Does Algorithmic Trading Affect Forced CEO Turnover?

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Abstract: We examine whether algorithmic trading (AT) affects the extent to which directors rely on stock returns when making CEO turnover decisions. We find that the sensitivity of forced CEO turnover to stock returns decreases with AT. This effect of AT is more pronounced when the information that AT crowds out is more likely to be new to directors, when there is more informed trading that AT dampens, when the directors' expertise allows them to extract decision-relevant information from stock returns, and when the directors' own information set is poor. In contrast, the effect of AT does not vary with the strength of firms' corporate governance. Further analysis suggests that directors rely more on non-market measures and meet more frequently as AT increases. Overall, our findings suggest that directors incorporate information in stock returns regarding the CEO-firm match quality into their CEO turnover decisions and that AT deters such learning.

Keywords: Algorithmic trading, CEO turnover, CEO-firm match quality, directors, learning

JEL classifications: G30, J63, L20, E44, G19

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1. Introduction

CEO turnover is one of the most important decisions that corporate directors need to make (Jensen and Ruback 1983; Holmstrom 2004; Armstrong, Guay, and Weber 2010). Prior studies mainly focus on how the properties and information content of performance measures affect the turnover-performance sensitivity (Engel, Smith, and Wang 2003; Bushman, Dai, and Wang 2010; Jenter and Kanaan 2015; Suk, Lee, and Kross 2021).[1] In this paper, we build on this literature and examine how algorithmic trading (AT), one of the most notable financial innovations in the last several decades (Stiglitz 2014; Menkveld 2016), affects the extent to which directors rely on stock returns when making CEO turnover decisions. We argue that stock returns provide a useful source of information to directors in their CEO turnover decisions (Hermalin and Weisbach 1998, 2003; Taylor 2010; Adams, Hermalin, and Weisbach 2010) and that AT alters the usefulness of this information source.

In formulating corporate strategies and making resource allocation decisions, managers need to consider potential changes in the firm's economic environment and adapt accordingly. In CEO retention decisions, directors should assess the CEO's adaptation ability, evaluate whether the CEO matches with the firm from a long-term perspective, and consider the costs of replacing the CEO (e.g., Taylor 2010). Stock returns provide directors with a useful source of information because they not only reflect the realized outcomes of managerial efforts but also incorporate investors' assessment of the CEO-firm match quality in enhancing firm performance. We use the term "CEO-firm match" to broadly refer to the extent to which the managerial actions and abilities are matched with the firm's long-term survival and success in increasing firm value. Indeed, Eisfeldt and Kuhnen (2013) and Guay, Taylor, and Xiao (2015) emphasize the importance of the CEO adapting to changes in the business environment. They

[1] Consistent with the view of Jensen and Ruback (1983) and Shleifer and Vishny (1997) that failure to replace a poorly performing CEO is the costliest manifestation of agency problems, prior studies generally focus on the effects of governance mechanisms on the turnover-performance sensitivity (e.g., Weisbach 1988; Denis, Denis, and Sarin 1997; Huson, Malatesta, and Parrino 2004; Guo and Masulis 2015; and Dasgupta, Li, and Wang 2018).

argue that boards should consider multiple internal and external characteristics when assessing the CEO-firm match quality in turnover decisions.

Prior research finds that stock returns reflect information about the CEO-firm match quality that cannot be extracted from the firms' accounting information (Holmstrom and Milgrom 1991; Engel et al. 2003). How AT affects the amount of this decision-relevant information in stock returns is ex-ante unclear. The existing literature on AT makes a crucial distinction between two key components of price discovery: "(1) acquiring new information and (2) incorporating existing information into prices" (Weller 2018, pg. 2184). On one hand, AT rapidly integrates public information into prices (e.g., Zhang 2017; Chakrabarty, Moulton, and Wang 2022) as AT orders more efficiently translate information into prices through increased quoting efficiency (Hendershott, Jones, and Menkveld 2011) and greater permanent price impacts (Brogaard, Hendershott, and Riordan 2014). This body of work highlights that AT improves market efficiency with respect to public information once the information is disclosed by other sources, suggesting that directors will increase the extent to which they rely on stock returns in CEO turnover decisions as AT increases. This prediction follows from the classical argument that boards' reliance on stock returns as a performance signal increases with its precision (Holmstrom and Milgrom 1991; Engel et al. 2003). We label this channel as the monitoring channel.

