45***	-0.28*	-0.24**
			(-3.76)	(-3.77)	(-1.89)	(-2.08)
Size	-0.11	-0.06	-0.14*	-0.09	-0.12	-0.07
	(-1.43)	(-1.08)	(-1.88)	(-1.57)	(-1.59)	(-1.22)
BM	0.41**	0.29**	0.42**	0.30**	0.40**	0.29**
	(2.17)	(2.17)	(2.18)	(2.16)	(2.14)	(2.14)
Ret(t-1)	-0.33	0.25	-0.44	0.19	-0.28	0.30
	(-0.16)	(0.23)	(-0.22)	(0.17)	(-0.14)	(0.28)
Ret(t-12,t-2)	0.37	0.63**	0.36	0.63**	0.38	0.64**
	(0.83)	(2.21)	(0.80)	(2.18)	(0.85)	(2.23)
Constant	3.55**		4.68***		3.84**	
	(2.27)		(3.14)		(2.48)	
Time FE	N	Y	N	Y	N	Y
Adj R^2	0.0027	0.1395	0.0024	0.1392	0.0028	0.1395
Observations	183919	183919	183919	183919	183919	183919
p(Buy Hi-Lo)	0.0013	0.0040			0.0012	0.0040
p(Sell Hi-Lo)			0.0097	0.0300	0.0106	0.0323

Table 4: The Insider's Role in the Firm Relates to their Information.

This table reports regressions of conditional probabilities (columns 1 and 2) and expectations (Columns 3 and 4) of informed insider trading on their role(s) within the firm as disclosed on the Form 4 filing. The mixture model is estimated each year using the latest average abnormal return and standard error for each insider with at least ten trades prior that year end. Based on the estimated parameters and each insider's average abnormal return and standard error, a conditional probability that the insider engages in informed trade and the conditional expectation of insider informed trade is calculated. Expectations are reported in percent. We include a dummy variable for each of the roles disclosed by the insider. Columns 1 and 3 include indicators for any role in the aggregate category displayed. Columns 2 and 4 estimate the model on indicators for all roles, but only display's coefficients for roles representing at least 5% of the sample. Standard errors are clustered by insider and year. t-statistics are reported below coefficient estimates, and statistical significance is represented by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

	(1) $\tilde{\pi}$	(2) $\tilde{\pi}$	(3) $\tilde{\alpha}$	(4) $\tilde{\alpha}$
C-Suite Executives	0.03***		0.23***	
	(7.23)		(6.37)	
Directors	0.00		-0.02	
	(1.17)		(-0.74)	
Insider Owners	0.07***		0.83***	
	(12.41)		(15.48)	
Non-C-Suite Officers	-0.02***		-0.17***	
	(-5.98)		(-4.84)	
Non-officer managers	0.00		0.04	
	(0.25)		(0.44)	
CEO		0.00		-0.03
		(0.58)		(-0.53)
CFO		0.03***		0.26***
		(6.17)		(4.74)
Inside Block > 10%		0.07***		0.93***
		(10.53)		(12.46)
Chairman		-0.01		-0.11**
		(-1.53)		(-2.09)
Director		-0.01***		-0.15***
		(-3.49)		(-3.38)
President		0.01*		0.12**
		(1.72)		(2.31)
Executive VP		-0.03***		-0.18***
		(-5.21)		(-3.61)
Senior VP		-0.03***		-0.25***
		(-5.62)		(-4.96)
VP		-0.00		0.05
		(-0.58)		(0.90)
Officer		-0.03***		-0.21***
		(-5.34)		(-4.44)
Divisional Officer		-0.01***		-0.14***
		(-3.03)		(-3.13)
Officer and Director		0.00		0.08
		(0.44)		(1.39)
Observations	966445	966445	966445	966445
Adjusted R^2	0.012	0.018	0.017	0.024

Table 5: The Prevalence of Informed Trading by Insiders Varies by Industry

This table reports the average conditional expected returns (in %) and probabilities of informed trading by insiders for each of the Fama-French 12 industries. Based on the estimated parameters and each insider's average abnormal return and standard error, a conditional probability that the insider engages in informed trade ($\tilde{\pi}$) and the conditional expectation of insider informed trade is calculated ($\tilde{\alpha}$). The insider-level measures are then averaged within each of the Fama-French 12 industries based on the SIC code reported in CRSP. These averages are presented in ascending order by the conditional expected alpha ($\tilde{\alpha}$)

