Detecting Informed Trade by Corporate Insiders

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Abstract

We introduce a two-dimensional mixture model that leverages the cross-section of insiders' buy and sell histories to infer which insiders make informed buys, informed sells, both, or neither. The method classifies *all* insiders, and insiders unclassified by leading alternative approaches exhibit a substantial propensity to use information. Out-of-sample returns are higher for stocks traded by insiders identified as more likely to use information. The model for insiders informs a person-specific mixture distribution that is used to classify whether *any* disclosed trade is informed. Whether trades are prescheduled, option-related, or by inside blockholders significantly relates to the probability they are informed.

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1. Introduction

Corporate insiders—such as managers and directors—possess private information about their firms, giving them a potential advantage in financial markets. To mitigate the risks associated with insider trading, which can reduce market liquidity and deter investor participation, the Securities and Exchange Act of 1934 introduced Rule 10b-5, which prohibits trading on the basis of material nonpublic information. However, enforcement remains challenging and costly, as insiders trade for various reasons, many of which are entirely legal. For instance, insiders often hold significant portions of their wealth in company stock and may trade for liquidity or diversification rather than due to an informational advantage. Compounding this difficulty, stock returns are inherently noisy. Some informed trades may appear unprofitable by chance, while profitable trades may just be lucky rather than informed.

In disentangling information from noise, regulators, traders, and academics all face a significant challenge: whether trade by corporate insiders is informed is not directly observable. However, for publicly traded firms in the U.S., we do observe the return histories of insiders' trades. These histories provide a very noisy signal about an insider's potential use of information. The signal-to-noise ratio is low not only because some insiders' trades are liquidity-motivated but also because individual stock returns are quite volatile and the historical record for many corporate insiders is short.

Indeed, notable existing proxies for informed trade by corporate insiders do not use past returns at all, instead utilizing the persistence in calendar timing of trade (Cohen, Malloy, and Pomorski, 2012) or the consistency of trading direction (Akbas, Jiang, and Koch, 2020). Others boost the signal-to-noise ratio by focusing on particular informational events such as profitable trading ahead of earnings announcements (Ali and Hirshleifer, 2017). These approaches convincingly show that some insider trades are informed. However, because they depend on observable trading patterns or specific trading windows, they cannot classify insiders with short trading histories, who, in fact, comprise the majority of all traders in the data. As a result, existing research does not speak to the overall prevalence of informed trading and cannot classify the full population of insiders.

In this paper, we take a different approach that allows for the classification of all insiders, regardless of trading history. Using only the return histories of realized trades, we develop a method that exploits cross-sectional differences in noise and profitability to infer the unconditional distribution of informed trading. Our approach leverages variation in the cross-section of returns to (1) estimate which insiders are more likely to engage in informed trading and (2) classify which individual trades are likely to be information-driven.

For all corporate insiders with disclosed stock trades from 1985 to 2024, we estimate about 33% are classified as trading on private information. Non-informational reasons for trade may differ between insider buys and sells, and prior work has generally found stronger results for the former. To incorporate these possible differences in information use, we jointly model buy and sell profitability as a mixture distribution, allowing insiders to trade on information for only their buys, only their sales, both, or neither. Empirically, we estimate that 26% of insiders make informed buys and 10% make informed sales. Only 2% of insiders appear to use information for both their buys and their sales. Conditional on making informed buys and/or sales, an insider's average profitability is a 5.2% abnormal return over the next month compared to an average profitability of zero (by construction) for insiders not trading on private information.

Using the estimated mixture model parameters and the realized average abnormal returns and standard errors for each individual insider's buys and sells, we estimate conditional probabilities that a given insider makes informed buys and sells as well as conditional expected average abnormal returns for both buys and sells. The mixture model essentially functions as a noise reduction method, where an insider's estimated probability of informed trade moves off the unconditional estimate as a function of the magnitude and precision of the realized returns. Intuitively, the econometrician should update more strongly that an insider trades on private information if the insider's average return is higher. However, estimation noise due to volatile returns or a short trading history should affect this inference. Consider two insiders who both have average abnormal buy 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 makes informed purchases 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 probabilities in the mixture model formally quantify this intuition.

To validate our model's ability to identify traders who are more likely to trade on private information, we test whether our estimates have economic content out of sample. At any point in time, we can estimate each insider's probabilities of making informed buys and sells using their full trade history up until that point. We conduct out-of-sample exercises testing whether the buys and sells of insiders with different ex-ante conditional buy and sell profitability expectations predict differences in stock returns. After sorting on these conditional expectations, the difference in future returns for stocks with buying activity by top-buy-quintile insiders relative to bottom-buy-quintile insiders is 92 basis points per month, or about 11% per year. Future returns for stocks with selling activity by top-sell-quintile insiders are 37 basis points lower per month (i.e., 4.4% annually) than returns of stocks sold by bottom-sell-quintile insiders. Our noise reduction technique substantially improves predictability compared to simpler estimators of past profitability like an insider's average abnormal return or its t-statistic, particularly for sales. We also provide evidence that prices are more efficient over time with respect to the trading behavior of insiders, coincident with increased information acquisition from the SEC website by sophisticated investors.

Our estimated conditional probabilities of an insider's propensity to buy or sell on private information are positively correlated with the existing proxies for informed insider trade mentioned above (Cohen et al., 2012; Ali and Hirshleifer, 2017; Akbas et al., 2020), but the mixture model estimates contain a significant amount of independent information. In particular, controlling for whether an 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 of the mixture model's conditional expectations.

We show how our method can be generalized to incorporate information in existing proxies. Importantly, we are able to classify *all* insiders, while prior proxies often entail substantial sample filters to classify insiders. The generalized models reveal that (1) insiders not classified by prior methods exhibit non-trivial probabilities of using information, (2) the probability an insider uses information for sales is relatively high for unclassified insiders, and (3) the uninformed category from prior classifications exhibits non-zero probabilities of trading on information.

Our ex-ante estimates of the likelihood that a given insider engages in informed trade allow for improved classification of whether any *single* trade is informed or not. In particular, we use a trade-level mixture model that utilizes an insider's probability of using information for buys or sells from the insider-level mixture model. The model results in an informed trade classification threshold that is customized based on the insider's return history. We are also able to use information from the full cross-section of insiders to classify *all* trades, including those made by insiders with short or even no trading history.

The estimation yields several empirical findings about informed insider trade. First, the prevalence of likely-informed buys is over twice as high as likely-informed sales. Second, the return thresholds necessary in order to classify trades as likely informed are often quite high. This helps explain why the SEC pursues relatively few cases against corporate insiders despite empirical evidence that some insiders' trades predict future returns. Third, we find that pre-scheduled 10b5-1 purchases are more likely to be informed, counter to policy goals. Option-related sales are less likely to be informed, consistent with liquidity motives for such trades. Further, CEOs and large inside blockholders make more informed trades.

A vast literature studies whether trades made by corporate insiders contain information relevant to future stock returns.[1] Within this literature, a number of papers document that some insiders are more likely to make informed trades than others (e.g., Cohen et al., 2012; Ali and Hirshleifer, 2017; Cline et al., 2017; Biggerstaff et al., 2020; Akbas et al., 2020; Goldie et al., 2023).[2] Our work relates to 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.

[1]For example, research over the last fifty years includes Jaffe (1974), Seyhun (1986), Seyhun (1992), Jeng, Metrick, and Zeckhauser (2003), Ravina and Sapienza (2010), and Cziraki and Gider (2021).

[2]Cline et al. (2017) also uses an insider's return history to classify persistently profitable insiders, but their classification does not utilize information from the cross-section of insiders nor the noise in an individual insider's trading history. It also does not classify all insiders. We show that the predictive power of the mixture model's conditional expectations is unchanged controlling for their measure.

So, while these papers convincingly show that some trades have information, they are less able to speak to the universe 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. A contribution of our paper is our ability to estimate (1) conditional probabilities that an insider makes informed buys and sells for *all* US corporate insiders, and (2) a conditional probability that a given trade is informed for *all* trades disclosed by US corporate insiders.

Our paper also makes a methodological contribution to the performance evaluation literature disentangling signal from noise (i.e., skill from luck). Mixture models have been used to assess the extent of repeatable performance of various financial market participants, including hedge funds (Chen, Cliff, and Zhao, 2017), mutual funds (Harvey and Liu, 2018), and security analysts (Crane and Crotty, 2020). To our knowledge, we are the first in this literature to incorporate two dimensions of skill, in particular by allowing for inference jointly based on buy and sell performance. Our multivariate approach represents an advance to the performance evaluation literature with many potential applications beyond insider trading. For instance, the methodology could be applied to mutual fund performance by jointly modeling the prevalence of security selection and market-timing ability.

It is worth emphasizing a distinction between our study of the economic informativeness of disclosed trades by corporate insiders and the literature studying illegal insider trading (e.g., Ahern, 2017; Kacperczyk and Pagnotta, 2019). Such studies primarily concern trades made following tipped information and do not necessarily directly involve corporate insiders. It is possible that some of the trading activity in our study is, in fact, illegal, but whether the economic materiality we document amounts to legal materiality is beyond the scope of this article.

Finally, a large literature discusses the costs and benefits of insider trading more generally (e.g., Hirshleifer, 1971; Dye, 1984; Leland, 1992). 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 all corporate insiders.

2. Detecting Which Insiders Trade on Information

2.1. Modeling the Cross-section of Insiders as a Mixture Distribution

Due the fact that some insiders may trade for non-informational reasons (e.g., liquidity) while others trade on information, it is natural to model the distribution of average insider profitability as a mixture distribution. To fix ideas and develop some intuition for the model, we first consider the case in which we only observe the average profitability for buy transactions made by corporate insiders. In this case, we model the distribution of insiders' average abnormal returns from buys as a mixture of two distributions: an uninformed distribution and an informed distribution. An insider can be of two types: (1) they make purchases that are, on average, informed, or (2) they make purchases that are uninformed. Denote the probability an insider is of the first type as π. Let z_i be a latent indicator variable for whether insider i makes informed purchases. Thus, π represents the expected value of z_i across insiders.

Empirically, the econometrician can estimate the average abnormal buy return for a given insider, denoted $\bar{r}_i$. The dispersion in the estimated average abnormal return across insiders belonging to either group is driven by two components: true variation in informed trading and noise. We assume that the (unobservable) true average abnormal buy return of uninformed insiders ($z_i = 0$) is a point mass at zero and that the true average abnormal return α_i of informed insiders ($z_i = 1$) is distributed exponentially with mean μ ($\alpha_i \sim \text{Exp}(1/\mu)$). Therefore, the true average abnormal buy return of insider i is $z_i\alpha_i$. Finally, the estimated abnormal return $\bar{r}_i$ is measured with noise, e_i, which is assumed independent of α_i and normally distributed around zero with a standard deviation of s_i. We model s_i as an estimate of the standard error of $\bar{r}_i$ to account for variation in abnormal returns due to the noise in stock returns. Thus, the estimated abnormal performance is $\bar{r}_i = z_i\alpha_i + e_i$.

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

Panel (b) of Figure 1 shows the effects of estimation noise on these component distributions. With noisy measures of 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 noise. We denote the distribution of $\bar{r}$ conditional on an insider trading on information and estimated noise s as $f_{\mathrm{I}}(\bar{r}|s)$.[3] Variation in this distribution is due both to variation in the degree of informed trading and variation due to noise in returns. The unconditional density function for insider i's estimated average abnormal return $\bar{r}_i$ is:

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

where $\phi(\cdot|s)$ is the density of a mean-zero normal variable with standard deviation s. In a slight abuse of terminology, we refer to f as the unconditional distribution of $\bar{r}$. In the example in Figure 1, the substantial overlap in the conditional distributions leads to an unconditional distribution that is unimodal with positive skewness.

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 makes informed purchases, conditional on the insider's realized average abnormal buy return $\bar{r}_i$, their standard error s_i, and the estimated parameters. Denote the conditional probability by $\tilde{\pi}_i$. The conditional probability that insider i makes informed purchases is:

$$\begin{aligned}\tilde{\pi}_i =& \Pr\left(z_i = 1|\bar{r}_i, s_i, \pi, \mu\right) \\ =& \frac{\pi\cdot f_{\mathrm{I}}(\bar{r}_i|s_i)}{(1-\pi)\cdot\phi(\bar{r}_i|s_i) + \pi\cdot f_{\mathrm{I}}(\bar{r}_i|s_i)}\,.\end{aligned} \tag{2}$$

We can also calculate the conditional expectation of the magnitude of an insider's trading

[3]For informed insiders, $\bar{r}$ is an exponentially-modified normal random variable. Its density admits a closed-form expression, which substantially reduces the computational burden of estimating the model. See Appendix A.1 for details.

profitability, conditional on their average abnormal buy return, standard error, and parameters π and μ. We denote this conditional expectation as $\tilde{\alpha}_i$, which is calculated as:

$$\begin{aligned} \tilde{\alpha}_i =& \mathbb{E}\left[z_i \alpha_i | \bar{r}_i, s_i, \pi, \mu\right] \\ =& \tilde{\pi}_i \tilde{\mu}_{I,i} \,, \end{aligned} \tag{3}$$

where $\tilde{\mu}_{I,i}$ denotes the expectation of insider i's profitability conditional on belonging to the informed component distribution. We show in Appendix B.1 that, under our distributional assumptions, $\tilde{\mu}_I$ is the mean of a truncated normal distribution, $f_{\alpha|\bar{r}}$, which is the density of the true abnormal return given the insider uses information and conditioning on an insider's realized average return.

Figure 2 illustrates the conditional probability (2) and conditional expectation (3) as a function of average abnormal return $\bar{r}$ and estimation noise s. Consistent with intuition, both are increasing functions of the average abnormal return.

The effect of estimation noise is more interesting. In Panel (a), 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 serves as a fair proxy for determining whether insiders trade on information. Negative abnormal returns are more likely to be from uninformed insiders, while positive abnormal returns are more likely to be from informed insiders. As estimation noise increases, however, the average abnormal return becomes a less reliable proxy for whether insiders trade 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. When the precision of the signal, $\bar{r}$, is lower (a higher s), our estimate shrinks $\bar{r}$ towards the unconditional (population) estimate more. A naive proxy one might think of using instead would be to calculate the t-statistic from $\bar{r}$ and s, or to simply use $\bar{r}$. However, as Figure 2 makes clear, due to the noise in returns, especially when the noise is high, you could estimate negative average returns and t-statistics for insiders making informed trades due to bad luck. Our methodology correctly accounts for this possibility, which we show makes a meaningful difference when predicting returns out-of-sample in Section 3.

The effects of estimation noise on 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 $\bar{r}$ 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 $\bar{r}$. Similarly, some insiders who do not trade on information may have been lucky and realized a positive $\bar{r}$. The mixture model approach essentially shrinks these realized returns to the unconditional estimate that we will estimate from the cross-section of insiders as a function of the precision of the signal, which is captured by the estimation noise s.

2.3. A Bivariate Model: Incorporating Information from Buys and Sells

The primary model we use to estimate informed trading builds on the intuition discussed above for purchases, but extends this model to incorporate a second dimension of informed trade for sales. The literature on insider transactions generally finds informed trading to be more robust for insiders purchases compared to sales, suggesting that purchases and sales are different. There are many non-informational reasons for insiders to sell shares (e.g., liquidity or diversification motives), which may make it harder to detect informed trade on this dimension. Since these types of trades are fundamentally different and may exhibit different information content and noise, we consider a mixture model that jointly considers the possibility that an insider makes informed trades on their buys and/or their sells.

We model the joint distribution of an insider's average returns for buys and sells ($\bar{r}_{b,i}$ and $\bar{r}_{s,i}$, respectively) as a mixture distribution. Let $z_{k,i}$ be a latent indicator variable for whether insider i uses information for trade direction $k \in \{b, s\}$. An insider can be one of four types: (1) they make trades that are uninformed for both buys and sells ($z_{b,i} = 0$, $z_{s,i} = 0$), (2) they make informed buys, but not informed sells ($z_{b,i} = 1$, $z_{s,i} = 0$), (3) they make informed sells, but not informed buys ($z_{b,i} = 0$, $z_{s,i} = 1$), or (4) they make both informed buys and informed sells ($z_{b,i} = 1$, $z_{s,i} = 1$). Denote the probability an insider is one of these four types as π_{00}, π_{b0}, π_{0s}, and π_{bs}, respectively. Note that this structure allows for a correlation in whether an insider uses information across buys and sells, $\text{corr}(z_{b,i}, z_{s,i})$.

As in the univariate model, we assume that if an insider uses information for a given trade direction, the true average abnormal return α_i is distributed exponentially with mean μ; otherwise, it is zero. The estimated abnormal return $\bar{r}_{k,i}$ for $k \in \{b, s\}$ is the unobserved true abnormal return plus estimation noise, $e_{k,i}$, which is assumed independent of α_i and normally distributed around zero with a standard deviation of $s_{k,i}$. The estimation noise in buys and sells is assumed to be independent. Thus, the estimated average abnormal returns for buys and sells are:

$$\begin{aligned} \bar{r}_{b,i} &= z_{b,i}\alpha_i + e_{b,i} \ , \\ \bar{r}_{s,i} &= z_{s,i}\alpha_i + e_{s,i} \ . \end{aligned} \tag{4}$$

When considering the performance of both buys and sells, note that the realizations of $\bar{r}_{b,i}$ and $\bar{r}_{s,i}$ are independent except for the case in which the insider trades on information for both buys and sells. For the cases in which the insider does not utilize information for both trade types, we can consider the component distributions of $\bar{r}_b$ and $\bar{r}_s$ separately. For insiders that trade on information using only trade type k, $\bar{r}_k$ is an exponentially-modified normal variable with distribution f_I, as in the univariate model, and the average return of the other trade type is normally distributed around zero. The distribution f_I is defined in Appendix A.1.

For insiders that utilize information for both buys and sells, the joint distribution of $\bar{r}_b$ and $\bar{r}_s$ is denoted by $f_{\text{both}}(\bar{r}_b, \bar{r}_s | s_b, s_s)$, which is the density of an exponentially-modified bivariate normal density. Like f_I, the density f_{both} can be written in closed form (see Appendix A.2), which substantially reduces the computational burden of estimating the model.

If an insider has both buys and sells in their history, the unconditional joint density function for insider i's estimated average abnormal returns $\bar{r}_{b,i}$ and $\bar{r}_{s,i}$ is:

$$\begin{aligned} f_{bs}(\bar{r}_{b,i}, \bar{r}_{s,i} | s_{b,i}, s_{s,i}) = {} & \pi_{00} \cdot \phi(\bar{r}_{b,i} | s_{b,i}) \cdot \phi(\bar{r}_{s,i} | s_{s,i}) \\ & + \pi_{b0} \cdot f_I(\bar{r}_{b,i} | s_{b,i}) \cdot \phi(\bar{r}_{s,i} | s_{s,i}) \\ & + \pi_{0s} \cdot \phi(\bar{r}_{b,i} | s_{b,i}) \cdot f_I(\bar{r}_{s,i} | s_{s,i}) \\ & + \pi_{bs} \cdot f_{\text{both}}(\bar{r}_{b,i}, \bar{r}_{s,i} | s_{b,i}, s_{s,i})\,. \end{aligned} \tag{5}$$

As in the previous sections, we again slightly abuse terminology and refer to densities as unconditional if they only condition on the volatility of estimation noise, s_{ki}. Denote the unconditional probability that an insider makes informed buys as $\pi_b = \pi_{b0} + \pi_{bs}$ and the probability that an insider makes informed sells as $\pi_s = \pi_{0s} + \pi_{bs}$. If insider i only has trades of type $k \in \{b, s\}$ in their history, the unconditional density function for their average abnormal returns $\bar{r}_{k,i}$ is:

$$f_k(\bar{r}_{k,i} | s_{k,i}) = (1 - \pi_k) \cdot \phi(\bar{r}_{k,i} | s_{k,i}) + \pi_k \cdot f_{\mathrm{I}}(\bar{r}_{k,i} | s_{k,i})\,. \tag{6}$$

This follows from equation (5), where we have marginalized over (integrated out) the unobserved dimension. Intuitively, this averages over all the unobserved values in that dimension, weighted by how likely each unobserved value is to occur. Note this model nests the univariate model discussed in Section 2.1. For an insider that only buys, the marginalized density in (6) for buys is the same as that in equation (1) in Section 2.1.