On the other hand, both Weller (2018) and Lee and Watts (2021) demonstrate that the positive effects of AT on the extent to which prices reflect disclosed information come at the cost of discouraging the acquisition of new information by investors. While algorithms for liquidity provision and smart execution decrease costs for typical trades, these lower average costs can stem from the enhanced ability of algorithmic liquidity providers to screen order flow and evade adverse selection (Han, Khapko, and Kyle 2014; Stiglitz 2014). This improved screening of informed order flow, in turn, hampers information acquisition by redirecting potential rents away from those acquiring information. Hence, AT can reduce price informativeness despite translating available information into prices. This line of work suggests that when AT increases, stock returns are less likely to incorporate informed investors' private information about the CEO-firm match quality, leading to directors relying less on stock returns in CEO turnover decisions. We label this channel as the learning channel.

To assess the effects of AT on directors' reliance on stock returns in CEO turnover decisions, our empirical analysis follows prior literature and uses the sensitivity of CEO turnovers to stock returns (i.e., the turnover-return sensitivity).[2] Using 11,828 firm-year observations between 2012 and 2019, we examine how AT affects the sensitivity of forced CEO turnover (hereafter simply CEO turnover) to stock returns. We find a negative relation between CEO turnover and stock returns, and more importantly, the sensitivity of CEO turnover to stock returns decreases with AT. When AT moves from the bottom to the top decile, the sensitivity of CEO turnover to stock returns is reduced by approximately 56.3%. These results are consistent with the learning channel, which suggests that AT reduces the amount of new information in stock returns to directors for their CEO turnover decisions.

To alleviate potential endogeneity concerns, we employ an instrumental variable approach. Specifically, we follow Weller (2018) and use lagged stock prices as an instrument. The intuition for this instrument is as follows: in the presence of a minimum tick size of one cent, high-price stocks have a relatively fine price mesh,[3] which favors algorithmic traders over human traders for continually replacing stale limit orders with updated quotes. As such, the level of stock prices is positively correlated with algorithmic trading activity (instrument

[2] Prior studies document a robust negative relation between the likelihood of CEO turnover and stock returns, suggesting that poorly performing CEOs are more likely to be fired (e.g., Weisbach 1988; Huson et al. 2004). Throughout the paper, we use the term *turnover-return sensitivity* to refer to the magnitude of the negative relation between the likelihood of CEO turnover and stock returns; thus, a decreased turnover-return sensitivity means a reduction in the magnitude of the negative relation.

[3] The minimum tick size, one cent, accounts for 10 basis points for a \$10 stock as compared to one basis point for a \$100 stock.

relevance). We further posit that the level of stock prices, measured before the measurement window of stock returns and algorithmic trading, is not directly associated with the turnover-return sensitivity (exclusion restriction). In the two-stage least square estimation (2SLS), we find that the turnover-return sensitivity decreases with AT.

We conduct three sets of cross-sectional analyses to investigate whether the effect of AT on the turnover-return sensitivity is greater in circumstances where theory predicts directors' learning to be more pronounced. First, we examine whether the effect of AT on the turnover-return sensitivity is stronger when the information that AT crowds out is more likely to be new to directors. Learning models commonly assume that investors collectively have information advantages in assessing growth opportunities and industry factors (Goldstein, Yang, and Zuo 2023). Such information helps directors assess the CEO-firm match quality in the context of the firm's changing industry environments (Guay et al. 2015; Pan, Wang, and Weisbach 2015). Moreover, investors' information advantages also stem from their geographic presence (Gao and Xiao 2022). As opposed to directors, investors are more geographically dispersed and thus can better impound local information into stock returns. Consistent with our expectation, we find that the effect of AT on the turnover-return sensitivity is more pronounced in growth firms, firms facing steeper product market competition, and firms with a geographically dispersed investor base.