Industry	$\tilde{\alpha}$	$\tilde{\pi}$
Utilities	0.663	0.24
Finance	0.831	0.26
Chemicals and Allied Products	0.949	0.27
Consumer Durables – Cars, TV's, Furniture, Household Appliances	1.054	0.28
Manufacturing – Machinery, Trucks, Planes, Off Furn, Paper, Com Printing	1.177	0.29
Consumer NonDurables – Food, Tobacco, Textiles, Apparel, Leather, Toys	1.218	0.30
Wholesale, Retail, and Some Services (Laundries, Repair Shops)	1.273	0.29
Oil, Gas, and Coal Extraction and Products	1.288	0.30
Other – Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment	1.438	0.31
Healthcare, Medical Equipment, and Drugs	1.462	0.31
Business Equipment – Computers, Software, and Electronic Equipment	1.501	0.31
Telephone and Television Transmission	1.721	0.32

Table 6: Conditional Informed Insider Measures and Existing Measures

This table reports regressions of conditional probabilities (Panel A) and expectations (Panel B) of informed insider trading on other classifiers of informed insider trading. The mixture model is estimated each year using the latest average abnormal return and standard error for each insider with at least ten trades prior to that year end. Based on the estimated parameters and each insider's average abnormal return and standard error, a conditional probability that the insider engages in informed trade and the conditional expectation of insider informed trade is calculated. Routine insiders are calculated following Cohen, Malloy, and Pomorski (2012). Investor horizon is calculated following Akbas, Jiang, and Koch (2020). High QEA Profitability represents the top quintile of insider profits ahead of quarterly earnings announcements and is calculated following Ali and Hirshleifer (2017). Standard errors are clustered by insider and year. t-statistics are reported below coefficient estimates, and statistical significance is represented by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

Panel A

	Dependent Variable: Conditional Probability		
	(1)	(2)	(3)
Non-Routine	0.04***		
	(15.13)		
Medium Horizon		0.04***	
		(12.10)	
Short Horizon		0.09***	
		(15.83)	
High QEA Profitability			0.05***
			(9.08)
Constant	0.22***	0.22***	0.25***
	(47.97)	(64.62)	(40.13)
Adj R^2	0.0066	0.0211	0.0052
Observations	131082	111584	24668

Panel B

	Dependent Variable: Conditional Expectation		
	(1)	(2)	(3)
Non-Routine	0.0029***		
	(17.10)		
Medium Horizon		0.0024***	
		(12.18)	
Short Horizon		0.0057***	
		(20.61)	
High QEA Profitability			0.0033***
			(9.04)
Constant	0.0060***	0.0057***	0.0078***
	(20.40)	(29.76)	(20.64)
Adj R^2	0.0061	0.0227	0.0058
Observations	131082	111584	24668

Table 7: Trades by Informed Insiders Predict Future Returns Controlling for Existing Measures

This table reports regressions of monthly stock returns as a function of insider buying and selling activity in the prior month. The mixture model is estimated each year using the latest average abnormal return and standard error for each insider with at least ten trades prior to that year end. Based on the estimated parameters and each insider's average abnormal return and standard error, the conditional expectation of insider informed trade is calculated. Insiders are sorted into quintiles on the basis of the conditional expectation. Buy Quintile 4 (Sell Quintile 4) is an indicator variable for whether any insider in the top quintile bought (sold) shares in month t. The other quintile indicators are similarly defined. Similar indicator variables are calculated for buys and sells made by three sets of insiders: (1) routine and non-routine insiders (Cohen et al., 2012); (2) long, medium, and short horizon insiders (Akbas et al., 2020); and (3) the highest quintile of QEA Profitability (Ali and Hirshleifer, 2017). Control variables include size, book-to-market, returns in month $t-1$ and months $t-12$ to $t-2$. Month fixed effects and controls are included in all columns. Standard errors are clustered by firm and month. t-statistics are reported below coefficient estimates, and statistical significance is represented by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$). p values for tests of whether the coefficients on the High and Low quintiles differ are reported in the table footer.