The model parameters to be estimated are $\Theta = \{\pi_{b0}, \pi_{0s}, \pi_{bs}, \mu\}$.[4] Consider a sample of N insiders where the first N_b insiders have only a buy history, the next N_s insiders have only a sell history, and the remaining $N - N_b - N_s$ insiders have both a buy and sell history. The likelihood function for the sample of average abnormal buy and sell returns of the N insiders conditional on the parameters and standard errors is:

$$\prod_{i=1}^{N_b} f_b(\bar{r}_{b,i} | s_{b,i}) \times \prod_{i=N_b+1}^{N_b+N_s} f_s(\bar{r}_{s,i} | s_{s,i}) \times \prod_{i=N_b+N_s+1}^{N} f_{bs}(\bar{r}_{b,i}, \bar{r}_{s,i} | s_{b,i}, s_{s,i})\,. \tag{7}$$

[4]Note that $\pi_{00} = 1 - \pi_{b0} - \pi_{0s} - \pi_{bs}$.

To estimate $\pi_{b0}, \pi_{0s}, \pi_{bs}$ and μ, we maximize (7) subject to the restrictions that $\{\pi_{b0}, \pi_{0s}, \pi_{bs}\} \in [0,1]^3$, $\pi_{b0} + \pi_{0s} + \pi_{bs} \leq 1$, and $\mu > 0$.

The bivariate mixture distribution allows us to estimate conditional probabilities that an insider belongs to each of the component distributions, $\tilde{\pi}_{b0,i}$, $\tilde{\pi}_{0s,i}$, and $\tilde{\pi}_{bs,i}$, respectively. The conditioning is on the insider's realized average abnormal buy and sell returns, standard errors, and the estimated parameters. The conditional probabilities that insider i makes informed purchases and informed sales are thus:

$$\begin{aligned} \tilde{\pi}_{b,i} &= \mathbb{E}\left[z_{b,i} \,|\, \bar{r}_{b,i}, \bar{r}_{s,i}, s_{b,i}, s_{s,i}, \Theta\right] = \tilde{\pi}_{b0,i} + \tilde{\pi}_{bs,i}\,, \\ \tilde{\pi}_{s,i} &= \mathbb{E}\left[z_{s,i} \,|\, \bar{r}_{b,i}, \bar{r}_{s,i}, s_{b,i}, s_{s,i}, \Theta\right] = \tilde{\pi}_{0s,i} + \tilde{\pi}_{bs,i}\,. \end{aligned} \tag{8}$$

Similarly, we can calculate the conditional expectation of insider i's profitability for purchases ($\tilde{\alpha}_{b,i}$) and informed sales ($\tilde{\alpha}_{s,i}$):

$$\begin{aligned} \tilde{\alpha}_{b,i} &= \mathbb{E}\left[z_{b,i}\alpha_i \,|\, \bar{r}_{b,i}, \bar{r}_{s,i}, s_{b,i}, s_{s,i}, \Theta\right] \\ \tilde{\alpha}_{s,i} &= \mathbb{E}\left[z_{s,i}\alpha_i \,|\, \bar{r}_{b,i}, \bar{r}_{s,i}, s_{b,i}, s_{s,i}, \Theta\right]\,. \end{aligned} \tag{9}$$

The calculations for the conditional probabilities and expectations are analogous to those described in Section 2.2, but are more complicated due to the two-dimensional nature of the data and the resulting additional mixture components relative to the univariate model. Details are presented in Appendix C.

2.4. 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 2024. We also use stock returns 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 buy trades by $j = 1, ..., n_{b,i}$ and their sell trades by $j = 1, ..., n_{s,i}$.[5] For trade j of trade direction k made by insider i on day t, we calculate a 21 trading day market-adjusted abnormal return

$$r_{kij} = D_{kij} \cdot \left(\prod_{\ell=1}^{21} (1 + r_{j,t+\ell}) - \prod_{\ell=1}^{21} (1 + r_{m,t+\ell}) \right) , \tag{10}$$

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

$$D_{kij} = \begin{cases} +1 & \text{for purchases } (k = b) \\ -1 & \text{for sales } (k = s) \, . \end{cases} \tag{11}$$

The mixture model described in Section 2.3 uses average abnormal buy and sell returns and their associated standard errors for each insider i as inputs to estimating parameters π_{b0}, π_{0s}, π_{bs}, and μ. We calculate the average abnormal return for insider i for trade direction $k \in \{b, s\}$ with any history $n_{ki} > 0$ as:

$$\bar{r}_{k,i} = \frac{1}{n_{k,i}} \sum_{j=1}^{n_{k,i}} r_{kij} \, . \tag{12}$$

We are interested in classifying the universe of trades made by insiders. In order to capture the expected estimation error in $\bar{r}$, we calculate a trade-specific volatility σ_{kij} using a GARCH(1, 1) model estimated on returns from the 63 days preceding the date of trade j. We use these to calculate the insider's standard error for the abnormal return of trade direction k:

$$s_{k,i} = \frac{\bar{\sigma}_{ki}}{\sqrt{n_{k,i}}} \, . \tag{13}$$

where $\bar{\sigma}_{ki}$ is the average of the trade-specific volatilities. Note that this will capture variation

[5]In our full-sample estimation, $n_{b,i}$ and $n_{s,i}$ are simply the total number of distinct buy and sell stock-date observations for insider i which can be zero if they have not made a buy (sell) yet. Our out-of-sample estimation estimates an annual time-series of π_{b0}, π_{0s}, π_{bs}, and μ using only past available data. For this analysis, $n_{b,i}$ and $n_{s,i}$ are the total number of distinct buy and sell stock-date observations for insider i as of the year-end of the estimation.

in volatility across time and across underlying securities.[6] To limit the effect of outliers, the sample is trimmed at the 1% and 99% levels of average abnormal returns before estimating the mixture model.

Table 1 reports distributional statistics of the average abnormal returns and estimated standard errors for buys and sells. The cross-section median and averages are positive for both buys and sell. The average $\bar{r}_b$ is 184 basis points. The average $\bar{r}_s$ is lower, but still sizable at 110 basis points. The fraction of average abnormal returns that are positive is similar across buys and sells (about 55%). Both $\bar{r}$ distributions exhibits slight positive skewness, consistent with some insiders trading on information using both trade type. There is substantial variation in the amount of estimation noise. The cross-sectional average standard error is 12.7% for buys and 8.3% for sells. The cross-sectional standard deviation of the standard error is also higher for buys than for sells. This suggests value in using an informed insider classification designed to explicitly account for estimation noise like the mixture model described in the previous sections.

2.5. Insider-Level Empirical Prevalence of Informed Insider Trading

Table 2 reports estimates of the mixture model described in Section 2.3. The fraction of insiders estimated to make informed purchases is 25.8% ($\hat{\pi}_b = \hat{\pi}_{b0} + \hat{\pi}_{bs}$). A smaller fraction, 9.7%, are estimated to make informed sales ($\hat{\pi}_s = \hat{\pi}_{0s} + \hat{\pi}_{bs}$). We estimate that only 2.1% of insiders make both informed buys and sales ($\hat{\pi}_{bs}$). The average abnormal profitability by insiders who trade on information, $\hat{\mu}$, is 5.2% per month.

The bivariate mixture structure allows for potential correlation in whether an insider uses information across buys and sells:

$$\text{corr}(z_b, z_s) = \frac{\pi_{bs} - \pi_b \pi_s}{\sqrt{\pi_b(1-\pi_b)\pi_s(1-\pi_s)}}. \tag{14}$$

Empirically, the implied correlation is -1.3%, indicating that informed trading using buys and sells is essentially uncorrelated. Therefore, based on past profitability alone, knowing if

[6] An alternative is to use the standard error calculated from realized returns. This would necessitate a reduction in sample size, but may also result in artificially low standard errors if the return windows overlap across trades.

an insider makes informed buys tells you no information about if they make informed sells, and vice versa.

The ability to estimate the latent relation between insiders' propensities to make informed buys and sells is novel to the literature. The small but negative correlation is important for understanding the nature of informed trade. In particular, it speaks to the possibility that firm insiders are not trading on private information, but instead are just better at interpreting public information. That is, they are just better 'stock pickers,' and we would expect to observe similar outperformance in trades of other stocks if they were observable. The fact that there is little correlation between informed buys and sells is inconsistent with this view, as it is not clear why a good 'stock picker' would only be skilled in one direction.

In addition to the full-sample estimation, we also estimate the model on expanding windows. Specifically, the mixture model is estimated annually using the latest average abnormal returns and standard errors for each insider with any trades made prior to that year's end. The time-series of $\hat{\pi}_b$, $\hat{\pi}_s$, and μ are plotted in Figure 3. There is some variation in the fraction of insiders making informed buys, with a brief reduction in the late 1990s before a steady rise over the remainder of the sample. The fraction of insiders making informed sales is more stable at around 10% throughout the sample. The average magnitude of the profitability has generally been between 5% and 6%. It has varied a bit over time, dropping from above 5% in the late 1980s to slightly below 5% in the mid-1990s before rising to over 6% in the early 2000s. After that, there has been a fairly steady but moderate decline in the magnitude of utilized information.

3. Out-of-Sample Predictability and Learning by Market Participants

In this section, we consider the out-of-sample performance of our mixture model estimates. To do so, we use the annual π_{b0}, π_{0s}, π_{bs}, and μ time series estimates using expanding windows described above to calculate a conditional expectation (3) of insider informed trade for each insider with at least one prior buy or sell trade prior to a given year-end. Insiders who have at least one buy (sell) are sorted into quintiles by the respective conditional expectation. We then test whether trades made by insiders with higher buy and sell conditional expectations, (9), predict returns using both predictive regressions and portfolio analyses.

3.1. Regression Analysis

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 that given stock. For instance, Buy Quintile 5 (Sell Quintile 5) is an indicator variable for whether any insider in the top quintile of the buy (sell) 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 buy or sell 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 buy or sell insider conditional expectation. As is standard, we control for a stock's market capitalization, book-to-market ratio, and lagged monthly and annual returns. We consider specifications both with (even-numbered columns) and without (odd-numbered columns) year-month fixed effects.

There is a substantial cross-sectional spread in future returns as a function of buying activity by insiders across conditional expectation quintiles. Without year-month fixed effects, the difference in future returns for stocks with buying activity by top-buy-quintile insiders relative to bottom-buy-quintile insiders is 92 basis points per month, or about 11% per year. The predictability remains just as strong with the inclusion of year-month fixed effects. The differences are statistically significant at the 1% level.

Selling activity also results in a cross-sectional spread in future returns as a function of an insider's ex-ante sell conditional expectation quintile (columns (3) and (4)). The Lo-Hi spread is about 37 bps per month without year-month fixed effects and 32 bps per month with fixed effects. These differences of around 4% per year 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 using buys and/or sells.

It is natural to ask how the mixture model approach compares to alternative methods that account for estimation noise differently. In the extreme, the econometrician could ignore the noise in the past average return and simply sort insiders based on their past average profitability, $\bar{r}_{ki}$ for $k \in \{b, s\}$. Alternatively, one could instead scale average returns by their standard error, sorting insiders by the t-statistic of their past profitability, $\bar{r}_{ki}/s_{ki}$. Panels A and B of Table 4 report Hi-Lo spreads when the sorting uses either past average returns or t-statistics, respectively, for buys and sells, following the specification of column (6) in Table 3. Panel C reports the results from the mixture model for ease of comparison. For buys, there are statistically significant cross-sectional differences in subsequent performance, even using past average buy returns. However, the economic magnitude of the difference is half that achieved by the mixture model (45 bps versus 91 bps per month), and the statistical significance is orders of magnitude weaker.

For sells, there is no predictive spread between Hi-Lo insiders for past average returns (Panel A); any information in past average returns alone is swamped by the noisiness of return histories. Even classifying insiders on the basis of past sell t-statistics (Panel B) is still too noisy, though the sign is now correct. By comparison, the mixture model's use of information from the cross-section of insider profitability and noise substantially improves the predictive power of insider sales (Panel C). t-statistics shrink towards a null of zero profitability, whereas our methodology shrinks towards the unconditional mixture distribution estimated from the cross-section of insiders. Therefore, shrinkage and using the information recovered from the cross-section of insiders is important in efficiently measuring informed trade, particularly for sales where there is a greater ex-ante reason to expect uninformed trading for liquidity motives.

3.2. Portfolio Analysis

An alternate way to test the predictive power of the mixture model estimates is to assess the abnormal performance of portfolios formed based on the trading activity of insiders with different ex-ante conditional expectations. Each year, we sort insiders into quintiles based on their conditional expected profitabilities for buys and sells, $\alpha_{b,i}$ and $\alpha_{s,i}$. We then form two sets of portfolios, one for buy transactions and one for sell transactions. A stock from a given buy trade enters the buy portfolio corresponding to the insider's $\alpha_{b,i}$ quintile in the month following the trade and is held for one month. The sell portfolios are formed analogously. Each portfolio is equal-weighted by insider-stock observations within it and is rebalanced each month based on the trading activity of insiders in that month. Note this is an out-of-sample exercise as the conditional expectation quintiles are formed using information about the insiders that is available as of the prior year's end for a given portfolio formation month.

Table 5 reports abnormal returns under various benchmark models for each of the 10 portfolios. The benchmark models are a market model benchmark, a three-factor Fama and French (1993) model augmented with a momentum factor (Carhart, 1997), and the five-factor Fama and French (2015) plus momentum model. For each conditional expectation quintile, the table also reports returns of the Buy minus Sell hedge portfolio.

Across all return measures and all conditional expectation quintiles, the point estimates of the Buy-Sell portfolios are positive, consistent with stronger buying activity by insiders predicting better subsequent performance than their selling activity. The economic magnitude of the Buy-Sell abnormal performance is increasing in the quintile of conditional expectations. Regardless of the benchmark model used, the economic magnitude of the Buy-Sell abnormal performance is just under 2% per month for the top quintile of conditional expectation. These results show that the mixture model is able to separate insiders who are more or less likely to trade using their information advantage. The results also show that sorting on the conditional expectation α_k results in differences in subsequent performance for both buys and sells, as in the regression analysis. The difference in High-Minus-Low performance is approximately 1% per month for buys and between 23 and 35 basis points per month for sales.

In Table IA.1 of the Internet Appendix, we report results for value-weighted portfolios. Regardless of the benchmark model used, the economic magnitude of the Buy-Sell abnormal performance is above 50 bps per month for the top quintile of conditional expectation and remains statistically significant. Sorting on conditional expectation α_s for sells does not spread subsequent returns when value-weighting, suggesting that informed sales disproportionately occur in small market capitalization stocks. The difference in performance for the High-Minus-Low α_b portfolio remains economically and weakly statistically significant at about 51–62 bps per month for buys.

3.3. Learning by the Market

We have shown that an econometrician can learn through a trader's return history, in conjunction with information from the cross-section of insider histories, which insiders are more or less likely to trade on information. Indeed, other proxies for this heterogeneity exist (e.g., whether an insider routinely trades in the same month each year as in Cohen et al. (2012)). We now turn to the extent to which the market has learned about this heterogeneity over time.

Figure 4 shows cumulative returns from several of the monthly portfolio strategies discussed above. The top panel of Figure 4 reports cumulative returns for hedge portfolios that buy stocks with past purchases and sell stocks with past sales. The black solid (red dashed) line represents this strategy for insiders in the top (bottom) quintile of ex-ante conditional expectations. The bottom panel reports the cumulative performance for hedge portfolios that either (1) buy the top $\tilde{\alpha}_{b,i}$ quintile's buys and shorts the bottom $\tilde{\alpha}_{b,i}$ quintile's buys (black solid line) or (2) buy the top $\tilde{\alpha}_{s,i}$ quintile's sells and shorts the bottom $\tilde{\alpha}_{s,i}$ quintile's sells (red dashed line), or (3) buys the first hedge portfolio of buys and shorts the second hedge portfolio of sells (blue dashed-dotted line).

Visual inspection of the cumulative returns indicates that these portfolio strategies performed well for the first 15 to 20 years or so of the sample but that the performance has been flatter since the mid-2000s. Interestingly, this coincides with the time the influential Cohen et al. (2012) paper was circulating.

This raises the question of whether the prevalence of informed insider trades has declined over time. To answer this, we estimate the insider-level mixture model on 10-year rolling windows. That is, we take insider-level average abnormal returns using the trades in a given 10-year window. These estimates are plotted in Figure IA.1 of the Internet Appendix. The fractions of insiders using information for buys, π_b, was actually increasing in the 2000s, while the fraction of insiders using information for sells, π_s, was fairly constant. The mean of informed trading has declined from about 6% in the decade ending in 2000, but has remained economically meaningful for all decades. Overall, there is still a substantial amount of informed trade by corporate insiders in the latter part of the sample.

What then can explain the reduced predictability at the monthly frequency over the last decade? We hypothesize that increased information acquisition and learning by market participants about which insiders trade on information has reduced the time horizon for market prices to reflect information embedded in insider trading activity. Below, we test this hypothesis. First, we show that portfolios double-sorted on an insider's ex-ante conditional expectation and buying or selling indicators are much more profitable if positions are rebalanced more frequently than the monthly horizon typically employed in the insider trading literature. Second, we provide evidence of dramatically increased information acquisition by sophisticated financial institutions around the same time the monthly strategy performance declines.

3.3.1. Higher Frequency Portfolio Formation

One potential explanation for the reduced profitability in the later part of the sample is that information is being incorporated into prices faster than at the monthly frequency at which portfolios are formed. To test this, we form portfolios as in the previous section, but with portfolio formation occurring daily. To gauge how quickly information is incorporated into prices, we vary the delay with which a stock enters the daily portfolio. Specifically, we consider portfolios that wait 1, 3, or 5 days post-trade to include a stock in the portfolio.[7] In each case, the stock exits the portfolio 20 trading days after the trade date.

The cumulative returns of these three portfolio formation delays for the high conditional expectation Buy-Sell portfolio are shown in Figure 5. As expected, the profitability is lower

[7] Until 2002, insiders had 10 days to file a Form 4 after a trade. Part of the Sarbanes-Oxley Act in 2002 reduced the reporting window to 2 days. Since trades need not be disclosed until 2 days after the trade, the first portfolio is not tradeable. Our objective is to show that the information embedded in insider trades is still economically material, not to demonstrate whether an investor could implement the portfolio.

if more time elapses before a stock enters the portfolio, particularly for the latter half of the sample.[8] This is consistent with faster convergence to market efficiency with respect to the information embedded in insider transaction reports.