Second, we examine whether the effect of AT on the turnover-return sensitivity varies with the extent of informed trading. A premise underlying the learning channel is that AT discourages investors' incentives to acquire and trade on private information about the CEO-firm match quality. The effect of AT on board learning is likely to be stronger when there is more active informed trading that AT potentially dampens. Therefore, we expect that AT reduces the turnover-return sensitivity to a greater extent when ex-ante informed trading intensity is greater. Using a measure of informed trading intensity computed from machine learning models (Bogousslavsky, Fos, and Muravyev 2023), we find evidence consistent with our expectation.

Third, we investigate whether the effect of AT on the turnover-return sensitivity varies with directors' expertise and information set. Gleaning decision-relevant information from stock returns can be challenging, and directors with greater expertise to do so are more likely to learn investor information from stock returns. Further, learning models posit that managers rely more on investor information when their own information set is poor (e.g., Chen, Goldstein, and Jiang 2007; Bai, Philippon, and Savoy 2016). A similar intuition can apply to directors. Consistent with these predictions, we find a stronger effect of AT on the turnover-return sensitivity when directors have industry expertise as CEOs and when directors are less informed (proxied by directors' insider trading activities and trading profitability). Overall, these cross-sectional tests corroborate our argument that the effect of AT on the turnover-return sensitivity is driven by a decrease in directors' learning from stock returns.

We perform several additional tests to provide further support to the learning channel. First, we conduct falsification tests to further rule out the board monitoring channel. Under the monitoring channel, we would expect the effect of AT on the turnover-return sensitivity to vary with the strength of corporate governance. We do not find such evidence.[4]

Second, we explore whether boards rely on information from other sources when AT increases. We examine whether directors rely more on non-market performance measures when AT is higher. If boards learn less from stock returns when AT increases, rational directors will turn to non-return-based performance signals. Consistent with our intuition, we find that, as AT increases, the sensitivity of CEO turnover to return on assets (i.e., accounting earnings)

[4] This evidence also helps alleviate the concern that some boards use the decreased informativeness of stock prices stemming from AT as an "excuse" for not dismissing CEOs in responses to poor firm performance.

increases.[5] Third, we find that AT is positively associated with the frequency of special board meetings and the relation is more marked when assessing the CEO-firm match quality is more difficult for directors. These findings provide evidence of rational boards taking actions in response to a decrease in learning investor information from stock returns, providing further support to board learning as the underlying mechanism.

We contribute to three strands of literature. First, we contribute to the CEO turnover literature. Prior research extensively examines the role of corporate governance and agency problems in explaining CEO turnovers and finds that the turnover-performance sensitivity increases with stronger corporate governance (e.g., Weisbach 1988; Denis et al. 1997; Huson et al. 2004; Guo and Masulis 2015; and Dasgupta et al. 2018). Research also examines whether the turnover-performance sensitivity increases with the precision of public signals such as stock returns and earnings (Engel et al. 2003; Bushman et al. 2010). This literature on CEO turnovers does not differentiate the two different components of price discovery, i.e., "(1) acquiring new information and (2) incorporating existing information into prices" (Weller 2018, pg. 2184), and it largely focuses on the former – incorporation of existing information into prices. Our study uses AT to explore the important tension between acquiring information and incorporating it into asset prices. Our findings suggest that corporate directors glean investor information from stock returns for CEO turnover decisions and that such learning is hindered by algorithmic trading as it reduces private information acquisition.

Second, we contribute to the emerging literature on how decision-makers learn investor information from price signals to guide their real decisions (Bond, Edmans, and Goldstein 2012; Goldstein 2023). Most studies provide evidence in support of this informational feedback from the market to corporate managers in making corporate investment decisions (e.g., Luo 2005;

[5] We also investigate CEO compensation contracts using Incentive Lab data and find that compensation contracts put a greater weight on non-financial performance metrics as AT increases (results tabulated in Table OA.5 of the Online Appendix).

Chen et al. 2007; Edmans, Jayaraman, and Schneemeier 2017; Bennett, Stulz, and Wang 2020; Jayaraman and Wu 2020; Pinto 2022; Ye, Zheng, and Zhu 2022) and corporate disclosure choices (e.g., Zuo 2016; Chen, Ng, and Yang 2021).[6] Recent studies extend to other decision-makers including credit rating agencies (Brockman, Subasi, Wang, and Zhang 2024), private lenders (De George, Donovan, Phillips, and Wittenberg-Moerman 2023), and auditors (Feng, Li, and Luo 2023). We contribute to this growing literature by exploring corporate directors as decision-makers who glean investor information from stock returns when making CEO turnover decisions.