	Dependent Variable: Return_{t+1}					
	(1)	(2)	(3)	(4)	(5)	(6)
Buy Quintile 0 (Lo)		0.24		0.17		0.11
		(1.22)		(0.87)		(0.55)
Buy Quintile 1		0.44***		0.38**		0.35**
		(2.66)		(2.42)		(2.11)
Buy Quintile 2		0.42**		0.38**		0.35**
		(2.58)		(2.46)		(2.33)
Buy Quintile 3		0.77***		0.74***		0.71***
		(3.51)		(3.65)		(3.61)
Buy Quintile 4 (Hi)		0.86***		0.80***		0.80***
		(5.11)		(4.68)		(4.97)
Sell Quintile 0 (Lo)		0.02		0.05		0.06
		(0.22)		(0.54)		(0.61)
Sell Quintile 1		-0.02		0.01		0.01
		(-0.19)		(0.11)		(0.06)
Sell Quintile 2		-0.18*		-0.15		-0.16
		(-1.78)		(-1.37)		(-1.65)
Sell Quintile 3		-0.22**		-0.19*		-0.21**
		(-2.20)		(-1.70)		(-2.07)
Sell Quintile 4 (Hi)		-0.25**		-0.21*		-0.24**
		(-2.21)		(-1.71)		(-2.11)
Nonroutine Buy	0.47***	-0.06				
	(3.06)	(-0.40)				
Nonroutine Sell	-0.17**	0.02				
	(-2.32)	(0.27)				
Routine Buy	-0.28	-0.73***				
	(-1.16)	(-2.87)				
Routine Sell	0.20	0.29**				
	(1.57)	(2.20)				
Long Horizon Buy			0.04	-0.36*		
			(0.19)	(-1.92)		
Med Horizon Buy			0.50**	0.11		
			(2.20)	(0.50)		
Short Horizon Buy			0.87***	0.45**		
			(3.65)	(2.00)		
Long Horizon Sell			-0.02	0.15		
			(-0.16)	(1.35)		
Medium Horizon Sell			-0.37***	-0.22**		
			(-4.15)	(-2.13)		
Short Horizon Sell			-0.38***	-0.18		
			(-3.49)	(-1.51)		
QEA Profitability Q5 Buy					0.66	0.19
					(1.65)	(0.47)
QEA Profitability Q5 Sell					-0.04	0.13
					(-0.19)	(0.68)
Time FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Adj R^2	0.1391	0.1396	0.1392	0.1396	0.1390	0.1395
Observations	183919	183919	183919	183919	183919	183919
p(Buy Hi-Lo)		0.0082		0.0071		0.0043
p(Sell Hi-Lo)		0.0499		0.0493		0.0324

Table 8: Existing Informed Insider Samples Exclude the Most Informed Insiders

This table reports regressions of conditional probabilities (Panel A) and expectations (Panel B) of informed insider trading on other indicators for whether an insider-year satisfies the sample filters used in alternative classifications of informed insider trading. The mixture model is estimated each year using the latest average abnormal return and standard error for each insider with at least ten trades prior that year end. Based on the estimated parameters and each insider's average abnormal return and standard error, a conditional probability that the insider engages in informed trade and the conditional expectation of insider informed trade is calculated. Routine insiders are calculated following Cohen, Malloy, and Pomorski (2012) and requires trading in each of the past 3 years. Investor horizon is calculated following Akbas, Jiang, and Koch (2020) and requires trading in four of the last ten years. High QEA Profitability represents the top quintile of insider profits ahead of quarterly earnings announcements and is calculated following Ali and Hirshleifer (2017); it requires trading placed in a window ahead of earnings announcements. Standard errors are clustered by insider and year. t-statistics are reported below coefficient estimates, and statistical significance is represented by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$).