3.3.2. Information Acquisition

In this section, we provide evidence of dramatic increases in information acquisition of insider trade disclosures by sophisticated investors. Several recent papers study information acquisition of public disclosures from the SEC website and their relation to investment performance and market efficiency (e.g., Chen, Cohen, Gurun, Lou, and Malloy, 2020a; Chen, Kelly, and Wu, 2020b; Crane, Crotty, and Umar, 2023). We follow the methodology in Crane et al. (2023) in identifying institutional information acquisition of Form 4 insider trading disclosures from the SEC EDGAR search logs.

Given the reduced profitability of monthly portfolios in the 2000s, we are interested in changes in information acquisition around this time. We focus on financial institutions that engage in large amounts of EDGAR activity (defined as having at least 200 days of EDGAR activity within at least one year and at least 50 daily downloads each day within that year). We identify a number of firms that exhibit dramatic increases in direct information acquisition of insider trade disclosures from EDGAR in the time period preceding publication of Cohen et al. (2012).

Figure 6 shows a time series of the number of weekly downloads of insider trade reports for a set of financial institutions that exhibited large increases during this time. These firms include some of the most sophisticated asset managers, including firms like D.E. Shaw and Renaissance Technologies. The structural break for some of these firms entails an initial set of extremely large-scale downloads (likely for historical database creation) followed by a fairly steady increased level of periodic downloads. Given this increased information acquisition by sophisticated investors, it is not surprising that the information embedded in insider trade disclosures is more quickly incorporated into prices over the subsequent years.

[8] Table IA.2 in the Internet Appendix shows the abnormal performance for the 3-day-delay daily portfolios is both economically and statistically significant in the period following 2012, the publication year of Cohen et al. (2012).

4. Relation 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 probability and expectation measures 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 has not been 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; insiders with some buying and selling activity within the year are classified as either medium- or short-term insiders. High quarterly earnings announcement (QEA) profitability insiders are those who trade ahead of quarterly earnings announcements and whose pre-QEA trades are associated with the highest quintile of QEA-window profitability.

We first show how the mixture model estimates relate to existing measures and that our estimates provide incremental information about the informativeness of insider-informed trading. We then show how our methodology can be generalized to incorporate these alternative proxies, and the importance of using the full sample of insiders.

4.1. Comparison to Existing Proxies of Informed Corporate Insiders

We first consider how the mixture model's conditional probability estimates $\tilde{\pi}_{b,i}$ and $\tilde{\pi}_{s,i}$ correlate with these measures. The results are reported in Panel A of Table 6. In general, we find positive and significant correlations between each proxy and the conditional probabilities, with the exception of the conditional probability of using information on buys for non-routine insiders. In percentage terms, the strongest relationship is for $\tilde{\pi}_{s,i}$ and short-termism. With increasing levels of short-termism, the conditional probability $\tilde{\pi}_{s,i}$ rises, consistent with Akbas et al. (2020). Medium-horizon insiders have 1% higher $\tilde{\pi}_{s,i}$, and short-horizon insiders have 2% higher $\tilde{\pi}_{s,i}$, compared to a baseline of 5% for long-horizon insiders.

Each of the proxies is also associated with higher mixture model conditional expectations ($\tilde{\alpha}_{b,i}$ and $\tilde{\alpha}_{s,i}$) as well (Panel B of Table 6).The spread in conditional expectation explained by existing proxies is strongest for short-horizon insiders insiders who buy. Long-horizon insiders have an average $\tilde{\alpha}_{b,i}$ of 118 bps; short-horizon insiders' average additional $\tilde{\alpha}_{b,i}$ is 38 bps, or about 30% higher. Top quintile QEA profitability insiders exhibit conditional expectations that are 29 bps higher than those of the remaining four quintiles for $\tilde{\alpha}_{b,i}$ and 19 bps higher than those of the remaining four quintiles for $\tilde{\alpha}_{s,i}$.

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 $\tilde{\pi}_k$ and $\tilde{\alpha}_k$. This suggests that our measures are capturing different information than prior work. To test this conjecture, we include these proxies in our out-of-sample predictability analysis.

Table 7 tabulates these out-of-sample results. When prior proxies are included as controls, they have little effect on the predictability of the mixture model conditional expectations $\tilde{\alpha}_k$. The economic and statistical significance of the differences in Hi-Lo coefficients are unchanged. On the other hand, controlling for the conditional expectations also has only modest effects on the profitability of the alternative proxies. This is consistent with the mixture model capturing independent information relative to existing proxies.

One advantage of our methodology relative to prior work is our ability to classify all insiders. The regressions in Table 7 also include indicator variables for buys and sells made by insiders that are unclassified by each of the prior proxies due to required sample filters. The estimated coefficients are instructive about the potential information lost due to data requirements of prior proxies. For all three proxies, buys (sells) made by unclassified insiders significantly predict future higher (lower) stock returns. This implies that there is more informed trading by corporate insiders than previously implied by the literature, which we take a further look at in the next section.

Cline et al. (2017) also uses an insider's return history to classify persistently profitable insiders, defined as insiders with more than 50% of their trades having positive signed abnormal returns over the prior 36 months. They require at least three unique months with trades in this 36 month period. In Table IA.3 of the Internet Appendix, we show similar results for their proxy as for the others in Table 7. In particular, the mixture model conditional expectations continue to strongly predict future returns controlling for their measure, as do trades made by insiders not classified under their methodology.

4.2. Incorporating Existing Measures into the Mixture Model

It is possible to incorporate an alternate proxy into the mixture framework. An existing proxy either classifies an insider as (1) one who uses informed, (2) one who does not use information, or (3) one that is not classified either way due to the insider not satisfying sample screens. Denote indicator variables for these three mutually exclusive classifications as $\mathbf{1}_{\text{Informed},i}$, $\mathbf{1}_{\text{Uninformed},i}$, and $\mathbf{1}_{\text{Unclassified},i}$, respectively. In the mixture model, we can parameterize the probability that an insider i makes informed buys and/or sells using these variables as:

$$\pi_{\ell,i} = \frac{\exp\left(\beta_{1,\ell}\mathbf{1}_{\text{Informed},i} + \beta_{2,\ell}\mathbf{1}_{\text{Uninformed},i} + \beta_{3,\ell}\mathbf{1}_{\text{Unclassified},i}\right)}{1 + \exp\left(\beta_{1,\ell}\mathbf{1}_{\text{Informed},i} + \beta_{2,\ell}\mathbf{1}_{\text{Uninformed},i} + \beta_{3,\ell}\mathbf{1}_{\text{Unclassified},i}\right)}, \tag{15}$$

for $\ell \in \{b0, 0s, bs\}$. This essentially results in distinct mixing probabilities for each classification.

Table 8 reports estimates of this extended model for each of the alternative proxies considered in Tables 6 and 7. Consistent with the existing literature, the estimated $\pi_{\ell,i}$'s are generally higher for the informed classification than the estimated $\pi_{\ell,i}$'s for the uninformed classification (equivalently, the uninformed probability π_{00} is lower for the informed classification). The estimation provides several novel facts. First, insiders that are unclassified based on existing work exhibit non-trivial probabilities of using information. These fractions range from 31% (AH) to 38% (CMP).[9] Second, the probability an insider uses information for sales is relatively high for unclassified insiders. For instance, the estimates of π_s for unclassified insiders across the three panels are 14.1%, 10.1% and 7.9%. These are all substantially higher

[9]It is worth noting that a substantial fraction of traders are unclassified by prior literature. Given the amount of unclassified traders who do sometimes make informed trades, it is important to consider these traders when studying insider trading.

than for the uninformed category for all three proxies and even exceed the corresponding π_s estimates for the "informed" category defined using non-routine or short-horizon proxies. Finally, while the insiders classified as "uninformed" by existing proxies have lower propensities to trade on information, their estimated $\pi_{\ell,i}$'s are non-zero. A significant fraction of these insiders also engage in informed trade.

We use these proxies to parameterize $\pi_{\ell,i}$'s to demonstrate this generalization of the model and to compare it to existing work. A regulatory agency may be interested in including additional characteristics of insiders, such as those considered in Section 5.4.

5. Detecting Which Trades Are Informed

5.1. A Trade-Level Mixture Model

In this section, we are interested in classifying whether any *individual* trade made by an insider was potentially informed or not. To do so, we estimate a probabilistic model that leverages each insider's return history and the cross-section of returns up to that point. Specifically, we use the expanding window estimates of the insider-level mixture distribution and each insider i's average returns $\bar{r}_{k,i}$ and standard error $s_{k,i}$ for $k \in \{b, s\}$ to calculate conditional probabilities that an insider makes informed trades on trade direction k, $\tilde{\pi}_{k,i}$. Let z_{kij} be a latent indicator for whether the j^{th} trade of trade direction k made by insider i uses information of magnitude α_{kij}. We model this individual trade's return, r_{kij}, as:

$$r_{kij} = z_{kij}\alpha_{kij} + \varepsilon_{kij}\,. \tag{16}$$

We assume that ε_{kij} is normally distributed with mean zero and standard deviation σ_{kij}. This trade-specific volatility is estimated using the GARCH(1, 1) model described in Section 2.4.

We use the history of trades to inform the probability that an insider uses information (i.e., $z_{kij} = 1$). Denote the probability that $z_{kij} = 1$ as p_{kij}. Note that this probability varies depending on whether the trade is a purchase ($k = b$) or a sale ($k = s$). For both trade types, we also let p_{kij} vary as a function of the insider's conditional probability of using information, $\tilde{\pi}_{k,i}$. This allows the insider's past history of trades to inform the model. For insiders trading for the first time, we use the estimated π_k, the unconditional estimate, as the insider's $\tilde{\pi}_{k,i}$ estimate, which implicitly utilizes information from the history of the cross-section of past traders. We model the probability that $z_{kij} = 1$ as:

$$p_{kij} = \frac{\exp(a_k + b_k \tilde{\pi}_{k,i})}{1 + \exp(a_k + b_k \tilde{\pi}_{k,i})} \,. \tag{17}$$

The coefficients a_b, b_b, a_s, and b_s are parameters that we estimate via maximum likelihood. In calculating $\tilde{\pi}_{k,i}$ in equations (8), we estimate π_{b0}, π_{0s}, π_{bs}, and μ in expanding annual windows, and we use trade-by-trade updating of $\bar{r}_{k,i}$ and $s_{k,i}$.

The insider-level model also helps to inform the distribution of α_{kij} conditional on the insider making an informed trade. For insiders trading for the first time ($j = 1$), the conditional distribution is simply the unconditional distribution of informed trade; that is, exponential with mean μ/p_{kij}.[10] For insiders with a past history of trades of type k ($j > 1$), the conditional distribution of α_{kij} is $f_{\alpha|\bar{r}_{k,i}}$, which is a truncated normal distribution with normal mean of $\bar{r}_{k,i} - s_{k,i}^2/(\mu/p_{kij})$ and standard deviation $s_{k,i}^2$.[11] Let $h_{\mathrm{I}}(r|\sigma, p)$ denote the distribution of r conditional on an informed trade ($z = 1$). Thus, $h_{\mathrm{I}}(r|\sigma, p)$ is either the distribution of a sum of an exponential random variable and a normal random variable ($j = 1$) or the distribution of a sum of a truncated normal random variable and a normal random variable ($j > 1$). In Appendix D, we show that the latter can be expressed in closed form, which substantially eases the computational burden of estimating the trade-level model.

The likelihood of observing return r_{kij} is a mixture:

$$h\left(r_{kij}|\sigma_{kij}, p_{kij}\right) = (1 - p_{kij}) \cdot \phi(r_{kij}|\sigma_{kij}) + p_{kij} \cdot h_{\mathrm{I}}(r_{kij}|\sigma_{kij}, p_{kij}) \,. \tag{18}$$

[10] Note that we have scaled the conditional mean parameter μ by p_{kij}. Recall that the estimate of μ captures the *average* abnormal return across trades of type k. In the trade-level model, this average can be approximated as the product of the probability a given trade is informed (p_{kij}) and a trade-level conditional mean. Thus, we use a trade-level conditional mean of μ/p_{kij}.

[11] Note that in the trade model, we are ignoring learning about the magnitude of information in buys contained in a insider's sell history and vice versa. We thus are taking a quasi-maximum-likelihood approach relative to the trade-model implied by the insider-level model. We do so for several reasons. The first reason is technical: the distribution of α_{kij} would be a mixture of two slightly different truncated normal distributions, which would entail numerical integration when convoluted with the noise distribution. The second reason is practical: the empirical estimate for π_{bs} is fairly small, so the approximation error of using a single truncated normal should be small.

We estimate the trade-level model via maximum likelihood using a sample of insider trades from 1985 through 2024. The estimated coefficients in Equation 17 are $\hat{a}_b = -1.92$, $\hat{b}_b = 2.06$, $\hat{a}_s = -2.75$, $\hat{b}_s = 3.92$. For both buys and sells, the estimated trade-level probability increases with the ex-ante probability $\tilde{\pi}_{k,i}$ that an insider uses information. The estimated trade-level probability p_{kij} is higher for buys than for sells for most empirically observed levels of $\tilde{\pi}_{k,i}$. The estimated functional form of p_{ij} is displayed in Figure IA.2 of the Internet Appendix.

To classify whether a given trade was likely informed, we calculate the conditional probability that $z_{kij} = 1$:

$$\tau(r_{kij}|\sigma_{kij}, p_{kij}) = \frac{p_{kij} \cdot h_{\mathrm{I}}(r_{kij}|\sigma_{kij}, p_{kij})}{(1 - p_{kij}) \cdot \phi(r_{kij}|\sigma_{kij}) + p_{kij} \cdot h_{\mathrm{I}}(r_{kij}|\sigma_{kij}, p_{kij})}. \tag{19}$$

An econometrician (or regulator) can choose a threshold probability above which one classifies trade r_{kij} as potentially informed. For instance, the model suggests that trades with $\tau(r_{kij}|\sigma_{kij}, p_{kij}) > 0.5$ are more likely informed than uninformed. Regulators with a limited investigative and enforcement budget might choose a higher threshold when considering which trades to investigate further.

5.2. Conditional Probabilities and Return Thresholds

An important feature of this model for insider trades is that the conditional probability a trade is informed is customized to each insider based on their history of returns (as well as indirectly on the history of other insiders through the estimates of Θ). We demonstrate graphically how the function τ varies as a function of an insider's historical average realized return and return standard deviation. Figure 7 plots the conditional probability (19) as a function of the realized trade return r_{kij}. The figure reports the probability conditional on an insider's past average abnormal return $\bar{r}_{ki}$ and the trade-level standard deviation σ_{kij}, which we assume equals the past average return standard deviation $\bar{\sigma}_{ki}$ for simplicity.

As is natural, higher realized returns translate into higher conditional probabilities that a given trade was informed. Each panel fixes the return standard deviation and whether the trade was a purchase or a sale. Consider the top left panel, which considers a purchase of a stock with a standard deviation of 10% made by an insider with a history of 5 buys. An insider's past average return is informative about whether a given trade was informed.

For an insider with a past average return of zero, the current trade return would need to be over 40% for the model to classify the trade as likely informed ($\tau_{kij} > 0.5$). This threshold is higher (lower) for insiders who have lost (gained) 5% on average on their past purchases. For sales, these differences increase, and even higher returns are needed to classify the trade as informed (compare the top and bottom rows). This is because the estimated ex-ante probability that a sale is informed, p_{sij}, is lower than that for a purchase, p_{bij}.

The effect of an increase in the noisiness of stock returns is to shift the conditional probability curves to the right (compare the left columns to the right column of Figure 7). With more noise in the trader's history, the model requires a higher current trade return r_{kij} to reach the same conditional probability level that the current trade was informed.

An alternative way to visualize these relations is shown in Figure 8, which plots the trade-level return thresholds at which the current trade is classified as likely informed ($\tau_{kij} > 0.5$). This corresponds to a preponderance-of-evidence burden of proof. Each panel plots the thresholds as a function of an insider's historical average return ($\bar{r}_{ki}$) and of the standard deviation of the insider's past trade returns, $\bar{\sigma}_{ki}$. The low, median, and high $\bar{\sigma}_{ki}$ levels correspond to the 10th, 50th, and 90th percentiles of empirical trade-level standard deviations for a given (binned) past average return. The top (bottom) panel shows thresholds for purchases (sales).

Empirically, $\bar{\sigma}_{ki}$ is strongly positively correlated with the absolute value of the past average returns; more extreme $\bar{r}_i$'s are associated with noisier underlying returns. As described above, the return threshold generally declines in past average return but increases in past return standard deviation. For insiders with negative past average returns, these two effects work in the same direction, and the return threshold declines as past average returns become less negative. For insiders with positive past average returns, however, the two effects work in opposite directions. As a result, the threshold for median $\bar{\sigma}_{ki}$ still declines with increasing $\bar{r}_{ki}$, but it does so at a lower rate than for insiders with negative $\bar{r}_{ki}$. For insiders with high levels of $\bar{\sigma}_{ki}$, the noise effect can dominate the past average return effect, leading to an increase in the threshold as $\bar{r}_{ki}$ increases.

One thing to note from these figures is that for some histories, the return threshold can be very high. This is particularly true for insider sales. This is because insiders generally have a limited trading history, and it is usually fairly noisy as well. For an insider with a past average return of zero with 10 trades that had a median return standard deviation, a current purchase would need an abnormal return of almost 50% over the next month to be classified as likely informed. Theory by Huddart et al. (2001) shows insiders may dissimulate, i.e., sometimes trade contrary to their information, if trades are disclosed publicly. Our results show that dissimulation will result in higher empirical return thresholds needed to classify a given trade as informed if dissimulation results in more moderate $\bar{r}_{ki}$.

5.3. Trade-Level Conditional Probabilities of Informed Insider Trade

We calculate the trade-level conditional probability τ_{ij} from equation (19) for a sample of *all* insider trades from 1985 through 2024. The probability depends on the estimates of a_b, b_b, a_s, and a_b (reported in Section 5.1) and on population parameters Θ estimated using expanding windows using all data up until the prior year-end (plotted in Figure 3).

Figure IA.3 plots histograms of insider-specific inputs to the conditional probability calculation: the trade abnormal return r_{kij} (Panel (a)), the predicted trade-level standard deviation σ_{ij} (Panel (b)), the past average abnormal return $\bar{r}_{ki}$ of an insider's past buy or sell trades (Panel (c)), and the standard error s_{ki} of an insider's past buy or sell trades (Panel (d)). There is considerable heterogeneity in trade abnormal returns. There is a slight asymmetry toward positive abnormal returns, but the most populated bins are around zero abnormal return. The past average abnormal return distribution (Panel c) is naturally much less dispersed than the trade-level return distribution. In general, there is substantial dispersion in predicted trade-level standard deviation reflecting the noisiness of stock returns. The trade-level mixture model will take this underlying noise into account in estimating informed trade at the individual trade level. Finally, the standard errors of return histories are substantially less noisy than the trade-level standard deviations, reflecting the fact that some insiders have a substantial number of past trades.