Third, we contribute to the literature on algorithmic trading. Prior research primarily focuses on AT's influence in capital market settings, such as liquidity and price discovery (e.g., Brogaard et al. 2014; Weller 2018; Chordia and Miao 2020; Lee and Watts 2021). We demonstrate that the effect of AT extends to directors' decisions on whether to replace poorly performing CEOs. On this point, our study is related to Ye et al. (2022), who document that stock price tick size affects managerial learning from stock prices in making investment decisions. The two studies on different decision makers (i.e., directors and managers) with different information needs are complementary and are of relevance to policymakers because any conclusions solely based on financial market effects may be incomplete in assessing the overall effect of algorithmic trading on the economy.[7]

[6] While not their primary focus, Bennett et al. (2020) also examine CEO turnovers. However, their empirical specification deviates from the performance-induced CEO turnover literature (including our paper) in two important ways. First, Bennett et al. (2020) do not examine the turnover decision with respect to stock returns but Tobin's q. Second, Bennett et al. (2020) include voluntary CEO turnovers in their analyses, which are driven by managers' cost-benefit analysis and not by directors' termination decisions (Garmaise 2011; Lin, Peters, and Seo 2022). In Table OA.2 of the Online Appendix, we provide evidence that AT does not affect the sensitivity of voluntary or other CEO turnovers to stock returns.

[7] Congress directed the U.S. Securities and Exchange Commission (SEC) to assess the benefits and risks of algorithmic trading as part of the Economic Growth, Regulatory Relief, and Consumer Protection Act of 2018. The report by SEC staff primarily analyzes the benefits and risks of algorithmic trading associated with financial markets (https://www.sec.gov/tm/reports-and-publications/special-studies/algo_trading_report_2020).

2. Related Literature and Hypothesis Development

2.1. CEO Turnover

CEOs are responsible for crafting corporate strategies and making resource allocation decisions. Subsequently, they assess potential shifts in the economic environment of the firm and adjust their strategies accordingly. As such, CEO turnover is arguably the most important decision that boards make due to its huge implications for firm value (Jensen and Ruback 1983; Holmstrom 2004; Armstrong et al. 2010). In making CEO retention decisions, directors evaluate the CEO's adaptability, assess the long-term compatibility between the CEO and the firm, and consider the costs associated with replacing the CEO (e.g., Taylor 2010). Prior research underscores the importance of the CEO's adaptability to changes in the business environment and argues that boards consider multiple internal and external performance measures to evaluate the CEO-firm match quality (Eisfeldt and Kuhnen 2013; Guay et al. 2015).

Prior research examines the relation between firm performance and forced CEO turnover (Weisbach 1988; Huson et al. 2004), particularly how the properties and the information content of performance measures affect the turnover-performance sensitivity. Bushman et al. (2010) find that the turnover-performance sensitivity is positively associated with the idiosyncratic component of stock returns, suggesting that directors' ability to learn about the unknown talent of a CEO increases with idiosyncratic risk in stock returns.[8] DeFond and Huang (2004) find that the turnover-return sensitivity decreases with stock return synchronicity in countries with strong law enforcement, suggesting that, conditional on strong governance mechanisms, directors' reliance on stock returns in CEO dismissal decisions increases with the extent to which stock returns reflect firm-specific information. Engel et al. (2003) find that the sensitivity of turnover to earnings increases with earnings timeliness,

[8] Similarly, Hayes, Tian, and Wang (2023) show that banking deregulation, which gives rise to more growth opportunities, is associated with a higher sensitivity of bank CEO turnover to the idiosyncratic portion of stock returns.

consistent with earnings being more useful in CEO retention decisions when they reflect information about managerial actions in a timelier fashion. Suk et al. (2021) find that the sensitivity of CEO turnover to accounting earnings increases with earnings persistence, consistent with directors placing a greater emphasis on earnings in CEO retention decisions when directors better understand the future performance implications associated with current earnings.