Panel A

	Dependent Variable: Conditional Probability			
	(1)	(2)	(3)	(4)
Constant	0.29***	0.30***	0.30***	0.29***
	(150.98)	(146.66)	(143.73)	(154.28)
Pass Routine Filters		-0.05***		
		(-21.32)		
Pass Horizon Filters			-0.05***	
			(-26.18)	
Pass QEA Profitability Filters				-0.03***
				(-6.48)
Adj R^2	0.0000	0.0033	0.0035	0.0003
Observations	966445	966445	966445	966445

Panel B

	Dependent Variable: Conditional Expectation			
	(1)	(2)	(3)	(4)
Constant	0.0125***	0.0131***	0.0131***	0.0126***
	(49.51)	(46.75)	(45.88)	(49.56)
Pass Routine Filters		-0.0051***		
		(-31.53)		
Pass Horizon Filters			-0.0059***	
			(-38.97)	
Pass QEA Profitability Filters				-0.0042***
				(-18.83)
Adj R^2	0.0000	0.0046	0.0053	0.0006
Observations	966445	966445	966445	966445

Table 9: Trade-level Mixture Model

This table reports mixture model parameter estimates for individual insider trades. The insider-level mixture model is estimated each year using the latest average abnormal return and standard error for each insider with at least ten trades prior to that year end. Based on the estimated parameters and each insider's average abnormal return and standard error, the conditional expectation of insider informed trade is calculated. Insiders are sorted into quintiles on the basis of the conditional expectation. In the trade-level mixture model reported in this table, the probability π that a trade is informed is parameterized to allow different probabilities for one of 6 groups. The first group are insiders not classified by the insider-level mixture model (that is, those that did not have at least 10 distinct trading days as of the prior year end). The remaining five groups are the five quintiles based on the expanding window insider-level conditional probabilities. To limit the effect of outliers, the sample is first trimmed at the 1 and 99% percentiles of abnormal returns. The point estimates, negative log-likelihood, and number of observations in the trimmed sample are reported.

Panel A: Purchases

	π	μ
		0.0715
Unclassified	0.1090	
Low Quintile	0.0660	
Q1	0.0925	
Q2	0.0821	
Q3	0.1208	
High Quintile	0.1404	
Negative Log-Likelihood	22,175,298.78	
Observations	696,533	

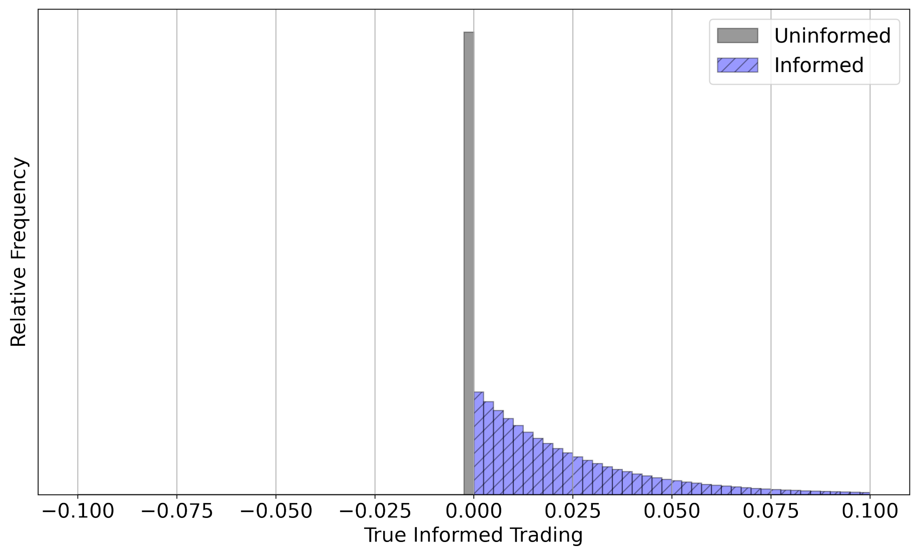
Panel B: Sales

	π	μ
		0.0667
Unclassified	0.0342	
Low Quintile	0.0359	
Q1	0.0377	
Q2	0.0393	
Q3	0.0423	
High Quintile	0.0492	
Negative Log-Likelihood	9,164,155.89	
Observations	1,439,867	

Figure 1: Distributions of True and Estimated Informed Insider Trading

This figure illustrates the mixture method of informed insider trading. Panel (a) shows the relative frequencies of true informed insider trading. A fraction π of insiders trade on information that is exponentially distributed with mean μ (the hatched purple bins). The remaining $1 - \pi$ insiders do not trade on information (grey bins). Panel (b) shows the relative frequencies of estimated abnormal returns for insiders that exploit private information (hatched purple), insiders that do not (grey bins), and the unconditional distribution (black line). Estimated abnormal returns exhibit additional variation due to error in estimating true informed trading, resulting in more dispersed distributions in Panel (b) than in Panel (a). The parameter values for this example are $\pi = 0.7$, $\mu = 0.025$, and a standard error $s_i = 0.015$ for all insiders.