Table 9 reports averages of the conditional probabilities τ and as well as an indicator for whether a trade is classified as likely informed ($\tau > 0.5$). The average conditional probability is about 12.5%, and only 3.6% of trades are likely informed. Consistent with prior work, the probability that a given trade is informed is strongly related to whether the trade is a purchase or a sale. The average conditional probability is higher for buys (20%) than for sales (9%), and about 6.3% of buys clear the 0.50 threshold compared to only 2.4% of sales. We also report summary statistics as a function of the number of past trades. The conditional probability increases with the number of past trades.

5.4. Applications of Trade-level Conditional Probabilities

The trade-level conditional probabilities allow researchers to explore economic questions of interest related to corporate insider trading. Table 10 reports regression results of the conditional probabilities for buys or sells on characteristics of the trade that are likely to relate to the trade's information content.

Pre-scheduled 10b5-1 trading plans are one potential policy remedy to mitigate informed trading by corporate insiders. These plans are not without controversy, however, as insiders may strategically cancel planned trades (Jagolinzer, 2009; Lenkey, 2019). Our results suggest that purchases made under the 10b5-1 plans are more informed than other purchases, while 10b5-1 sales are not significantly more or less informed than other sales. The conditional probability of 10b5-1 purchases is not elevated when we include insider-level fixed effects, suggesting that insiders who make informed 10b5-1 purchases also make informed non-10b5-1 purchases.

Trades in smaller market capitalization firms are more likely to be informed, particularly for sales. This is consistent with the previous portfolio analyses, which showed that performance was stronger under equal-weighting compared to value-weighting.

Results are heterogeneous across buys and sales with respect to the magnitude of the trade in dollars as well as the predicted trade-level standard deviation. Larger-sized purchases are more likely to be informed, while larger sales are slightly less likely to be informed. This is consistent with markets interpreting larger sales as more likely to be liquidity-motivated. Similarly, buys made in more volatile stocks are more likely to be informed, while sales made in more volatile stocks are less likely to be informed.

For sales, we are also able to control for whether or not the selling is related to an option position. Option-related sales are less likely to be informed, consistent with insiders diversifying following option vesting. Most of this relation is due to cross-sectional differences across insiders, as the point estimate flips signs when insider fixed effects are included.

We also consider whether sustained trading by an insider or correlated trading by others at the same firm is related to elevated adverse selection due to insiders. For both buys and sells, sustained trading by an insider is positively related to an elevated probability of an informed insider trade. There does not seem to be a strong relation between other insiders trading and the probability of an informed trade. Buys are slightly more likely to be informed if others at the firm are also buying, while sells are less likely to be informed if others at the firm are also selling. This suggests that clustered selling is likely liquidity-driven.

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 private 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. While prior work documents that the profitability of some types of insiders' trades is higher (e.g., CFOs' Wang et al., 2012), it is still unclear how this relates to the prevalence of informed trade at the transaction level. That is, is the CFOs' outperformance due to consistent information-based trading, or is it due to occasional valuable trades mixed in among liquidity-driven transactions? While this distinction is key to understanding the adverse selection issues inherent in markets, it is challenging to address without a trade-level measure of informed trading. Using the roles in the firm as disclosed on Form 4s, we test if likely informed trades are a function of their role. The results for buys and sells are tabulated in Table 11.

Both buys and sells made by CEOs are more likely to be informed. Buys made by CFOs and chairmen are also more likely to be informed buys. Interestingly, the insider characteristic most associated with informed trade is whether or not the insider holds a block of at least 10% of shares. The probability a purchase (sale) is informed is 4.5% (3.3%) higher for these insiders.

6. Conclusion

Corporate insiders have access to private information about their firms. We employ mixture model methods that leverage the cross-section of insiders and their trading histories to classify which insiders are likely trading on information and which trades are most likely to contain information. Importantly, these methods account for the significant amount of noise in trading performance. Out-of-sample tests confirm that our measures provide new economic content regarding the information embedded in trades by insiders identified as likely to trade on private information, even after controlling for prior literature's proxies.

Our model is able to classify all insiders and incorporates information on two dimensions of insider's profitability. It can also incorporate information from existing measures. When we augment our model with proxies from prior literature, we confirm that insiders classified as informed are indeed more likely to trade on private information. However, for some proxies, the substantial fraction of insiders excluded due to sample selection criteria appear just as likely to trade on information as those classified as informed.

Our insider-level model generates an insider-specific mixture model for trade returns, helping determine the likelihood any given trade was informed. We find that buys related to 10b5-1 plans are more likely to be informed, while option-related sales are less likely to be informed. Informed insider trade is more likely in smaller market capitalization stocks. Trades made by CEOs and inside blockholders are more likely to contain private information. Finally, the model's conditional probability of an informed trade can help regulators allocate enforcement resources more effectively when monitoring corporate insider trading.

Appendix A. Conditional Distributions of Observed Average Returns

The component distributions of the mixture model use the conditional probability of the observed average realized abnormal return(s). Here we provide details on the conditional distributions, f_{I} and f_{both}.

Appendix A.1. Analytical Expression for f_I

The density $f_{\mathrm{I}}(\bar{r}|s)$ is the distribution of the sum of an exponentially-distributed variable with mean μ and a zero-mean normal random variable with standard deviation s. This is known as an exponentially-modified normal variable. The density is the convolution of the exponential and normal densities:

$$f_{\mathrm{I}}(\bar{r}|s) = \int_{-\infty}^{\infty} g(\bar{r} - a; \mu) \cdot \phi(a|s) \; \mathrm{d}a \, , \tag{A.1}$$

where $\phi(\cdot|s)$ is the density of a mean-zero normal variable with standard deviation s and $g(\cdot;\mu)$ is the density of an exponential variable with mean μ. Equation A.1 can be written:

$$\frac{1}{2\mu} \exp\left(\frac{1}{2\mu}(s^2/\mu - 2\bar{r})\right) \cdot \mathrm{erfc}\left(\frac{s^2/\mu - \bar{r}}{\sqrt{2}s}\right) . \tag{A.2}$$

Appendix A.2. Analytical Expression for f_{both}

The density $f_{\mathrm{both}}(\bar{r}_b, \bar{r}_s|s_b, s_s)$ is an exponentially-modified bivariate normal density, which is the convolution of a bivariate normal density and an exponential density:

$$f_{\mathrm{both}}(\bar{r}_b, \bar{r}_s|s_b, s_s) = \int_{-\infty}^{\infty} g(a;\mu) \cdot \phi_2(\bar{r}_b - a, \bar{r}_s - a|s_b, s_s) \; \mathrm{d}a \, , \tag{A.3}$$

where $\phi_2(\cdot,\cdot|s_1, s_2)$ is the joint density of two mean-zero, uncorrelated normal variables with standard deviations s_1 and s_2. Equation A.3 can be written:

$$\frac{1}{2\mu\sqrt{2\pi}\sqrt{s_b^2 + s_s^2}} \exp\left(-\frac{\frac{-s_b^2 s_s^2}{\mu^2} + (\bar{r}_b - \bar{r}_s)^2 + \frac{2(s_s^2\bar{r}_b + s_b^2\bar{r}_s)}{\mu}}{2(s_b^2 + s_s^2)}\right) \cdot \mathrm{erfc}\left(\frac{\frac{s_b^2 s_s^2}{\mu} - s_s^2\bar{r}_b - s_b^2\bar{r}_s}{\sqrt{2}s_b s_s\sqrt{s_b^2 + s_s^2}}\right) . \tag{A.4}$$

Appendix B. Conditional Distributions of Latent Average Returns

Here we provide details on the conditional distributions, $f_{\alpha|\bar{r}}$ and $f_{\alpha|\bar{r}_b,\bar{r}_s}$.

Appendix B.1. Derivation of $f_{\alpha|\bar{r}}$

The density of α_i conditional on an insider trading on information and having a realized average return $\bar{r}_i$ is denoted $f_{\alpha|\bar{r}}$. We show here that $f_{\alpha|\bar{r}}$ is the density of a normal variable with a mean of $\bar{r}_i - s_i^2/\mu$ and standard deviation of s_i that is truncated below at zero.

Using more general notation, we are interested in the distribution of x conditional on w, where $w = x + y$ with x distributed exponentially with mean $\mu = 1/\lambda$ and y distributed normally with mean zero and standard deviation s. First, note that using Bayes' rule, we can write

$$f_{x|w}(x|w) = \frac{f_x(x) f_{w|x}(w|x)}{f_w(w)} = \frac{f_x(x) f_y(w-x)}{f_w(w)},$$

where the second equality follows from the fact that $f_{w|x}$ is just the distribution of y shifted by x. We plug in the functional forms of f_x and f_y to obtain

$$f_{x|w}(x|w) \propto \mathbf{1}[x > 0] \exp(-\lambda x) \exp\left(-\frac{(w-x)^2}{2s^2}\right). \tag{B.1}$$

We want to show that this can be written in the form of a univariate truncated normal density with normal mean $\tilde{m} = w - \lambda s^2$ and variance s^2 truncated below at 0.

With some algebra, equation (B.1) can be written

$$\propto \mathbf{1}[x > 0] \exp\left(-\frac{(x - (w - \lambda s^2))^2}{2s^2}\right), \tag{B.2}$$

which is the kernel of the conjectured distribution.

Appendix B.2. Derivation of $f_{\alpha|\bar{r}_b,\bar{r}_s}$

The density of α_i conditional on an insider making informed buys and sells ($z_{b,i} = 1, z_{s,i} = 1$) and realized average returns $\bar{r}_{i,b}$ and $\bar{r}_{s,i}$ is denoted $f_{\alpha|\bar{r}_b,\bar{r}_s}$. We show here that $f_{\alpha|\bar{r}_b,\bar{r}_s}$ is the density of a univariate normal variable with a mean of $\frac{\bar{r}_b s_s^2 + \bar{r}_s s_b^2 - \lambda s_b^2 s_s^2}{s_s^2 + s_b^2}$ and variance of $\frac{s_s^2 s_b^2}{s_s^2 + s_b^2}$ that is truncated below at zero.

Using more general notation, we are interested in the distribution of x conditional on w_b and w_s, where $w_b = x + y_b$ and $w_s = x + y_s$ with x distributed exponentially with mean $\mu = 1/\lambda$ and y_b and y_s distributed normally with mean zero and standard deviation s_b and

s_s, respectively. First, note that using Bayes' rule, we can write

$$f_{x|w_b,w_s}(x|w_b, w_s) = \frac{f_x(x) f_{w_b,w_s|x}(w_b, w_s|x)}{f_{w_b,w_s}(w_b, w_s)} = \frac{f_x(x) f_{y_b}(w_b - x) f_{y_s}(w_s - x)}{f_{w_b,w_s}(w_b, w_s)},$$

where the second equality follows from the fact that $f_{w_b,w_s|x}$ is just the distribution of y_b and y_s shifted by x. We plug in the functional forms of f_x, f_{y_b} and f_{y_s} to obtain

$$f_{x|w_b,w_s}(x|w_b, w_s) \propto \mathbf{1}[x > 0] \exp(-\lambda x) \exp\left(-\frac{(w_b - x)^2}{2s_b^2} - \frac{(w_s - x)^2}{2s_s^2}\right). \tag{B.3}$$

We want to show that this can be written in the form of a univariate truncated normal density with normal mean $\tilde{m} = \frac{w_b s_s^2 + w_s s_b^2 - \lambda s_b^2 s_s^2}{s_s^2 + s_b^2}$ and variance $\frac{s_s^2 s_b^2}{s_s^2 + s_b^2}$ truncated below at 0.

With some algebra, equation (B.3) can be written

$$\propto \mathbf{1}[x > 0] \exp\left(-\frac{(x - (\frac{w_b s_s^2 + w_s s_b^2 - \lambda s_b^2 s_s^2}{s_s^2 + s_b^2}))^2}{2\frac{s_s^2 s_b^2}{s_s^2 + s_b^2}}\right), \tag{B.4}$$

which is the kernel of the conjectured distribution.

Appendix C. Buy/Sell Model Conditional Probabilities and Expectations

Given estimates for π_{b0}, π_{0s}, π_{bs} and μ, the bivariate model for buy and sell abnormal returns allows calculations of the conditional probability that a particular insider i makes informed buys and/or sells, conditional on the insider's realized average abnormal returns $\bar{r}_{b,i}$ and $\bar{r}_{s,i}$, their standard errors $s_{b,i}$ and $s_{s,i}$, and the estimated parameters. Denote the conditional probabilities for the corresponding states as $\tilde{\pi}_{b0,i}$, $\tilde{\pi}_{0s,i}$, and $\tilde{\pi}_{bs,i}$.

Appendix C.1. Insiders with a history of both buys and sells

We first consider the case where an insider has a history of both buys and sells. The conditional probability that insider i makes informed buys, but not informed sells is:

$$\tilde{\pi}_{b0,i} = \frac{\pi_{b0} \cdot f_I(\bar{r}_{b,i}|s_{b,i}) \cdot \phi(\bar{r}_{s,i}|s_{s,i})}{f_{bs}(\bar{r}_{b,i}, \bar{r}_{s,i}|s_{b,i}, s_{s,i})}. \tag{C.1}$$

Similarly, the conditional probability that insider i makes informed sells, but not informed buys is:

$$\tilde{\pi}_{0s,i} = \frac{\pi_{0s} \cdot \phi(\bar{r}_{b,i}|s_{b,i}) \cdot f_I(\bar{r}_{s,i}|s_{s,i})}{f_{bs}(\bar{r}_{b,i}, \bar{r}_{s,i}|s_{b,i}, s_{s,i})} \,. \tag{C.2}$$

Finally, the conditional probability that insider i uses information for both buys and sells is:

$$\tilde{\pi}_{bs,i} = \frac{\pi_{bs} \cdot f_{\text{both}}(\bar{r}_{b,i}, \bar{r}_{s,i}|s_{b,i}, s_{s,i})}{f_{bs}(\bar{r}_{b,i}, \bar{r}_{s,i}|s_{b,i}, s_{s,i})} \,. \tag{C.3}$$

Let $\tilde{\mu}_{I_k,i}$ denote the expectation of insider i's profitability conditional on belonging to the informed component distribution for only a single trade type k (with conditioning on the realized $\bar{r}_{k,i}$, $s_{k,i}$, and the parameter values as well). Similarly, let $\tilde{\mu}_{\text{both},i}$ denote the expectation of insider i's profitability conditional on belonging to the group that uses information on both buys and sells. Note that the conditional expectation of insider i's information for trade type k is zero for any component where an insider does not use information for trade type k. Thus, the conditional expectations of the magnitudes of an insider's trading profitability for buys and sells, $\tilde{\alpha}_{b,i}$ and $\tilde{\alpha}_{s,i}$ (defined in equation (3)) are:

$$\begin{aligned} \tilde{\alpha}_{b,i} =& \tilde{\pi}_{b0,i}\tilde{\mu}_{I_b,i} + \tilde{\pi}_{bs,i}\tilde{\mu}_{\text{both},i} \\ \tilde{\alpha}_{s,i} =& \tilde{\pi}_{0s,i}\tilde{\mu}_{I_s,i} + \tilde{\pi}_{bs,i}\tilde{\mu}_{\text{both},i} \,. \end{aligned} \tag{C.4}$$

Recall from Section 2.2 and Appendix B.1 that $\tilde{\mu}_{I_k,i}$ is the mean of a truncated normal distribution $f_{\alpha|\bar{r}}$, where the underlying normal distribution has a mean of $\bar{r}_{k,i} - s_{k,i}^2/\mu$ and standard deviation of $s_{k,i}$ and the truncation is below at zero. Similarly, Appendix B.2 shows that $\tilde{\mu}_{\text{both},i}$ is the mean of a truncated normal distribution $f_{\alpha|\bar{r}_b,\bar{r}_s}$, where the underlying normal distribution has a mean of $\frac{\bar{r}_{b,i}s_{s,i}^2+\bar{r}_{s,i}s_{b,i}^2-s_{b,i}^2 s_{s,i}^2/\mu}{s_{s,i}^2+s_{b,i}^2}$ and variance of $\frac{s_{s,i}^2 s_{b,i}^2}{s_{s,i}^2+s_{b,i}^2}$, and the truncation is below at zero.

Appendix C.2. Insiders with a history of only one type of trade

The conditional expectations can also be calculated for insiders that only have a one-dimensional history. First, consider insiders that only have a sell history. In this case, the conditional probability that insider i makes informed buys, but not informed sells is:

$$\tilde{\pi}_{b0,i} = \frac{\pi_{b0} \cdot \phi(\bar{r}_{s,i}|s_{s,i})}{f_s(\bar{r}_{s,i}|s_{s,i})} \,. \tag{C.5}$$

Similarly, the conditional probability that insider i makes informed sells, but not informed buys is:

$$\tilde{\pi}_{0s,i} = \frac{\pi_{0s} \cdot f_I(\bar{r}_{s,i}|s_{s,i})}{f_s(\bar{r}_{s,i}|s_{s,i})} \,. \tag{C.6}$$

Finally, the conditional probability that insider i uses information for both buys and sells is:

$$\tilde{\pi}_{bs,i} = \frac{\pi_{bs} \cdot f_I(\bar{r}_{s,i}|s_{s,i})}{f_s(\bar{r}_{s,i}|s_{s,i})} \,. \tag{C.7}$$

The conditional expectations are thus:

$$\begin{aligned} \tilde{\alpha}_{b,i} &= \tilde{\pi}_{b0,i}\mu + \tilde{\pi}_{bs,i}\tilde{\mu}_{I_s,i} \\ \tilde{\alpha}_{s,i} &= (\tilde{\pi}_{0s,i} + \tilde{\pi}_{bs,i})\tilde{\mu}_{I_s,i} \,. \end{aligned} \tag{C.8}$$

Conditional probabilities and expectations are defined analogously for insiders that only have a buy history.

Appendix D. Normally-Modified Truncated Normal Distribution

The distribution of r_{kij} conditional on $z_{kij} = 1$ is the convolution of the random variables α_{kij} and ε_{kij} :

$$h_{\mathrm{I}}(r_{kij}|\sigma_{kij}, p_{kij}) = \begin{cases} \displaystyle\int_{-\infty}^{\infty} g\left(r_{kij} - a|\mu/p_{kij}\right) \cdot \phi(a|\sigma_{kij}) \, \mathrm{d}a & \text{if } j = 1 \\ \displaystyle\int_{-\infty}^{\infty} f_{\alpha|\bar{r}_{k,i}}\left(r_{kij} - a\right) \cdot \phi(a|\sigma_{kij}) \, \mathrm{d}a & \text{otherwise}\,. \end{cases} \tag{D.1}$$

The first case in equation (D.1) is an exponentially-modified normal distribution, for which Appendix A.1 presents an analytical formula. The second case is the convolution of a truncated normal random variable and a zero-mean normal random variable, which we term a normally-modified truncated normal distribution. Here we derive the analytical formula for this density.