Overall, these studies establish that performance measures such as stock returns and accounting earnings reflect the implications of the CEO-firm match quality for future cash flows. However, prior research does not explore directors' acquisition of private information about the CEO-firm match quality in CEO turnover decisions. We posit investor information in stock returns as one such private information and study how algorithmic trading affects the extent to which directors rely on stock returns when determining CEO turnover decisions.

2.2. Directors' Use of Stock Returns in CEO Turnover Decisions

Stock returns serve as a valuable information source for directors, as stock returns not only indicate the actual outcomes of managerial efforts but also reflect investors' evaluations of the CEO-firm match quality in improving future firm performance. Directors' use of stock returns in CEO turnover decisions builds on two conditions: (i) a firm's stock price reflects market expectations about its future performance, and a change in stock price reflects a change in market expectations about future performance; (ii) the change in market expectations about future performance provides directors with a useful source of information in making CEO turnover decisions.

These two conditions are well established in prior research. For the first condition, Beaver, Lambert, and Morse (1980) provide initial evidence that stock prices are useful in forecasting future earnings. This finding is confirmed in several follow-up studies that use reverse regressions in which changes in earnings are regressed on lagged values of changes in stock prices (e.g., Beaver, Lambert, and Ryan 1987; Collins, Kothari, and Rayburn 1987). Zuo (2016) reinforces this finding by using management earnings forecasts. For the second condition, Rappaport (1987) has long noted that a company's insiders "can learn a lot if they analyze what the stock price tells them about the market's expectations for their company's performance," and he advocates a "market signals approach" in his consulting work. Mauboussin and Rappaport (2021) elaborate on the process through which managers can extract market expectations about future performance from stock prices.[9] This approach is conceptually akin to the implied cost of capital approach (e.g., Lee, So, and Wang 2021).[10]

Directors can use the market signals approach to evaluate executive performance (Rappaport 1987). Specifically, directors can infer the corporate rate of return implied by the company's stock price and compare this price-implied expectation with their own assessment. Stock price changes can be driven by changes in market expectations about future performance, changes in a company's cost of capital, or noise. If changes in stock price are driven by changes in market expectations about future performance, directors can rely on this signal, combined with their own assessment, to update the CEO-firm match quality and make retention decisions.[11]

2.3. Hypothesis Development

We argue that the effect of AT on the turnover-return sensitivity depends on how AT affects the extent to which changes in stock prices reflect market expectations about the CEO-firm match quality. Prior research characterizes the informativeness of stock prices in two ways

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[9] Michael Mauboussin is Head of Consilient Research at Counterpoint Global, Morgan Stanley Investment Management. Alfred Rappaport is the Leonard Spacek Professor Emeritus at Northwestern University's Kellogg School of Management. They provide extensive consulting work based on the market signals approach. Refer to their website for more information about expectations investing: https://www.expectationsinvesting.com/.

[10] The market signals approach takes the cost of capital obtained from external sources as an input into a discounted cash flow model to infer the implied performance. In contrast, the implied cost of capital approach takes future performance obtained from external sources as an input into a discounted cash flow model to infer the implied cost of equity.

[11] A reduction in stock prices can also reflect an increase in market expectations about the future cost of capital. This discount rate news can be interpreted as a signal about the CEO-firm match quality as the management is not expected by the market to generate a commensurate increase in future cash flows.

(Bond et al. 2012): (i) the extent to which prices reflect *existing* information in financial markets and (ii) the extent to which prices reveal *private* information that would otherwise be dispersed among investors. Crucially, prior studies find that AT not only facilitates the incorporation of existing information into prices but also discourages investors' private information acquisition (Weller 2018; Lee and Watts 2021). Consequently, it is ex-ante unclear how AT affects the usefulness of stock returns as a signal for the CEO-firm match quality.