(a) True Informed Insider Trading



(b) Estimated Abnormal Return

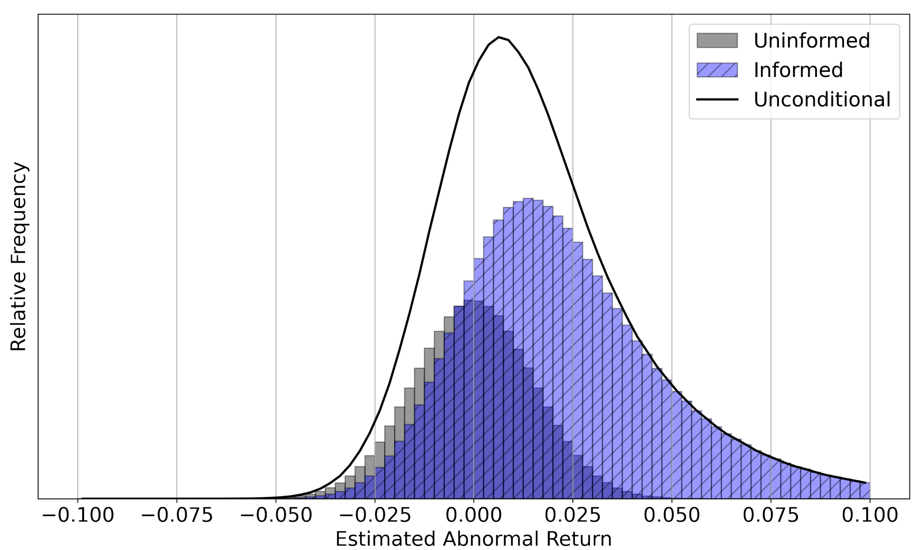
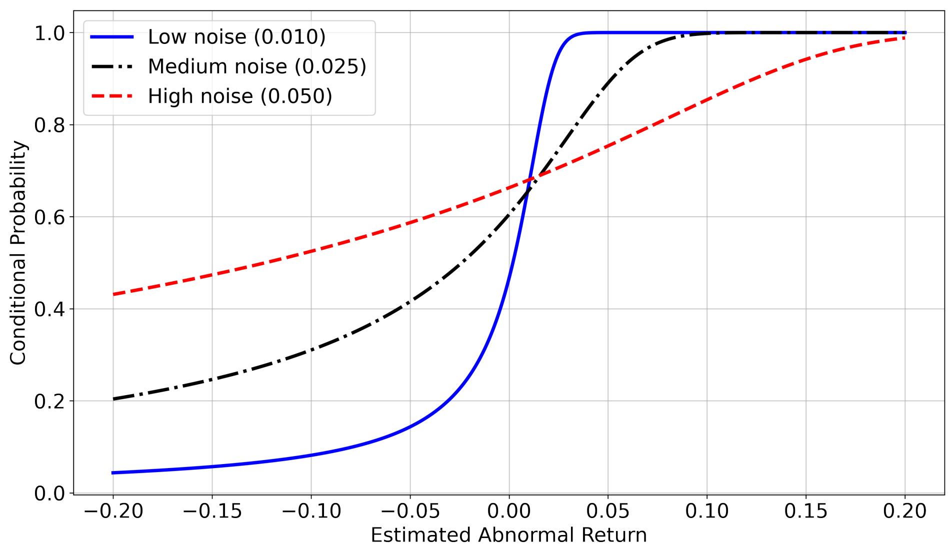


Figure 2: Conditional Probabilities and Expectations
This figure illustrates conditional probabilities and expectations in the mixture method of informed insider trading as a function of the estimated average abnormal return and its standard error (i.e. its noise). Panel (a) shows the probability an insider trades on information conditional on their average abnormal return and its standard error. Panel (b) shows the conditional expectation of an insider's information, conditional on their average abnormal return and its standard error. The parameter values for this example are $\pi = 0.7$, $\mu = 0.025$, and the standard errors (noise) indicated in the legend.