Using more general notation, we are interested in the distribution of $w = y + x$ with x being a zero-mean normal random variable with standard deviation s and y being a normally distributed variable with mean μ and standard deviation σ that is truncated below at zero. We will show that the convolution of y and x is:

$$f_W(w) = \int_{-\infty}^{\infty} f_Y(a) f_X(w-a)\ \mathrm{d}a = \frac{\exp\left(-\frac{(w-\mu)^2}{2(s^2+\sigma^2)}\right)}{\sqrt{2\pi(s^2+\sigma^2)}\Phi(\mu/\sigma)} \Phi\left(\frac{A}{\sigma\sqrt{B}}\right). \tag{D.2}$$

where $B = s^2/(s^2+\sigma^2)$ and $A = B\mu + (1-B)w$. Below denote ϕ and Φ as the standard normal density and cumulative distribution functions. Since y is truncated below at zero, we have

$$\begin{aligned} f_W(w) &= \int_0^{\infty} f_Y(a) f_X(w-a)\ \mathrm{d}a \\ &= \int_0^{\infty} \frac{\phi(\frac{a-\mu}{\sigma})}{\sigma[1-\Phi(-\mu/\sigma)]} \cdot \frac{\phi(\frac{w-a}{s})}{s}\ \mathrm{d}a \\ &= \frac{1}{\sqrt{2\pi}\sigma s \Phi(\mu/\sigma)} \int_0^{\infty} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left[\left(\frac{a-\mu}{\sigma}\right)^2 + \left(\frac{w-a}{s}\right)^2\right]\right)\ \mathrm{d}a\,. \end{aligned} \tag{D.3}$$

Expanding the term in brackets in the last line, we have

$$\begin{aligned} \left(\frac{a-\mu}{\sigma}\right)^2 + \left(\frac{w-a}{s}\right)^2 &= \frac{s^2}{s^2\sigma^2}\left(a^2 - 2a\mu + \mu^2\right) + \frac{\sigma^2}{s^2\sigma^2}\left(a^2 - 2aw + w^2\right) \\ &= \frac{1}{s^2\sigma^2}\left[\left(s^2+\sigma^2\right)a^2 - 2s^2 a\mu - 2\sigma^2 aw + s^2\mu^2 + \sigma^2 w^2\right] \\ &= \frac{s^2+\sigma^2}{s^2\sigma^2}\left[a^2 - 2aA + B\mu^2 + (1-B)w^2\right] \\ &= \frac{1}{\sigma^2 B}\left[(a-A)^2 - A^2 + B\mu^2 + (1-B)w^2\right]. \end{aligned}$$

Plugging in the expression for A, the last three terms can be reduced:

$$\begin{aligned}\frac{1}{\sigma^2 B}\Big[-A^2+B\mu^2+(1-B)w^2\Big] &= \frac{1}{\sigma^2 B}\Big[-\big(B^2\mu 2+(1-B)^2w^2+2B(1-B)\mu w\big)+B\mu^2+(1-b)w^2\Big] \\ &= \frac{1}{\sigma^2 B}\Big[\mu^2(B-B^2)-2B(1-B)\mu w+w^2\left(1-B-(1-B)^2\right)\Big] \\ &= \frac{1}{\sigma^2 B}\Big[B(1-B)(w-\mu)^2\Big] \\ &= \frac{(w-\mu)^2}{s^2+\sigma^2}.\end{aligned}$$

Thus, we can rewrite (D.3) to obtain the distribution in (D.2):

$$\begin{aligned} f_W(w) &= \frac{\exp\left(-\frac{(w-\mu)^2}{2(s^2+\sigma^2)}\right)}{\sqrt{2\pi}\sigma s\Phi(\mu/\sigma)}\int_0^\infty \frac{1}{\sqrt{2\pi}}\exp\left(-\frac{1}{2}\left(\frac{a-A}{\sigma\sqrt{B}}\right)^2\right)\,\mathrm{d}a \\ &= \frac{\sqrt{B}\exp\left(-\frac{(w-\mu)^2}{2(s^2+\sigma^2)}\right)}{\sqrt{2\pi}s\Phi(\mu/\sigma)}\frac{1}{\sigma\sqrt{B}}\int_0^\infty \frac{1}{\sqrt{2\pi}}\exp\left(-\frac{1}{2}\left(\frac{a-A}{\sigma\sqrt{B}}\right)^2\right)\,\mathrm{d}a \\ &= \frac{\sqrt{B}\exp\left(-\frac{(w-\mu)^2}{2(s^2+\sigma^2)}\right)}{\sqrt{2\pi}s\Phi(\mu/\sigma)}\left(1-\Phi\left(\frac{-A}{\sigma\sqrt{B}}\right)\right) \\ &= \frac{\exp\left(-\frac{(w-\mu)^2}{2(s^2+\sigma^2)}\right)}{\sqrt{2\pi(s^2+\sigma^2)}\Phi(\mu/\sigma)}\Phi\left(\frac{A}{\sigma\sqrt{B}}\right).\end{aligned}$$

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Table 1: Summary Statistics of Insider Trading History

This table reports cross-sectional distributional statistics of average 21-trading day abnormal returns and standard errors following trades made by corporate insiders split by buy versus sell. Average abnormal returns are defined in Equation (12) and are the average of long positions in purchased stocks for buys (Panel A) and short positions in sold stocks for sells (Panel B), relative to the market benchmark. The standard error is the ratio of the average of trade-specific predicted volatilities, scaled by the square root of the number of trades, as defined in Equation (13). The sample contains all insiders who traded from 1985 to 2024. Because mixture model methods can be sensitive to outliers, the sample is trimmed at the 1% and 99% level of average abnormal returns. The table also reports the distribution of the number of distinct trading days. The table reports the fraction of insiders with sample average abnormal returns that are (1) positive and (2) significantly positive at a 10% level (in a one-sided test). 55,853 insiders have at least one buy and one sell in the full sample.

Panel A: Buys

	Average Abnormal Return	Standard Error	#(Trades)
Mean	0.0184	0.1274	7
SD	0.1079	0.1168	25
P1	-0.2524	0.0123	1
P10	-0.1002	0.0316	1
P25	-0.0368	0.0525	1
P50	0.0097	0.0918	2
P75	0.0650	0.1606	5
P90	0.1492	0.2631	12
P99	0.3580	0.6331	70
Skewness	0.53	2.46	38
Excess Kurtosis	1.79	8.14	2,868
Fraction positive	0.56		
Significant 10%	0.06		
N	108,331		

Panel B: Sells

	Average Abnormal Return	Standard Error	#(Trades)
Mean	0.0110	0.0829	10
SD	0.0854	0.0878	24
P1	-0.2261	0.0095	1
P10	-0.0750	0.0197	1
P25	-0.0271	0.0317	2
P50	0.0053	0.0560	4
P75	0.0437	0.1005	10
P90	0.1047	0.1724	23
P99	0.2943	0.4534	91
Skewness	0.55	3.44	24
Excess Kurtosis	3.55	17.36	1,603
Fraction positive	0.55		
Significant 10%	0.07		
N	151,947		

Table 2: A Mixture Model of the Cross-Section of Insiders

This table reports mixture model parameter estimates for the cross-section of corporate insider average abnormal returns. Equation (7) is numerically maximized in π_{b0}, π_{0s}, π_{bs}, 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 insiders 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_{b0}	π_{0s}	π_{bs}	μ
Parameter Estimate	0.2369	0.0756	0.0213	0.0521
Confidence Interval:				
Lower	0.2241	0.0694	0.0165	0.0501
Upper	0.2518	0.0826	0.0271	0.0539
Negative Log-Likelihood		-291,922.88		
Number of Insiders		204,425		

Table 3: Trades by Informed Insiders Predict Future Returns–Regression

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 in an expanding window fashion each year using the latest average abnormal returns and standard errors for buys and sells for each insider prior to that year's end. Based on the estimated parameters and each insider's average abnormal returns and standard errors up to that month, the conditional expectations of insider informed buy and sell profitability are calculated. Insiders who have at least one buy (sell) are sorted into quintiles by the respective conditional expectation. Buy Quintile 5 (Sell Quintile 5) is an indicator variable for whether any insider in the top buy (sell) 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 1 (Lo)	0.13	0.11			0.08	0.04
	(0.76)	(0.64)			(0.44)	(0.22)
Buy Quintile 2	0.27	0.18			0.22	0.12
	(1.46)	(1.40)			(1.19)	(0.98)
Buy Quintile 3	0.91***	0.76***			0.87***	0.70***
	(4.02)	(5.00)			(3.76)	(4.70)
Buy Quintile 4	0.94***	0.82***			0.90***	0.76***
	(3.61)	(5.37)			(3.41)	(4.94)
Buy Quintile 5 (Hi)	1.05***	1.02***			1.00***	0.95***
	(3.77)	(7.26)			(3.52)	(6.86)
Sell Quintile 1 (Lo)			-0.10	-0.10	0.10	0.05
			(-0.79)	(-1.27)	(0.88)	(0.70)
Sell Quintile 2			-0.28***	-0.27***	-0.14*	-0.15**
			(-3.21)	(-4.31)	(-1.66)	(-2.53)
Sell Quintile 3			-0.26***	-0.25***	-0.12	-0.13**
			(-2.89)	(-3.49)	(-1.43)	(-2.00)
Sell Quintile 4			-0.24*	-0.27**	-0.08	-0.15
			(-1.75)	(-2.32)	(-0.67)	(-1.39)
Sell Quintile 5 (Hi)			-0.47***	-0.42***	-0.29**	-0.28***
			(-3.45)	(-3.93)	(-2.29)	(-2.81)
Size	-0.10	-0.06	-0.13*	-0.08	-0.11	-0.06
	(-1.32)	(-1.02)	(-1.72)	(-1.45)	(-1.39)	(-1.07)
BM	0.47***	0.37***	0.48***	0.36***	0.47***	0.36***
	(2.94)	(3.21)	(2.89)	(3.08)	(2.89)	(3.16)
Ret(t-1)	-0.25	0.64	-0.41	0.55	-0.19	0.71
	(-0.15)	(0.65)	(-0.24)	(0.55)	(-0.11)	(0.72)
Ret(t-12,t-2)	0.38	0.66**	0.37	0.65**	0.39	0.67**
	(0.99)	(2.44)	(0.94)	(2.41)	(1.01)	(2.48)
Constant	3.44**		4.48***		3.61**	
	(2.22)		(3.00)		(2.36)	
Time FE	N	Y	N	Y	N	Y
Adj R^2	0.0027	0.1233	0.0022	0.1229	0.0028	0.1234
Observations	338,502	338,502	338,502	338,502	338,502	338,502
p(Buy Hi-Lo)	0.0014	0.0001			0.0013	0.0001
p(Sell Hi-Lo)			0.0272	0.0091	0.0191	0.0062

Table 4: Return Predictions Using Average Return, t-statistic, and Conditional Expectation

This table reports comparisons of regressions of monthly stock returns as a function of insider buying and selling activity in the prior month. Insiders are sorted into quintiles each month based on their past average returns for buys or sells (Panel A), the t-statistic of their past average returns for buys or sells (Panel B), or their conditional expectations for buys or sells (Panel C), as in Table 3. Each measure is estimated in an expanding window fashion each year, as described in Table 3. The regression specification corresponds to the last column of Table 3. The table reports the regression coefficients on the High and Low quintile indicators for buys and sells, their difference, and the p values for tests of whether the coefficients on the High and Low quintiles differ. Panel C of this table repeats information from the last column of Table 3 for ease of comparison.

Panel A. Average Return

	Low (Q1)	High (Q5)	Hi-Lo	p-value
Buy	0.83	1.24	0.41	0.0641
Sell	-0.39	-0.28	0.11	0.3851

Panel B. t-statistic

	Low (Q1)	High (Q5)	Hi-Lo	p-value
Buy	0.26	0.71	0.45	0.0186
Sell	-0.10	-0.12	-0.02	0.7993

Panel C. Mixture Model Conditional Expectation

	Low (Q1)	High (Q5)	Hi-Lo	p-value
Buy	0.04	0.95	0.91	0.0001
Sell	0.05	-0.28	-0.33	0.0062

Table 5: Trades by Informed Insiders Predict Future Returns–Portfolios

This table reports returns for portfolios formed by sorting on (1) an insider's conditional expected profitability $\tilde{\alpha}_{k,i}$ and (2) the trade direction. The mixture model is estimated in an expanding window fashion each year using the latest average abnormal returns and standard errors for buys and sells for each insider. Based on the estimated parameters and each insider's average abnormal returns and standard errors, the conditional expectations of insider informed buy and sell profitability are calculated. Insiders are sorted into quintiles by the conditional expectations. This sorting is done based on an insider's trade history up to the prior year's end for a given month's portfolio formation. The second sort is if it was a buy or sell. A stock from a given trade enters the buy or sell portfolio the following month and is held until the next month. Portfolios are equal-weighted by insider-stock observations within each of the 10 combinations. Panels A, B, and C report alphas using market, Fama-French-Carhart, and Fama-French Five Factor + momentum benchmarks, respectively. In each panel, t-statistics are reported in parenthesis.

Panel A: CAPM Alpha

	Conditional Expectation					
	Low	2	3	4	High	Hi-Lo
Sells	0.0055	0.0042	0.0040	0.0049	0.0020	-0.0035
	(1.94)	(1.45)	(1.33)	(1.44)	(0.58)	(-2.01)
Buys	0.0120	0.0144	0.0184	0.0178	0.0208	0.0092
	(4.40)	(3.97)	(5.30)	(4.59)	(5.61)	(4.22)
Buys Minus Sells	0.0059	0.0102	0.0144	0.0143	0.0188	0.0123
	(3.20)	(4.42)	(5.81)	(5.14)	(7.75)	(4.90)

Panel B: Fama-French Three Factor + Momentum Alpha

	Conditional Expectation					
	Low	2	3	4	High	Hi-Lo
Sells	0.0059	0.0048	0.0049	0.0054	0.0027	-0.0033
	(1.96)	(1.57)	(1.53)	(1.49)	(0.73)	(-1.85)
Buys	0.0123	0.0147	0.0194	0.0182	0.0211	0.0092
	(4.15)	(3.89)	(5.00)	(4.48)	(5.46)	(4.21)
Buys Minus Sells	0.0057	0.0099	0.0146	0.0141	0.0184	0.0121
	(2.83)	(4.12)	(5.36)	(4.80)	(7.56)	(4.73)

Panel C: Fama-French Five Factor + Momentum Alpha

	Conditional Expectation					
	Low	2	3	4	High	Hi-Lo
Sells	0.0061	0.0056	0.0054	0.0056	0.0037	-0.0023
	(1.90)	(1.72)	(1.62)	(1.50)	(0.98)	(-1.26)
Buys	0.0126	0.0153	0.0198	0.0189	0.0222	0.0100
	(4.05)	(3.89)	(4.90)	(4.49)	(5.50)	(4.60)
Buys Minus Sells	0.0059	0.0098	0.0144	0.0141	0.0185	0.0119
	(2.76)	(3.91)	(5.10)	(4.47)	(7.24)	(4.66)

Table 6: Conditional Informed Insider Measures and Existing Measures

This table reports regressions of conditional probabilities (Panel A) and expectations (Panel B) of insider informed buy and sell profitability on other classifiers of informed insider trading. The mixture model is estimated in an expanding window fashion each year using the latest average abnormal returns and standard errors for buys and sells for each insider. Based on the estimated parameters and each insider's average abnormal returns and standard errors, the conditional probabilities that an insider engages in profitable buy and sell trades and the conditional expectations of insider informed buy and sell profitability are 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					
	Buys ($\tilde{\pi}_{b,i}$)			Sells ($\tilde{\pi}_{s,i}$)		
	(1)	(2)	(3)	(4)	(5)	(6)
Non-Routine	0.00			0.01***		
	(0.27)			(3.89)		
Medium Horizon		0.02***			0.01***	
		(5.87)			(5.55)	
Short Horizon		0.02***			0.02***	
		(7.11)			(9.11)	
High QEA Profitability			0.01*			0.02***
			(1.93)			(5.52)
Constant	0.22***	0.22***	0.25***	0.06***	0.05***	0.06***
	(28.42)	(31.03)	(28.32)	(24.62)	(29.62)	(22.76)
Adj R^2	-0.0000	0.0032	0.0003	0.0010	0.0083	0.0041
Observations	109,157	83,392	16,998	165,752	126,544	26,012

Panel B

	Dependent Variable: Conditional Expectation					
	Buys ($\tilde{\alpha}_{b,i}$)			Sells ($\tilde{\alpha}_{s,i}$)		
	(1)	(2)	(3)	(4)	(5)	(6)
Non-Routine	0.0012**			0.0007***		
	(2.69)			(7.18)		
Medium Horizon		0.0021***			0.0008***	
		(3.74)			(7.14)	
Short Horizon		0.0038***			0.0015***	
		(7.09)			(10.59)	
High QEA Profitability			0.0029***			0.0019***
			(3.66)			(8.06)
Constant	0.0122***	0.0118***	0.0151***	0.0021***	0.0017***	0.0025***
	(19.84)	(21.65)	(20.06)	(13.90)	(18.10)	(15.96)
Adj R^2	0.0002	0.0024	0.0009	0.0009	0.0053	0.0047
Observations	109,157	83,392	16,998	165,752	126,544	26,012

Table 7: Return Predictability 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. Buy and sell quintile indicators for whether any insider in the respective conditional expectation quintile traded in the month t is calculated as described in Table 3. 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). If an insider does not make the sample screen for that proxy, the indicator for unclassified is turned on. 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 1 (Lo)		-0.36**		-0.35**		-0.28
		(-2.00)		(-1.98)		(-1.59)
Buy Quintile 2		-0.24*		-0.23*		-0.14
		(-1.72)		(-1.75)		(-1.04)
Buy Quintile 3		0.34**		0.34**		0.43***
		(2.02)		(2.14)		(2.70)
Buy Quintile 4		0.39**		0.41**		0.49***
		(2.29)		(2.45)		(2.94)
Buy Quintile 5 (Hi)		0.56***		0.54***		0.65***
		(3.30)		(3.47)		(4.06)
Sell Quintile 1 (Lo)		0.14*		0.13		0.18**
		(1.78)		(1.48)		(2.28)
Sell Quintile 2		-0.04		-0.04		-0.04
		(-0.67)		(-0.58)		(-0.55)
Sell Quintile 3		-0.01		-0.01		-0.01
		(-0.19)		(-0.11)		(-0.22)
Sell Quintile 4		-0.02		-0.01		-0.02
		(-0.16)		(-0.14)		(-0.22)
Sell Quintile 5 (Hi)		-0.15		-0.14		-0.15
		(-1.49)		(-1.30)		(-1.47)
Unclassified Buy	0.63***	0.56***	0.64***	0.56***	0.42***	0.30**
	(6.77)	(4.61)	(6.38)	(4.72)	(4.12)	(2.40)
Unclassified Sell	-0.35***	-0.32***	-0.29***	-0.27***	-0.50***	-0.46***
	(-4.78)	(-3.99)	(-3.58)	(-2.90)	(-4.94)	(-4.47)
Nonroutine Buy	0.34***	0.36***				
	(2.71)	(2.61)				
Nonroutine Sell	0.01	-0.02				
	(0.08)	(-0.21)				
Routine Buy	-0.40*	-0.23				
	(-1.75)	(-1.05)				
Routine Sell	0.28**	0.25**				
	(2.31)	(1.98)				
Long Horizon Buy			-0.07	0.07		
			(-0.41)	(0.42)		
Med Horizon Buy			0.32	0.33		
			(1.49)	(1.63)		
Short Horizon Buy			0.91***	0.85***		
			(4.12)	(3.98)		
Long Horizon Sell			0.19**	0.15		
			(2.43)	(1.58)		
Medium Horizon Sell			-0.18**	-0.19**		
			(-2.33)	(-2.09)		
Short Horizon Sell			-0.30***	-0.29**		
			(-2.99)	(-2.49)		
QEA Profitability Q5 Buy					0.41	0.24
					(1.02)	(0.60)
QEA Profitability Q5 Sell					0.01	-0.01
					(0.08)	(-0.05)
Time FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Adj R^2	0.1233	0.1235	0.1233	0.1236	0.1232	0.1235
Observations	338,502	338,502	338,502	338,502	338,502	338,502
p(Buy Hi-Lo)		0.0001		0.0001		0.0001
p(Sell Hi-Lo)		0.0173		0.0203		0.0075

Table 8: Incorporating Existing Proxies

This table reports mixture model parameter estimates for the cross-section of corporate insider average abnormal returns. The model parameterizes π_{b0}, π_{0s}, and π_{bs} as a function of whether the indicated empirical proxy either classifies an insider as one who uses information, one who does not use information, or does not classify the insider due to the insider not satisfying sample screens (Equation 15). 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 the fractions of traders and trades in the trimmed sample are reported.