Prior research shows that AT rapidly incorporates public information into prices (Zhang 2017; Chakrabarty et al. 2022). Orders based on algorithms exhibit enhanced quoting efficiency (Hendershott et al. 2011) and have greater permanent price impacts (Brogaard et al. 2014). In particular, Brogaard et al. (2014) show that high-frequency trades, a subset of algorithmic trading, forecast price changes several seconds in advance and tend to exhibit permanent price effects. As such, AT impounds public information into prices more efficiently. This research underscores that AT enhances market efficiency concerning information already disclosed by other sources. Consequently, this role of AT suggests that directors rely more on stock returns in their CEO turnover decisions as AT increases, and we expect the sensitivity of CEO turnover to stock returns to increase. We label this channel as the monitoring channel.

On the contrary, the effect of AT on the acceleration of information disclosed by other sources into prices may be offset or outweighed by its effect on discouraging investors' private information acquisition (Weller 2018; Lee and Watts 2021). Algorithms reduce trading costs for typical trades via liquidity provision and smart execution. However, such benefits result from the increased ability of algorithmic liquidity providers to screen order flow from informed traders and thus avoid adverse selection (Han et al. 2014; Stiglitz 2014). The improved screening of informed order flow, in turn, impedes investors' private information acquisition by ex-ante decreasing the expected returns to such activities. Therefore, as AT becomes more prevalent, stock returns may be less likely to incorporate investors' private information, some of which may concern the CEO-firm match quality. Consequently, as AT increases, directors may rely less on stock returns in their CEO turnover decisions, and we expect the sensitivity of CEO turnover to stock returns to decrease. We label this channel as the learning channel.

It is pertinent to note the following two points. First, one need not assume that investors are more informed than directors about the CEO-firm match quality for learning to arise. Rather, directors can learn from stock returns so long as they are not fully aware of all information and investors collectively provide some information that may be unknown to directors (Bond et al. 2012; Goldstein 2023). Second, distinguishing between changes in stock prices due to investors' information relevant to assessing the CEO-firm match quality versus those stemming from noise trading is not a trivial task. As elaborated in Section 2.2., we maintain that rational directors, on average, extract relevant information from changes in stock prices to use in decision-making.[12] However, we also acknowledge that whether directors can understand the sources of price changes is ultimately an empirical question. Thus, we present our hypothesis in null form.

***H1**: Algorithmic trading is unrelated to the sensitivity of forced CEO turnover to stock returns.*

3. Research Design

3.1. Empirical Specification

To examine the effects of AT on the turnover-return sensitivity, we estimate the following OLS regression model with firm and year fixed effects.[13]

[12] Goldstein (2023, pg. 3) states that "[a]nother counterargument is that prices are very noisy, or that it is difficult to interpret them because it is not known what kind of information they are conveying. While there is certainly noise in prices, the idea of the feedback effect is that, after taking the noise into account, prices are still informative. Rational economic agents will update, fully aware of the possibility of noise, and still find the price informative."

[13] Following prior studies (e.g., Cornelli, Kominek, and Ljungqvist 2013; Guo and Masulis 2015; Dasgupta et al. 2018), we employ a linear probability model for two primary reasons. First, a linear probability model allows us to include firm fixed effects to control for unobservable firm-specific characteristics that are endogenously determined with CEO turnover decisions (e.g., Hermalin and Weisbach 1998). Including high-dimensional fixed effects in the nonlinear specification is inappropriate due to the incidental parameter problem (Neyman and Scott 1948). Second, when the model is nonlinear, the marginal effects of two interacted variables in cross-sectional tests differ from the marginal effects of changing just the interaction terms (Ai and Norton 2003).

$$
\begin{aligned}
FORCED \; = \; & \beta_1\, RET + \beta_2\, AT + \boldsymbol{\beta_3\, RET \times AT} + \beta_4\, SIZE + \beta_5\, BTM + \beta_6\, VOL \\
& + \beta_7\, EARNVOL + \beta_8\, AIM + \beta_9\, ROA + \beta_{10}\, ANALYST + \beta_{11}\, IOR \\
& + \beta_{12}\, DIV + \beta_{13}\, DUALITY + \beta_{14}\, OWN + \beta_{15}\, AGE + \beta_{16}\, TENURE \\
& + \sum RET \times Firm\ Characteristics + \phi_i + \eta_t + \varepsilon,
\end{aligned} \tag{1}
$$

where *Forced* is an indicator variable that equals one if forced CEO turnover occurs in period *t*, and zero otherwise.[14] *RET* is based on the industry-adjusted stock returns measured over the periods *t* and *t-1* (*RETURN*). Jenter and Lewellen (2021) find that corporate boards put a greater weight on stock price performance in tenure years 0 and -1 than in prior years. The industry adjustments are based on the equal-weighted Fama-French 48 industry returns. We rank *RETURN* into deciles, ranging from 0 and 9, and scale it by 9 to create *RET*. We use a decile-ranked measure of stock returns since stock returns are skewed.[15]