(a) Conditional Probability Insider is Informed



(b) Conditional Expectation of Insider Information

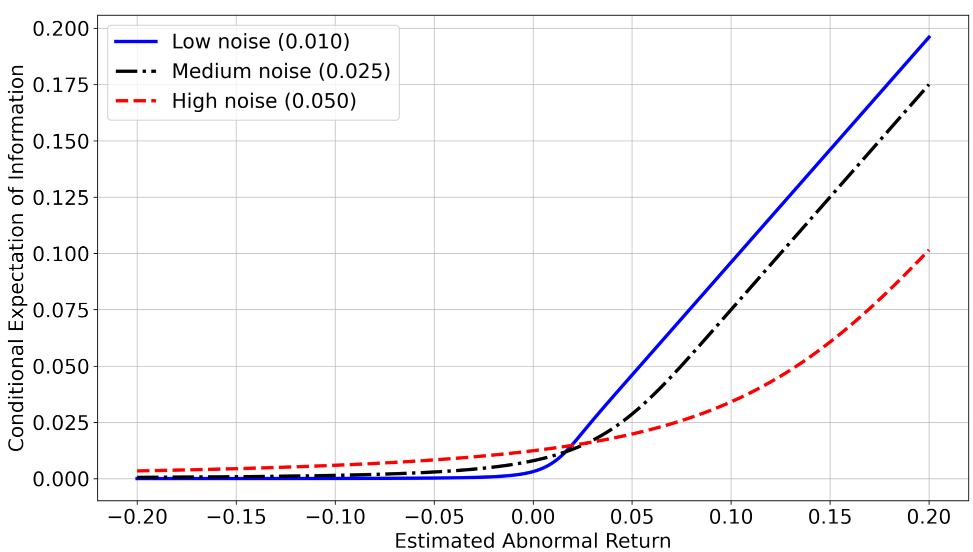
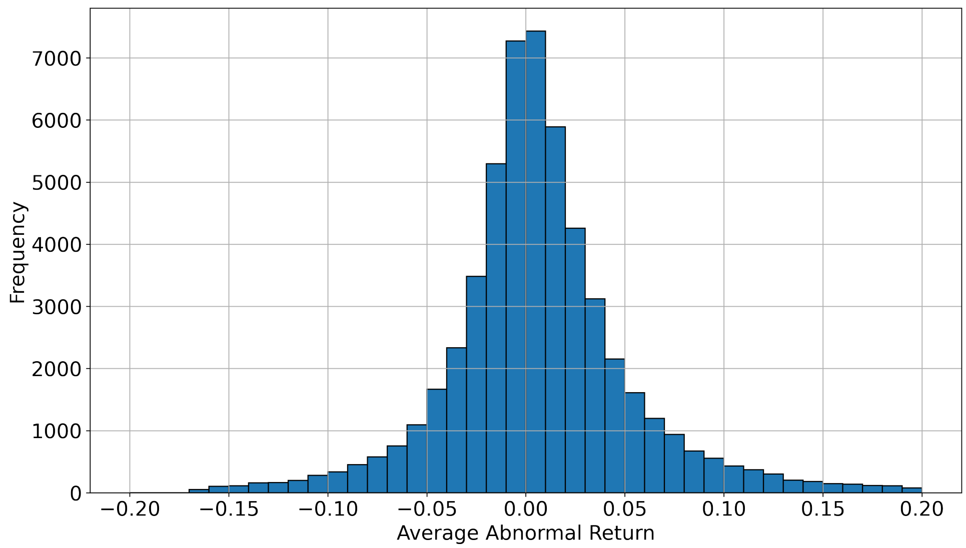


Figure 3: Distributions of Average Abnormal Returns and Standard Errors
For each trade, a buy-and-hold abnormal return over the market is calculated over the 21 trading days following the transaction. An average abnormal return and its standard error is estimated for each insider reporting trades on at least ten distinct dates. Panel (a) plots the histogram of average abnormal returns for each insider with an average abnormal return between -20% and 20%. Panel (b) plots the histogram of the standard error of the average abnormal return for each insider with a standard error below 20%.