Panel A. Informed: Non-Routine (Cohen, Malloy, and Pomorski, 2012)

	Unclassified	Uninformed	Informed	μ
π_{00}	0.6242	0.8184	0.6442	
π_{b0}	0.2155	0.1328	0.2983	
π_{0s}	0.1407	0.0256	0.0406	0.0506
π_{bs}	0.0196	0.0232	0.0169	
Fraction of Traders	0.6957	0.0268	0.2775	
Fraction of Trades	0.2893	0.0932	0.6175	
Negative Log-Likelihood		-292,317.32		
Number of Traders		204,425		

Panel B. Informed: Short Horizon (Akbas, Jiang, and Koch, 2020)

	Unclassified	Uninformed	Informed	μ
π_{00}	0.6352	0.7450	0.5033	
π_{b0}	0.2303	0.2285	0.3968	
π_{0s}	0.1072	0.0235	0.0514	0.0508
π_{bs}	0.0273	0.0030	0.0485	
Fraction of Traders	0.8491	0.1237	0.0272	
Fraction of Trades	0.5774	0.3569	0.0657	
Negative Log-Likelihood		-292,350.38		
Number of Traders		204,425		

Panel C. Informed: High QEA Profitability (Ali and Hirshleifer, 2017)

	Unclassified	Uninformed	Informed	μ
π_{00}	0.6913	0.6054	0.3327	
π_{b0}	0.2108	0.3398	0.5205	
π_{0s}	0.0786	0.0381	0.1067	0.0527
π_{bs}	0.0193	0.0167	0.0401	
Fraction of Traders	0.9391	0.0392	0.0217	
Fraction of Trades	0.6717	0.1688	0.1595	
Negative Log-Likelihood		-292,123.53		
Number of Traders		204,425		

Table 9: Conditional Probability that an Individual Trade is Informed

This table reports summary statistics of the conditional probability that a trade is informed (τ_{kij} as defined in Equation (19)) for individual insider trades. The first column reports the sample average of the conditional probability for the sample indicated for each row. The second column reports the sample average of an indicator for whether the conditional probability is greater than 50% (Likely Informed). The third column reports the number of observations in each row. The statistics are reported separately for the overall sample, for purchases and sales, and for the number of past buy or sell trades made by the insider.

	Average Conditional Probability	Fraction Likely Informed	Observations
Overall	0.1252	0.0358	2,215,409
Trade Direction			
Purchases	0.1998	0.0627	692,100
Sales	0.0914	0.0236	1,523,309
Purchases: #(Past Buy Trades)			
Less than 5	0.1661	0.0335	298,083
5-10	0.1970	0.0381	109,972
11-20	0.2064	0.0476	80,622
More than 20	0.2480	0.1246	203,423
Sales: #(Past Sell Trades)			
Less than 5	0.0725	0.0105	511,291
5-10	0.0928	0.0153	291,224
11-20	0.0977	0.0231	247,335
More than 20	0.1076	0.0433	473,459

Table 10: Conditional Probability an Individual Trade is Informed and Trade Characteristics

This table reports regressions of the conditional probability that a trade was informed (τ_{kij} as defined in Equation (19)) on trade level characteristics. The independent variables include if the trade was a scheduled 10b5-1 trade, which is voluntarily disclosed, the log of the trade size in dollars, the log of the estimated 21-day volatility of the stock, the log of the market equity of the stock, if the sale was related to an option execution, and the number of other traders in the firm that traded or days the insider traded in the past five days. We control for prior proxies of informed insiders and denote which fixed effects are used at the bottom of each row. 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 *** ($p < 0.01$).

	Buy τ_{ij}'s		Sell τ_{ij}'s	
	(1)	(2)	(3)	(4)
10b5-1 Trade	0.0536***	0.0013	0.0029	0.0004
	(2.83)	(0.25)	(1.46)	(0.40)
log(Trade Size)	0.0048***	0.0014***	-0.0006	-0.0004***
	(8.24)	(3.58)	(-1.67)	(-2.82)
log(Estimated SD)	0.0083***	-0.0011	-0.0047***	-0.0100***
	(2.85)	(-0.61)	(-2.91)	(-9.84)
log(Market Cap.)	-0.0020**	0.0013	-0.0045***	-0.0107***
	(-2.32)	(1.24)	(-5.38)	(-16.28)
Option Related Sell			-0.0031**	0.0013**
			(-2.63)	(2.69)
# Days Buying in Past Week	0.0200***	0.0062***		
	(14.08)	(10.83)		
# Other Traders Buying in Past Week	0.0006	0.0005		
	(0.63)	(1.20)		
# Days Selling in Past Week			0.0148***	0.0054***
			(12.37)	(14.63)
# Other Traders Selling in Past Week			-0.0004	-0.0006***
			(-0.63)	(-4.84)
Controls for Prior Proxies	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Insider FE	N	Y	N	Y
Adj. R^2	0.1008	0.4580	0.0477	0.5098
Observations	689,832	648,158	1,520,027	1,483,219

Table 11: Conditional Probability an Individual Trade is Informed and Insider Roles

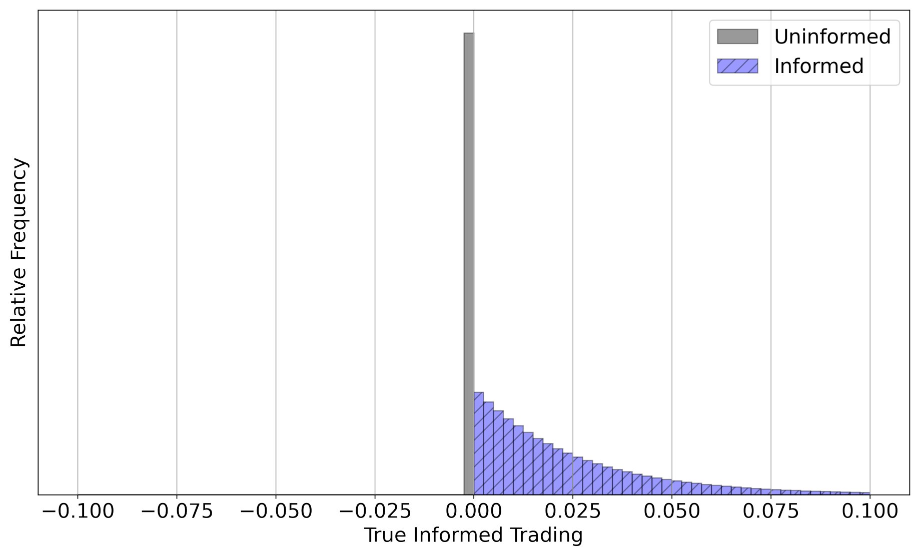
This table reports regressions of the conditional probability that a trade was informed (τ_{kij} as defined in Equation (19)) on insiders' role(s) within the firm. The independent variables are dummy variables for roles disclosed by the insider or if they were a direct owner in the firm. We control for prior proxies of informed insiders as well as year fixed effects. 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 *** ($p < 0.01$).

	Buy τ_{ij}'s	Sell τ_{ij}'s
	(1)	(2)
CEO	0.0153**	0.0102**
	(2.76)	(3.07)
CFO	0.00819***	0.00109
	(3.69)	(0.40)
Inside Block > 10%	0.0454***	0.0332***
	(7.13)	(7.08)
Chairman	0.0205**	-0.00131
	(3.05)	(-0.41)
Director	-0.00867*	-0.00233
	(-2.34)	(-0.83)
Officer	-0.0135***	-0.00735**
	(-4.35)	(-3.05)
Officer and Director	-0.00377	-0.00135
	(-0.91)	(-0.51)
Vice Presidents	-0.00230	-0.00270
	(-0.69)	(-1.82)
Direct Ownership	-0.0143**	-0.0108***
	(-3.07)	(-4.72)
Controls for Prior Proxies	Y	Y
Year FE	Y	Y
Adj R^2	0.0732	0.0224
Observations	692,100	1,523,309

Figure 1: Distributions of True and Estimated Informed Insider Trading

This figure illustrates the one-dimensional 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 noise 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

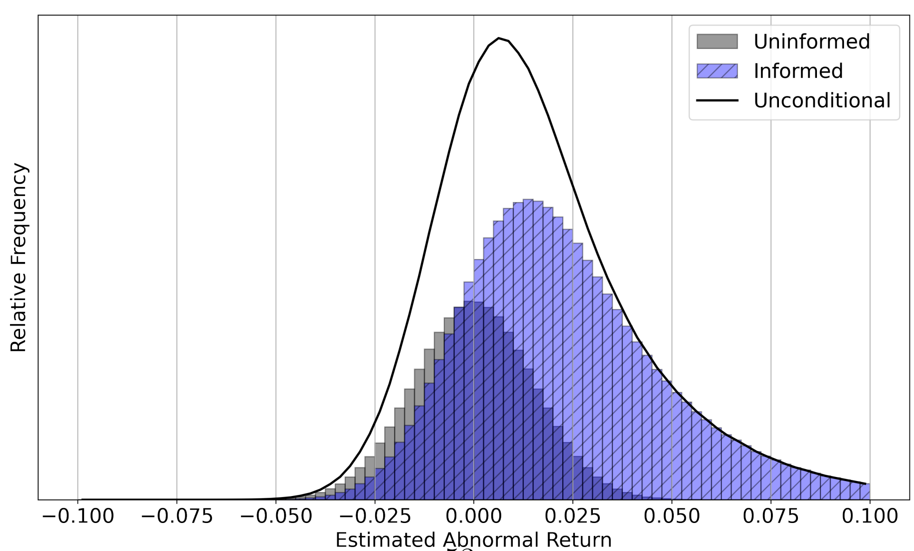
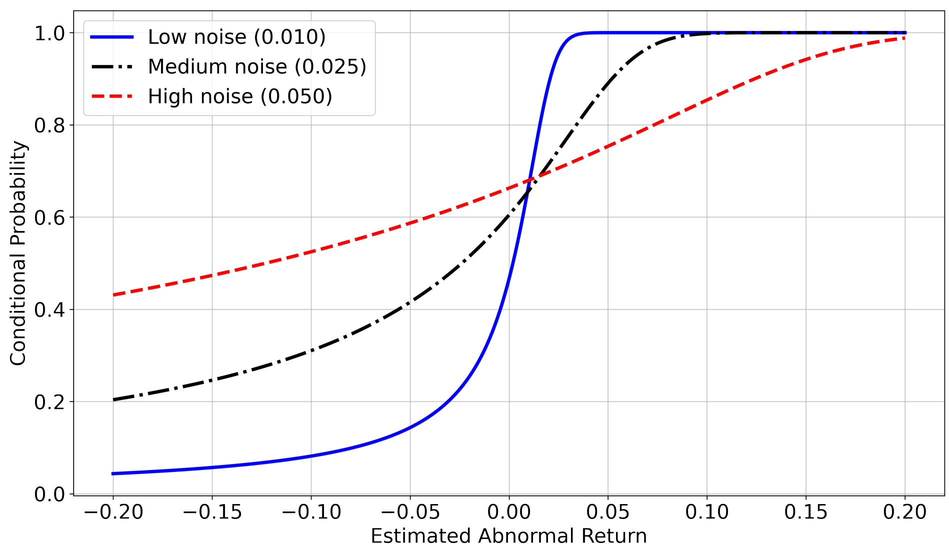


Figure 2: Conditional Probabilities and Expectations

This figure illustrates conditional probabilities and expectations in the one-dimensional mixture model 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

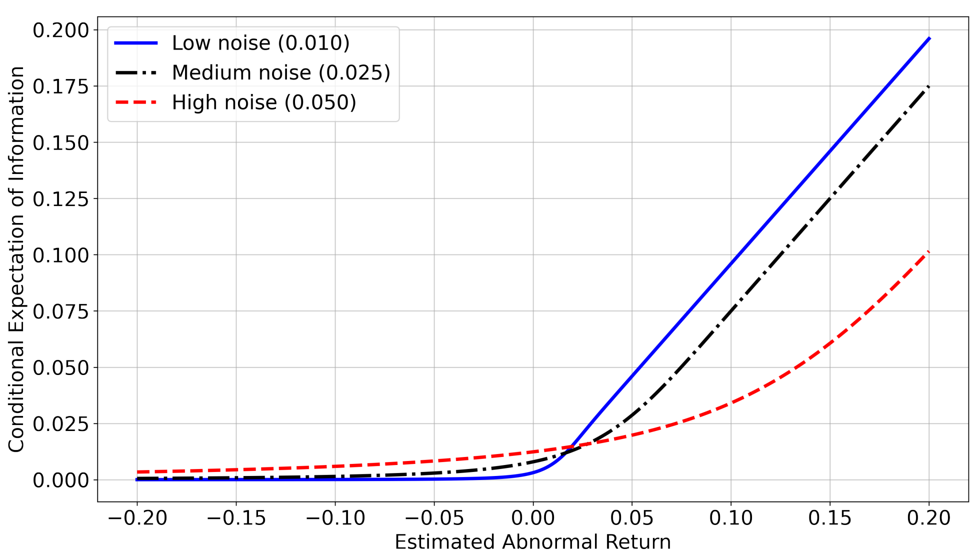
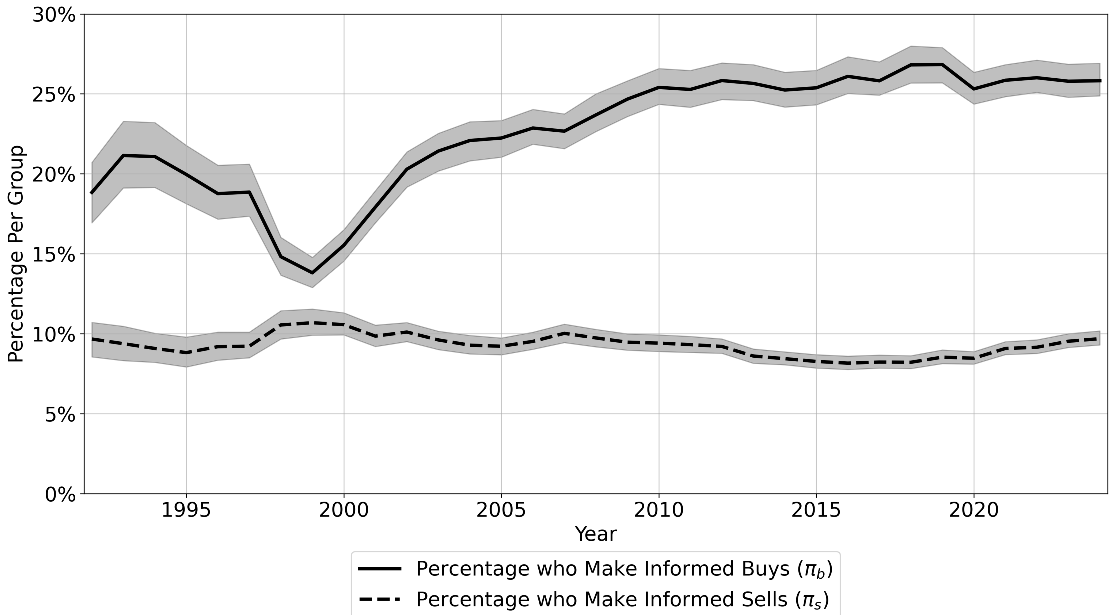


Figure 3: Time-Series of Estimated Parameters

The two-dimensional mixture model is estimated each year using the latest average abnormal returns and standard errors for buys and sell for each insider (using an expanding window). Panel (a) plots the time series of the probability of informed buys (π_b) and informed sells (π_s). Panel (b) plots the time series of the expected profitability for informed insiders (μ). The shaded region represents the 1st and 99th percentiles of the parameters estimated from 1,000 bootstrapped samples (with replacement).

(a) Percentage per Group (π's)



(b) Mean of Informed Trading (μ)

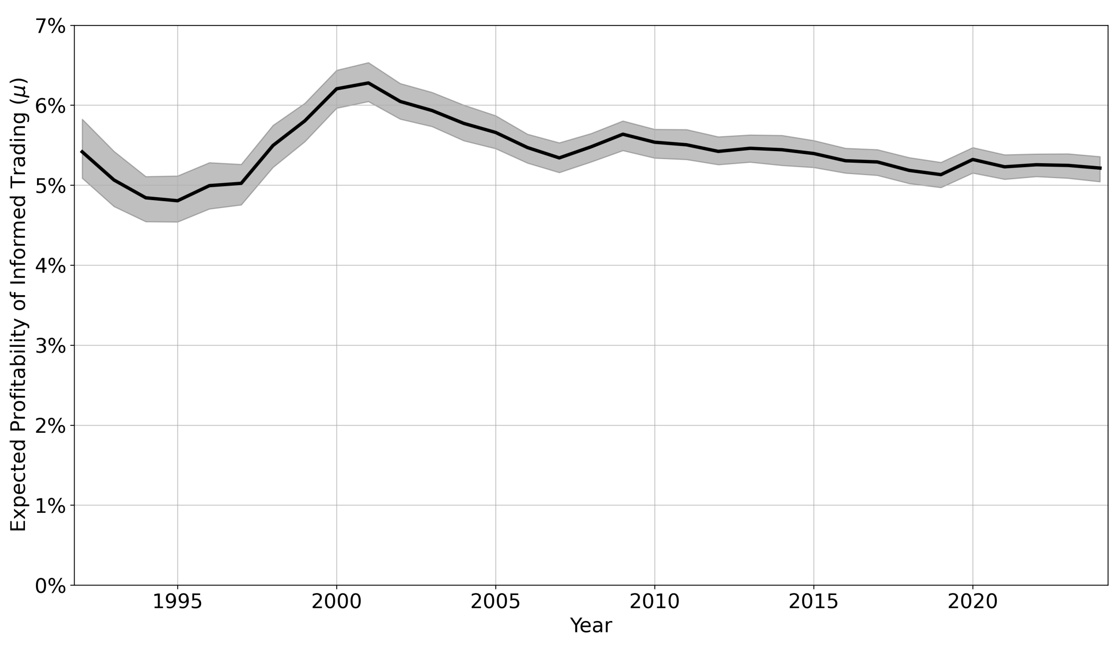
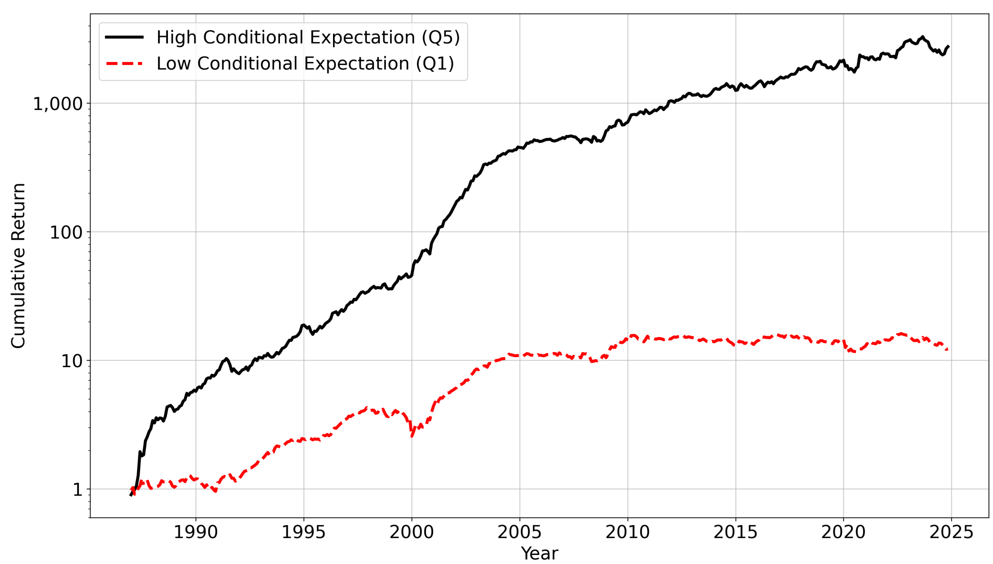


Figure 4: Cumulative Returns

This figure plots cumulative returns for portfolios formed by sorting on (1) an insider's conditional expected profitability $\tilde{\alpha}_{k,i}$ and (2) whether the trade is a buy or a sell. The two-dimensional mixture model is estimated in an expanding window fashion each year using the latest average abnormal return and standard error for each insider. Based on the estimated parameters and each insider's average abnormal returns and standard errors for buys and sells, the conditional expectations of insider informed buy and sell profitability are calculated. Insiders are sorted into quintiles by the conditional expectations. This sorting is done based on an insider's trade history up to the prior year's end for a given month's portfolio formation. The second sort is if the trade was a buy or sell. A stock from a given trade enters the buy or sell portfolio the following month and is held until the next month. Portfolios are equal-weighted by insider-stock observations within each of the 10 combinations. Panel A reports cumulative returns for hedge portfolios that buy stocks purchased by insiders and short stocks sold by insiders. The black solid (red dashed) line represents this strategy for insiders in the top (bottom) quintile of ex-ante conditional expectations. Panel B reports the cumulative performance for hedge portfolios that either (1) buy the top $\tilde{\alpha}_{b,i}$ quintile's buys and shorts the bottom $\tilde{\alpha}_{b,i}$ quintile's buys (black solid line) or (2) buy the top $\tilde{\alpha}_{s,i}$ quintile's sells and shorts the bottom $\tilde{\alpha}_{s,i}$ quintile's sells (red dashed line), or (3) buys the first hedge portfolio of buys and shorts the second hedge portfolio of sells (blue dashed-dotted line).