The primary variable of interest is *AT*, which is the decile-ranked variable using a composite measure of algorithmic trading (*ATPCA*) based on four AT proxies: Odd Lot Ratio (*OLR*), Cancel-to-Trade Ratio (*CTR*), Trade-to-Order Ratio (*TTOR*), and Average Trade Size (*ATS*) (Weller 2018; Lee and Watts 2021).[16] *OLR* is the natural logarithm of the equal-weighted average of the daily odd lot ratio, and *CTR* is the natural logarithm of the equal-weighted average of the daily cancel-to-trade ratio. Higher values of *OLR* and *CTR* are associated with higher levels of algorithmic trading. *TTOR* is the natural logarithm of the equal-weighted average of the daily trade-to-order ratio, and *ATS* is the equal-weighted average of the daily average trade size. Lower values of *TTOR* and *ATS* are associated with higher levels of algorithmic trading. All four proxies are averaged over the same measurement period of the industry-adjusted stock returns (i.e., periods *t* and *t-1*). *ATPCA* is the first principal component

[14] Forced turnover data are from https://www.florianpeters.org/ and https://doi.org/10.5281/zenodo.4543893.
[15] Our inferences are similar when we use raw industry-adjusted returns (*RETURN*) instead of the decile-ranked industry-adjusted returns (*RET*). See Table OA.1 of the Online Appendix.
[16] Refer to Lee and Watts (2021) for a brief motivation behind each proxy and the details of the calculation.

of the four algorithmic trading proxies.[17] We rank *ATPCA* into deciles, ranging from 0 and 9, and scale it by 9 to create *AT*. Therefore, in Eq. (1), the coefficient on *RET* reflects the turnover-return sensitivity when the firm's level of algorithmic trading is in the bottom decile and the coefficient on the interaction between *RET* and *AT* represents the differential turnover-return sensitivity when the firm's algorithmic trading activities move from the bottom to the top decile.

We follow prior studies and include the following set of control variables in the regression model (e.g., Guo and Masulis 2015; Weller 2018): Firm size (*SIZE*), book-to-market ratio (*BTM*), stock return volatility (*VOL*), earnings volatility (*EARNVOL*), Amihud's (2002) stock illiquidity measure (*AIM*), return on assets (*ROA*), the number of financial analysts following the firm (*ANALYST*), institutional ownership (*IOR*), and an indicator variable equal to one if the firm is a dividend-payer (*DIV*), an indicator variable equal to one if the CEO is the chairman of the board (*DUALITY*), the percentage of shares owned by the CEO (*OWN*), the natural logarithm of CEO age (*AGE*), and the natural logarithm of CEO tenure (*TENURE*). ϕ_i and η_t represent firm fixed effects and year fixed effects, respectively. We also include *RET* interacted with firm characteristics to control for the possibility that the turnover-return sensitivity varies by firm characteristics that are correlated with AT. We cluster standard errors by firm. Appendix A provides more details on variable construction.

3.2. Data and Descriptive Statistics

We combine several data sources. We calculate stock returns, stock return volatility, and stock liquidity measures using data from the Center for Research in Security Prices (CRSP). We retrieve firms' financial statement data from Compustat. We obtain data on proxies for algorithmic trading from the Market Information Data Analytics System (MIDAS) database.

[17] Principal component analysis explains the variance structure of data by linear combinations of variables and thus reduces the data to a few principal components but retains a maximum of information contained in the original variables with less noise. We find that the first principal component of the four AT proxies explains about 51.1% of their common variation (untabulated).