(a) Average Abnormal Return



(b) Standard Error of Average Abnormal Return

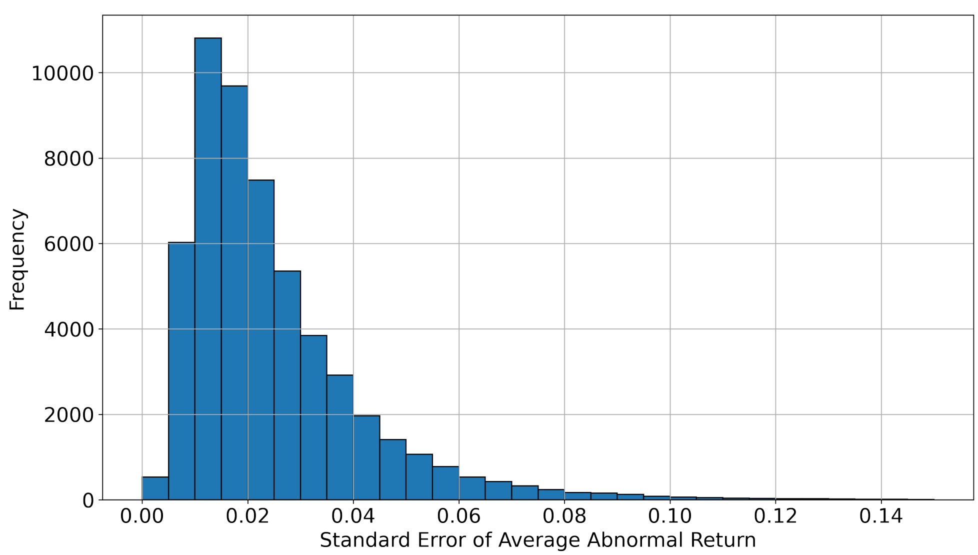
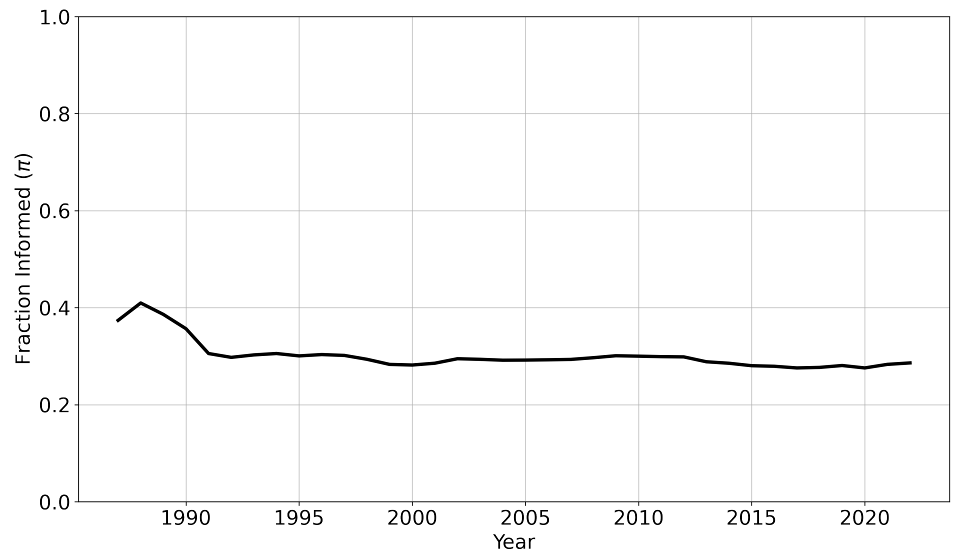


Figure 4: Time-series of Estimated Paramaters

The mixture model is estimated each year using the latest average abnormal return and standard error for each insider with at least ten trades prior that year end. Panel (a) plots the time-series of the probability an insider is informed (π). Panel (b) plots the time-series of the average information for informed insiders (μ).