(a) Buys - Sells



(b) High Minus Low Conditional Expectation

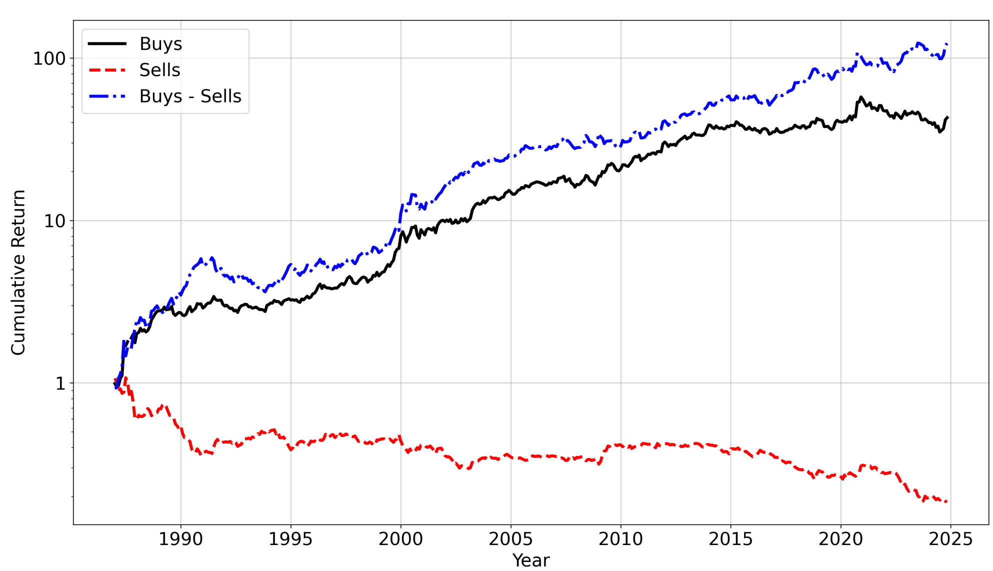


Figure 5: Insiders' Information and Convergence to Market Efficiency

This figure plots cumulative returns for portfolios formed by sorting on (1) an insider's conditional expected profitability $\tilde{\alpha}_{k,i}$ and (2) whether the trade is a buy or a sell. A stock from a given trade enters the buy or sell portfolio at the indicated number of days following the trade. The portfolio holds all stocks included in the portfolio that day at equal weights. Portfolio formation differs only in the entry date of a stock into the portfolio. A stock from a given trade enters a portfolio either 1 (black solid line), 3 (blue dashed), or 5 (red dashed-dotted line) trading days following the trade date; in each case, the stock leaves the portfolio twenty trading days after the trade date. The figure reports cumulative returns for hedge portfolios that buy stocks when high-buy-quintile insiders buy and sell stocks when high-sell-quintile insiders sell.

High Conditional Expectations (Q5): Buys - Sells

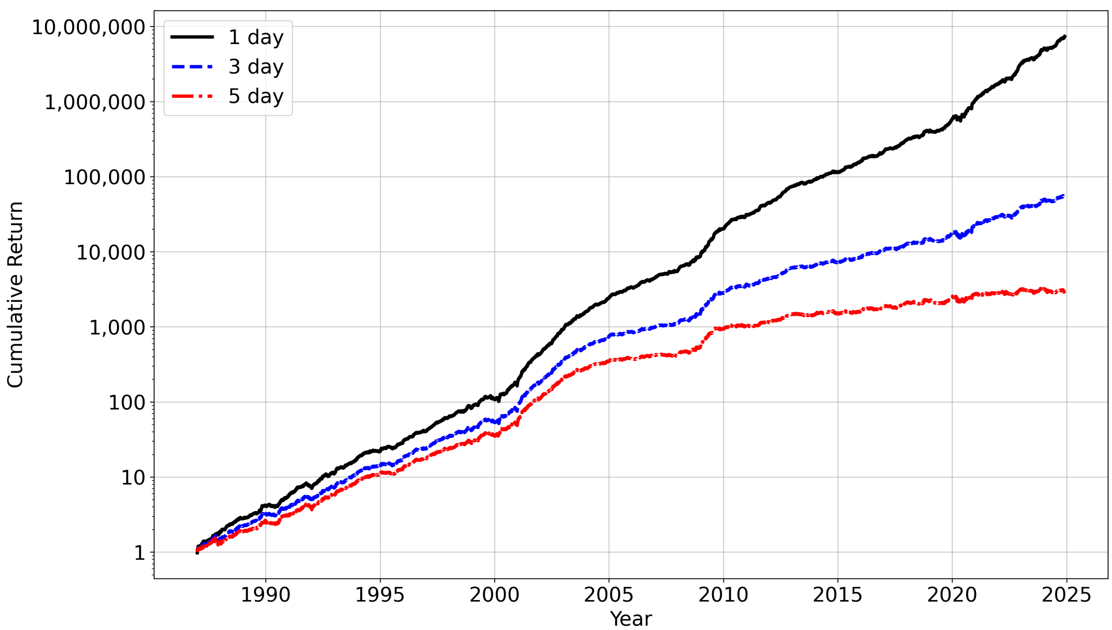


Figure 6: Jumps in Information Acquisition by Sophisticated Market Participants
The figure reports the weekly number of insider trading disclosures accessed by the indicated financial institutions.

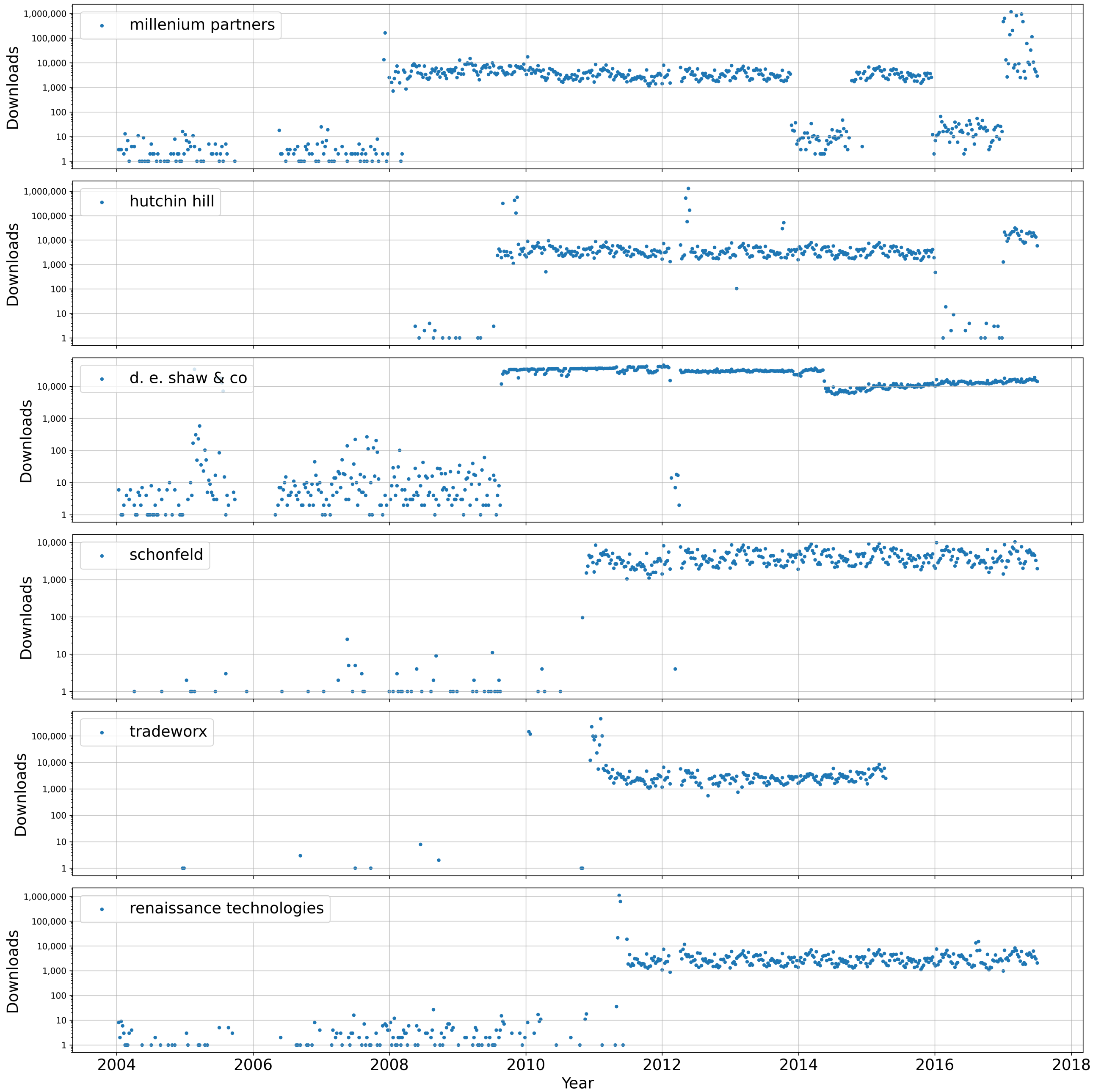


Figure 7: Conditional Probability an Insider's Trade is Informed

The figure plots the conditional probability that a trade made by a corporate insider was informed (Equation 19) as a function of the realized trade return r_{ij}, whether the trade was a purchase or sale, and attributes of the insider's past trading history. Specifically, the probability is conditioned on the insider's past average abnormal return $\bar{r}_{k,i}$ and the standard deviation of the stock return σ_{ij}. For simplicity, we assume the past average return standard deviation $\bar{\sigma}_i$ equals the current trade's σ_{ij} and that the number of past trades is held fixed at ten past trades. We also assume that the trader only has a history of trades for trade direction k. Each panel shows conditional probability curves for the standard deviation in the panel header and for past average returns $\bar{r}_{k,i}$ of -5%, 0%, and 5%. The top (bottom) row shows the curves for purchases (sales).

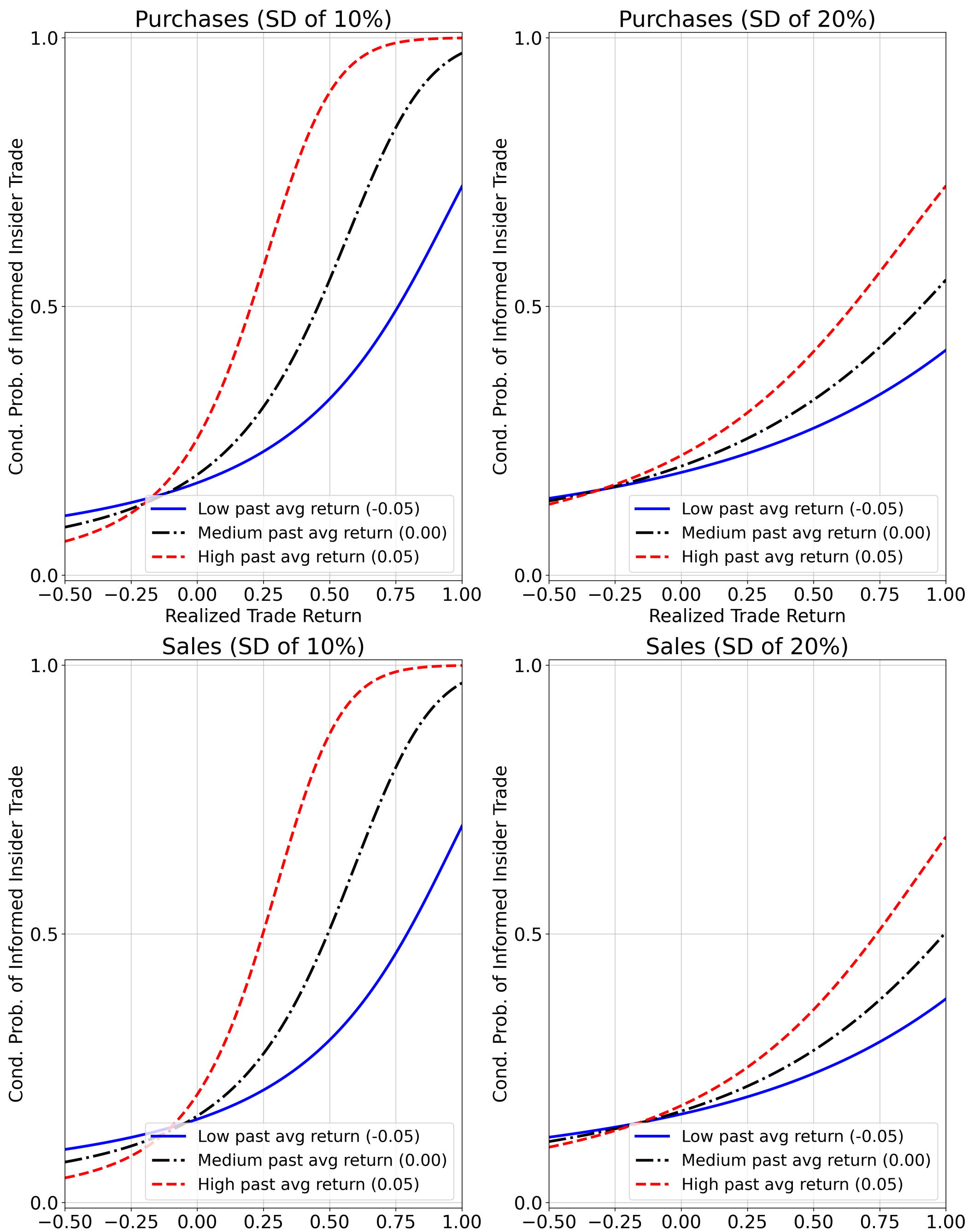
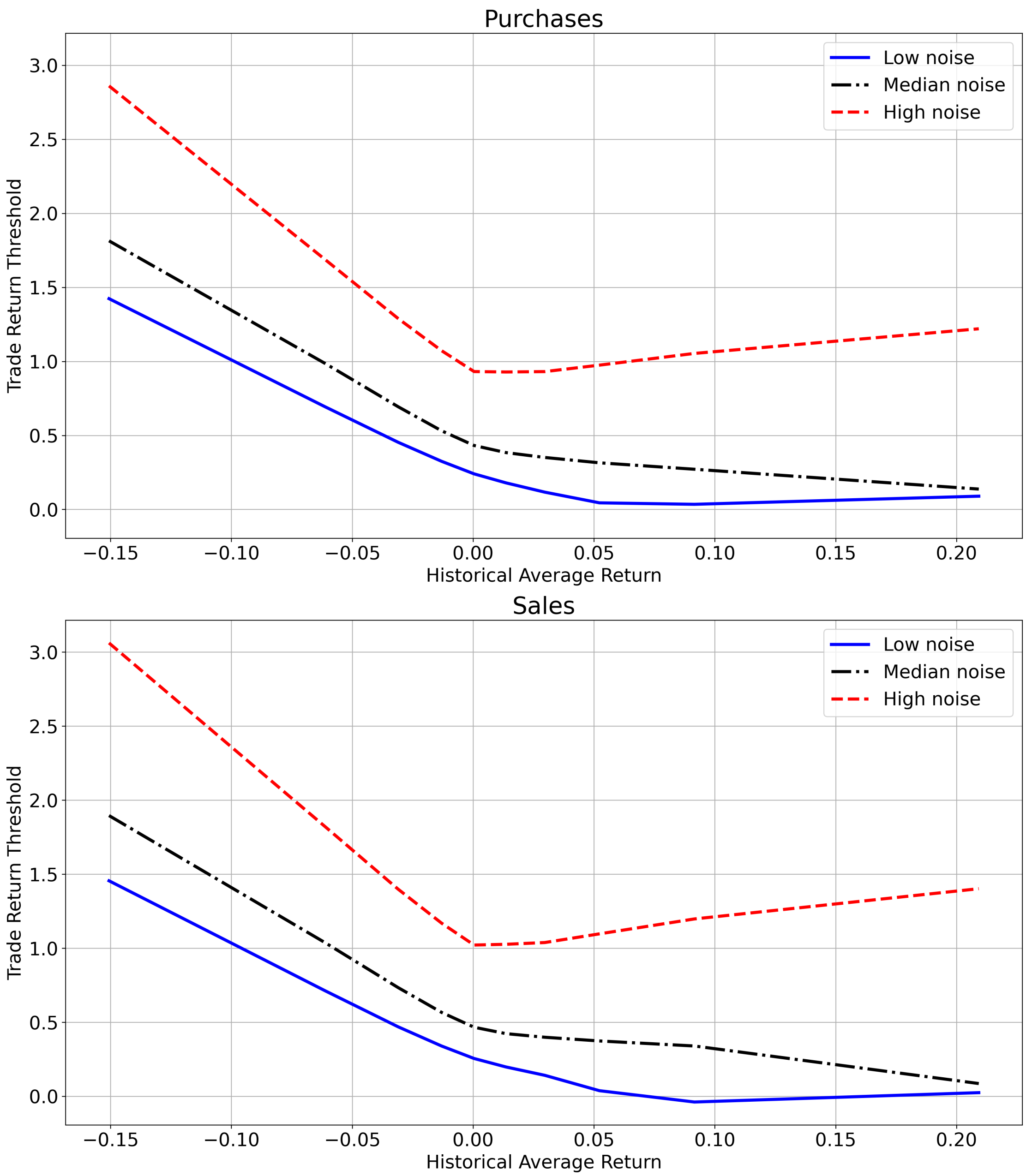


Figure 8: Insider-specific Return Thresholds

The figure plots the trade-level signed abnormal return threshold at which it is more likely than not that a trade made by a corporate insider was informed. The threshold depends on the insider's past average abnormal return $\bar{r}_{ki}$, whether the trade was a purchase or sale, the standard deviation of the stock return σ_{ij}, the standard deviation of their previous returns $\bar{\sigma}_i$, and the number of past trades. The top (bottom) row shows the curves for purchases (sales). For simplicity, we assume the past average return standard deviation $\bar{\sigma}_i$ equals the current trade's σ_{ij} and that the number of past trades is held fixed at ten past trades. We also assume that the trader only has a history of trades for trade direction k. The thresholds are plotted as a function of the insider's past average return for three levels of trade-level standard deviations. These low, median, and high noise levels correspond to the 10th, 50th, and 90th percentiles of trade-level standard deviations for a given (binned) past average return.