(a) Fraction Informed (π)



(b) Mean of Informed Trading (μ)

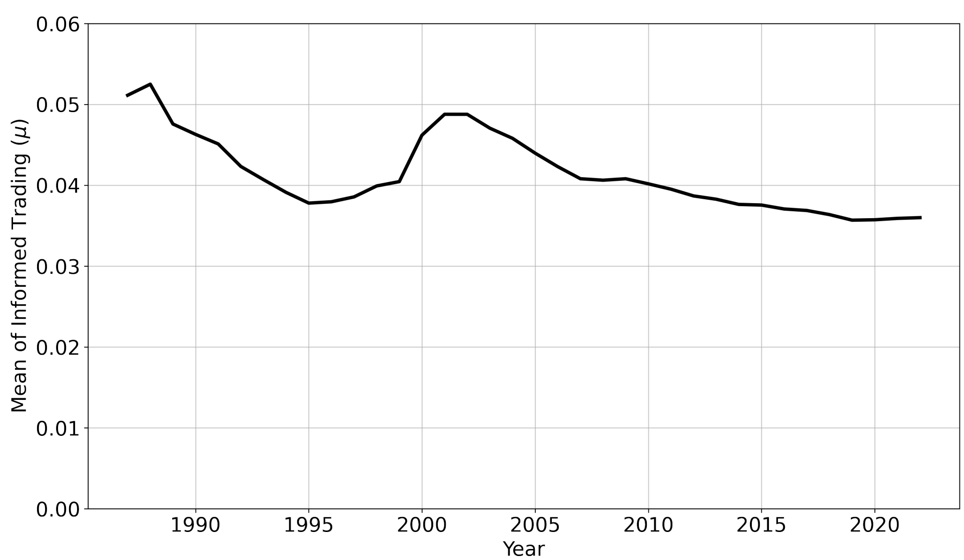
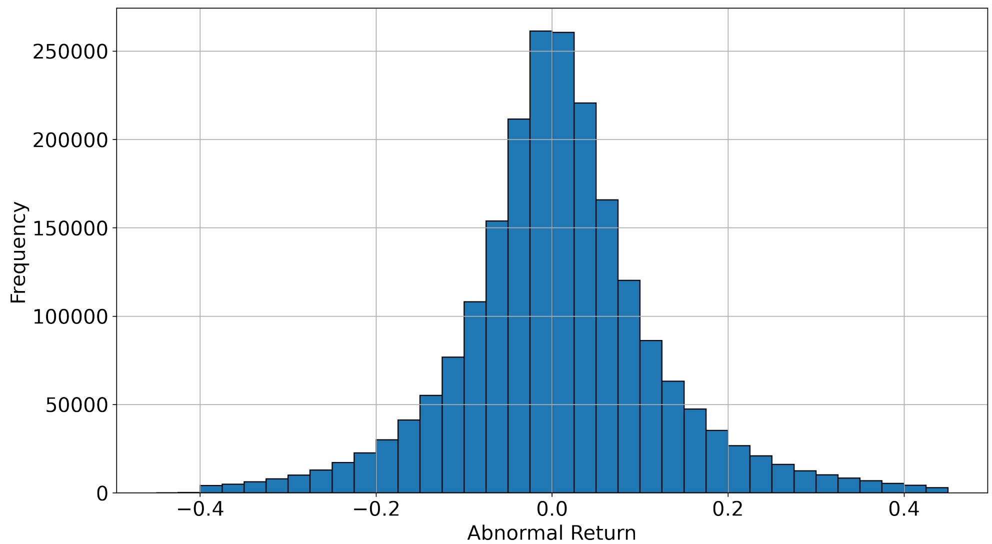


Figure 5: Distributions of Trade-Level Abnormal Returns and Standard Deviations
For each trade, a buy-and-hold abnormal return over the market is calculated over the 21 trading days following the transaction. A corresponding 21-day stock-level standard deviation is calculated using the 42 trading days prior to the trading date. Panel (a) plots the histogram of abnormal returns for each trade with an abnormal return between -45% and 45%. Panel (b) plots the histogram of the stock-level standard deviations falling below 50%.

(a) Average Abnormal Return



(b) Stock Standard Deviation