Internet Appendix:
Detecting Informed Trade by Corporate Insiders

Internet Appendix A. Additional Analyses

This appendix contains the following additional analyses.

- Table IA.1 reports value-weighted returns for monthly portfolios formed by sorting on (1) an insider's conditional expectations $\tilde{\pi}_b$ or $\tilde{\pi}_s$ and (2) whether the trade is a buy or a sell.

- Table IA.2 reports post-2012 returns for daily portfolios formed by sorting on (1) an insider's conditional expectations $\tilde{\pi}_b$ or $\tilde{\pi}_s$ and (2) whether the trade is a buy or a sell.

- Table IA.3 reports predictive regressions of monthly stock returns as a function of buying and selling activity by insiders classified as persistently profitable or not (or unclassified) following Cline et al. (2017) as well as quintiles of the mixture model's conditional expectations in the prior month.

- Figure IA.1 plots the time series of the probability an insider is informed (π) and of the average information for informed insiders (μ) estimated over rolling windows.

- Figure IA.2 plots the estimated ex-ante probability that a trade made by a corporate insider was informed.

- Figure IA.3 plots histograms of the inputs to the trade-level mixture model estimated in Section 5.

Table IA.1: Trades by Informed Insiders Predict Future Returns–Value Weighted Portfolios

This table reports returns for portfolios formed by sorting on (1) an insider's conditional expected profitability $\tilde{\alpha}_{k,i}$ and (2) the trade direction. The mixture model is estimated in an expanding window fashion each year using the latest average abnormal returns and standard errors for buys and sells for each insider. Based on the estimated parameters and each insider's average abnormal returns and standard errors, the conditional expectations of insider informed buy and sell profitability are calculated. Insiders are sorted into quintiles by the conditional expectations. This sorting is done based on an insider's trade history up to the prior year's end for a given month's portfolio formation. The second sort is if it was a buy or sell. A stock from a given trade enters the buy or sell portfolio the following month and is held until the next month. Portfolios are value-weighted by insider-stock observations within each of the 10 combinations. Panels A, B, and C report alphas using market, Fama-French-Carhart, and Fama-French Five Factor + momentum benchmarks, respectively. In each panel, t-statistics are reported in parenthesis.

Panel A: CAPM Alpha

	Conditional Expectation					
	Low	2	3	4	High	Hi-Lo
Sells	0.0061	0.0060	0.0053	0.0081	0.0060	-0.0001
	(2.17)	(2.10)	(1.67)	(2.51)	(1.95)	(-0.04)
Buys	0.0071	0.0108	0.0126	0.0089	0.0113	0.0052
	(2.38)	(2.80)	(3.32)	(2.56)	(3.31)	(2.00)
Buys Minus Sells	-0.0000	0.0046	0.0074	0.0019	0.0054	0.0051
	(-0.00)	(1.61)	(2.47)	(0.67)	(1.87)	(1.55)

Panel B: Fama-French Three Factor + Momentum Alpha

	Conditional Expectation					
	Low	2	3	4	High	Hi-Lo
Sells	0.0066	0.0063	0.0059	0.0088	0.0065	0.0000
	(2.20)	(2.06)	(1.80)	(2.64)	(2.03)	(0.00)
Buys	0.0074	0.0114	0.0137	0.0088	0.0123	0.0059
	(2.25)	(2.81)	(3.32)	(2.44)	(3.39)	(2.24)
Buys Minus Sells	-0.0002	0.0050	0.0078	0.0011	0.0059	0.0058
	(-0.09)	(1.67)	(2.41)	(0.38)	(1.96)	(1.71)

Panel C: Fama-French Five Factor + Momentum Alpha

	Conditional Expectation					
	Low	2	3	4	High	Hi-Lo
Sells	0.0074	0.0068	0.0069	0.0088	0.0071	-0.0003
	(2.35)	(2.12)	(2.03)	(2.59)	(2.10)	(-0.13)
Buys	0.0077	0.0111	0.0141	0.0097	0.0128	0.0061
	(2.30)	(2.76)	(3.49)	(2.60)	(3.43)	(2.37)
Buys Minus Sells	-0.0008	0.0041	0.0073	0.0015	0.0058	0.0062
	(-0.26)	(1.39)	(2.29)	(0.47)	(1.91)	(1.86)

Table IA.2: Post-2012 Daily Portfolio Analysis of Informed Insiders

This table reports post-2012 returns for portfolios formed by sorting on (1) an insider's conditional expectation $\tilde{\alpha}_{k,i}$ and (2) whether the trade is a buy or a sell. The mixture model is estimated in an expanding window fashion each year using the latest average abnormal returns and standard errors for each insider. Based on the estimated parameters and each insider's average abnormal returns and standard errors, the conditional expectations of insider informed buy and sell profitability are calculated. Insiders are sorted into quintiles by the conditional expectations. This sorting is done based on an insider's trade history up to the prior year's end for a given date's portfolio formation. The second sort is based on whether the trade is a buy or a sell. A stock from a given trade enters the buy or sell portfolio three days following the trade and is included for twenty days. The portfolio holds all stocks included in the portfolio that day at equal weights. The portfolio returns are converted to monthly returns for comparability with the monthly portfolio analysis. Panels A, B, and C report alphas using market, Fama-French-Carhart, and Fama-French Five Factor + momentum benchmarks, respectively.

Panel A: CAPM Alpha

	Conditional Expectation					
	Low	2	3	4	High	Hi-Lo
Sells	-0.0023	-0.0037	-0.0037	-0.0038	-0.0057	-0.0035
	(-1.58)	(-2.15)	(-1.85)	(-1.50)	(-2.25)	(-2.11)
Buys	0.0066	0.0049	0.0112	0.0081	0.0123	0.0057
	(2.49)	(1.65)	(3.19)	(2.04)	(3.87)	(2.53)
Buys Minus Sells	0.0089	0.0086	0.0149	0.0118	0.0180	0.0092
	(3.73)	(3.36)	(4.89)	(3.28)	(6.87)	(3.85)

Panel B: Fama-French Three Factor + Momentum Alpha

	Conditional Expectation					
	Low	2	3	4	High	Hi-Lo
Sells	-0.0011	-0.0022	-0.0020	-0.0016	-0.0035	-0.0024
	(-1.34)	(-2.47)	(-1.83)	(-1.05)	(-2.24)	(-1.69)
Buys	0.0085	0.0073	0.0138	0.0108	0.0149	0.0063
	(5.26)	(3.68)	(5.03)	(3.29)	(6.42)	(3.05)
Buys Minus Sells	0.0096	0.0096	0.0158	0.0124	0.0183	0.0087
	(5.87)	(4.71)	(5.70)	(3.60)	(7.61)	(3.81)

Panel C: Fama-French Five Factor + Momentum Alpha

	Conditional Expectation					
	Low	2	3	4	High	Hi-Lo
Sells	-0.0005	-0.0015	-0.0012	-0.0004	-0.0021	-0.0016
	(-0.64)	(-1.85)	(-1.16)	(-0.32)	(-1.55)	(-1.21)
Buys	0.0088	0.0079	0.0147	0.0119	0.0159	0.0072
	(5.41)	(3.99)	(5.45)	(3.67)	(7.12)	(3.60)
Buys Minus Sells	0.0092	0.0094	0.0159	0.0123	0.0180	0.0088
	(5.68)	(4.62)	(5.71)	(3.56)	(7.49)	(3.85)

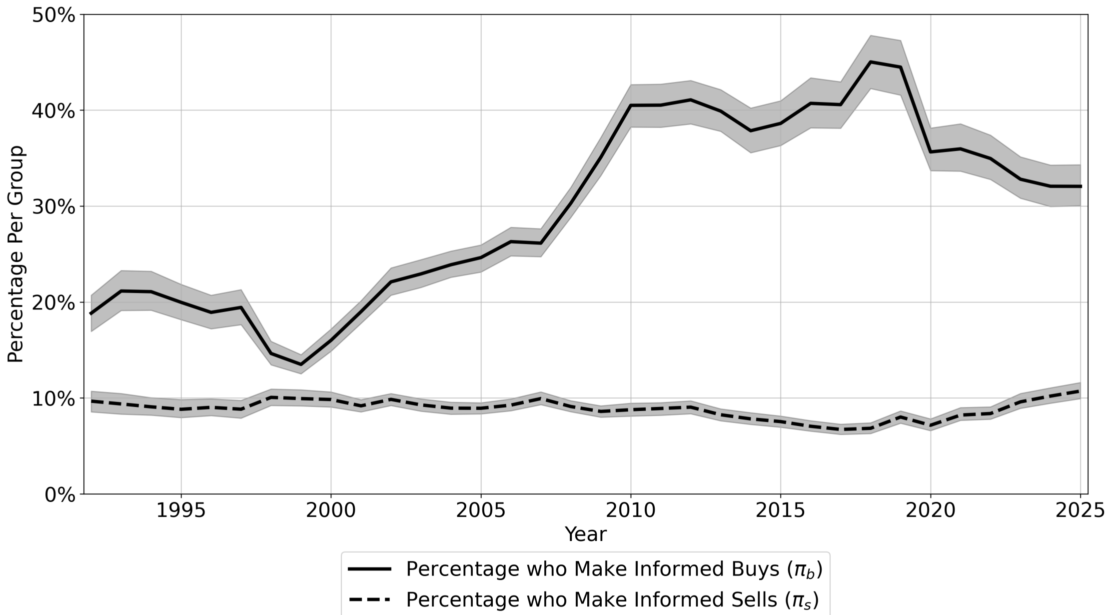
Table IA.3: Return Predictability Controlling for Cline, Gokkaya, and Liu (2017)

This table reports regressions of monthly stock returns as a function of insider buying and selling activity in the prior month. Buy and sell quintile indicators for whether any insider in the respective conditional expectation quintile traded in the month t are calculated as described in Table 3. Similar indicator variables are calculated for buys and sells made by a classification scheme following Cline et al. (2017). Specifically, in a given month, an insider is classified as persistently profitable if more than 50% of their trades over the prior 36 months have positive signed 21-day abnormal returns. To be classified in a given month, the insider needs to have made trades in at least three separate months in the 36-month window. If an insider does not meet this sample screen, the indicator for unclassified is turned on. 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)
Buy Quintile 1 (Lo)		-0.61***
		(-3.14)
Buy Quintile 2		-0.47***
		(-3.29)
Buy Quintile 3		0.10
		(0.62)
Buy Quintile 4		0.16
		(0.94)
Buy Quintile 5 (Hi)		0.33**
		(2.03)
Sell Quintile 1 (Lo)		0.12
		(1.41)
Sell Quintile 2		-0.07
		(-1.11)
Sell Quintile 3		-0.04
		(-0.55)
Sell Quintile 4		-0.04
		(-0.35)
Sell Quintile 5 (Hi)		-0.18
		(-1.64)
Persistently Profitable Buy	0.58***	0.68***
	(5.48)	(5.00)
Persistently Profitable Sell	-0.05	-0.01
	(-0.69)	(-0.18)
Not Persistently Profitable Buy	0.34**	0.69***
	(2.38)	(4.45)
Not Persistently Profitable Sell	0.10	0.07
	(1.31)	(0.91)
Unclassified Buy	0.86***	0.95***
	(7.68)	(6.68)
Unclassified Sell	-0.24***	-0.20**
	(-3.28)	(-2.40)
Time FE	Y	Y
Controls	Y	Y
Adj R^2	0.1234	0.1236
Observations	338,502	338,502
p(Buy Hi-Lo)		0.0001
p(Sell Hi-Lo)		0.0210

Figure IA.1: Time-Series of Estimated Parameters: Rolling Windows
The mixture model is estimated each year using the latest average abnormal returns and standard errors for buys and sells for each insider (using a 10-year rolling window). Panel (a) plots the time series of the probability of informed buys (π_b) and informed sells (π_s). Panel (b) plots the time series of the expected profitability for informed insiders (μ). The shaded region represents the 1st and 99th percentiles of the parameters estimated from 1,000 bootstrapped samples (with replacement).

(a) Percentage per Group (π's)



(b) Mean of Informed Trading (μ)

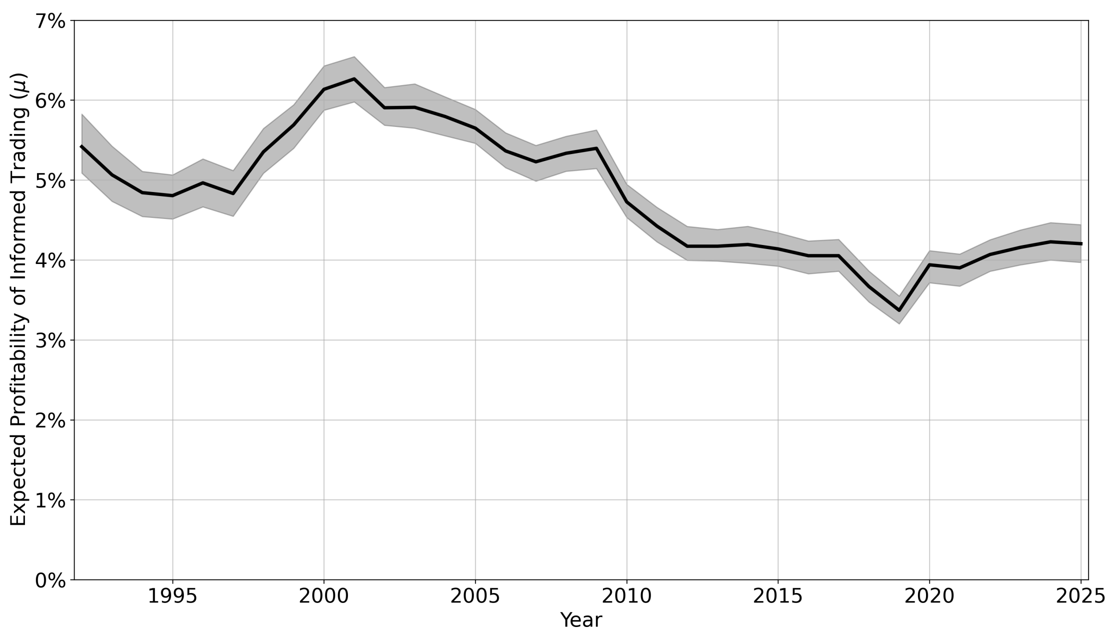


Figure IA.2: Estimated Ex-Ante Probability an Insider's Trade is Informed

The figure plots the estimated ex-ante probability that a trade made by a corporate insider was informed. The probability is a function of whether the trade is a purchase or a sale and the insider's ex-ante probability of making informed buys ($\tilde{\pi}_{b,i}$) or informed sells ($\tilde{\pi}_{s,i}$). The estimated parameters for the coefficients in Equation (17) are $\hat{a}_b = -1.92$, $\hat{b}_b = 2.06$, $\hat{a}_s = -2.75$, $\hat{b}_s = 3.92$. The plotted confidence intervals correspond to the 1% and 99% estimates obtained from 1,000 bootstrapped samples.

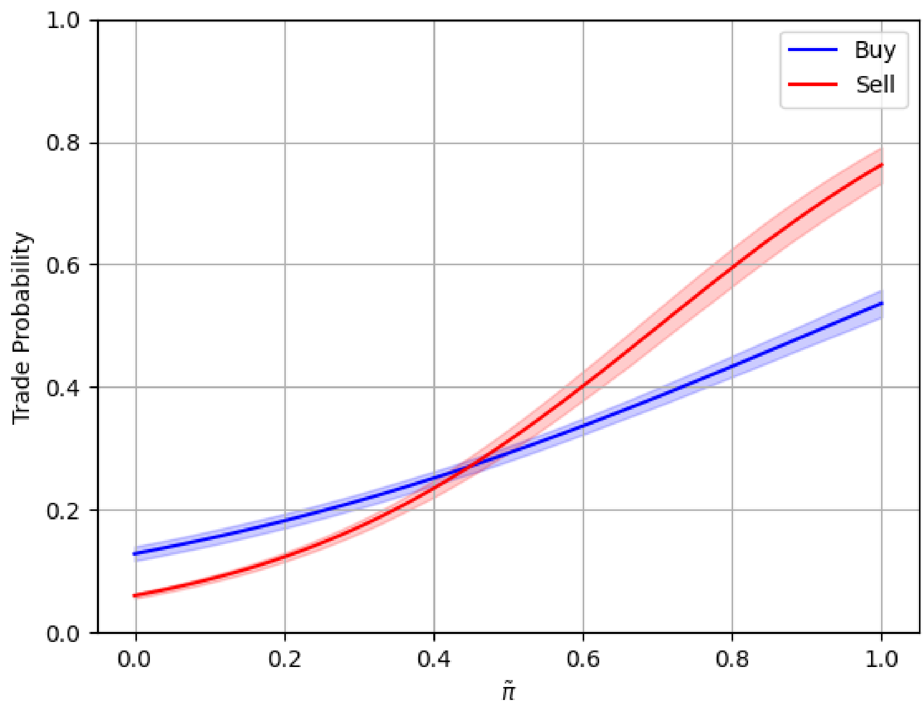


Figure IA.3: Distributions of Trade-Level Returns and Insider History

For each trade, a buy-and-hold abnormal return over the market is calculated over the 21 trading days following the transaction. A corresponding predicted 21-day trade-level standard deviation is calculated using a GARCH(1, 1) model for the traded stock. The left and right columns report histograms for buys and sells, respectively. 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 predicted trade-level standard deviations falling below 40%. Panel (c) plots the histogram of past average abnormal returns between between -45% and 45%. Panel (d) plots the histogram of the standard errors of the past average abnormal return that fall below 40%.