MIDAS significantly improves the identification of algorithmic trading and has collected order data across all major U.S. stock exchanges since 2012. We construct the CEO turnover sample with all firms in ExecuComp, which provides data on CEO titles (i.e., whether the CEO is the chairman), tenure, age, and stock ownership. We obtain the number of analysts following the firm from the Thomson Reuters I/B/E/S database and institutional holdings information from the 13F database. We also collect outside directors' identities and employment histories from the BoardEx employment file. We require non-missing values for AT proxies, stock returns, and other variables used in our regressions. The above data requirements yield a sample of 11,828 firm-year observations that correspond to 1,739 unique firms over the sample period between 2012 and 2019. We winsorize all continuous variables at the 1^{st} and 99^{th} percentiles to reduce the influence of outliers.

Panel A of Table 1 reports the descriptive statistics of the CEO turnover variables, proxies for algorithmic trading, and control variables. The mean value of the likelihood of forced CEO turnover (*FORCED*) is approximately 3.6%, which is similar to that in prior studies (e.g., Guo and Masulis 2015; Jenter and Lewellen 2021). The statistics of control variables are also similar to those reported in prior studies (Guo and Masulis 2015; Dasgupta et al. 2018; Jenter and Lewellen 2021).

Panel B of Table 1 provides unconditional Pearson correlations among the four AT proxies. We find that all proxies are correlated with each other in the expected direction with some individual variation (Weller 2018). As expected, *ATPCA* is highly correlated with the four input variables: it is significantly positively correlated with *OLR* (0.851) and *CTR* (0.697) and significantly negatively correlated with *TTOR* (-0.684) and *ATS* (-0.737). The high correlations indicate that *ATPCA* effectively captures the common variation attributable to AT.

Next, we examine the determinants of algorithmic trading. We select variables based on Weller (2018). We present the results in Appendix B. We find that algorithmic trading is positively associated with firm size (*SIZE*), stock illiquidity (*AIM*), stock return (*RET*), accounting performance (*ROA*), and institutional ownership (*IOR*), but negatively with book-to-market (*BTM*) and analyst following (*ANALYST*). We control for the effects of these variables on the turnover-return sensitivity through interaction terms.

4. Empirical Results

4.1. Effect of AT on the Sensitivity of CEO Turnover to Stock Returns

Table 2 provides the estimation results using Eq. (1). In Column (1), we first estimate the regression model without the interaction term, $RET \times AT$, and find a significantly negative coefficient on *RET* at the 1% level (Coeff. = -0.058). The coefficient estimate suggests that moving from the bottom to the top decile of *RET* is associated with a 5.8% decrease in the likelihood of the forced CEO turnover (i.e., the turnover-return sensitivity). In Columns (2) and (3), we include the interaction term $RET \times AT$. Focusing on Column (3), where *RET* is additionally interacted with firm characteristics, we find a significantly negative coefficient on *RET* at the 5% level (Coeff. = -0.151) while the coefficient on $RET \times AT$ is significantly positive at the 1% level (Coeff. = 0.085). The result indicates that the turnover-return sensitivity exhibits a notable decline of approximately 56.3% when *AT* shifts from the bottom to the top decile (-0.563 = 0.085/-0.151). We find similar results in Column (2). Overall, these findings align with the notion of the learning channel, which suggests that AT diminishes the amount of investor information in stock returns that may be new to directors for CEO turnover decisions.

We mitigate the potential endogeneity concern associated with our inference by employing an instrumental variable (IV) approach. We follow Weller (2018) and use lagged stock prices as an instrument for algorithmic trading.[18] We construct our instrument, *PRICE*,

[18] Weller (2018, pg. 2186-2187) states that "The 'sub-penny' rule (SEC Rule 612) imposes a minimum tick size of one cent for securities covered by Reg NMS, and this minimum price increment translates into variation in the fineness of the price grid as a function of price. High price stocks have a relatively fine price mesh, which favors algorithms over humans for continually updating limit orders for liquidity provision or monitoring for stale limit orders in liquidity taking."

measured as the decile-ranked average stock price in period *t-2*, preceding the measurement window of *RET* in periods *t* and *t-1*. Thus, this instrument captures the ex-ante effects of AT on the turnover-return sensitivity rather than the endogenous response of AT to firm performance.

We present the estimation results from the 2SLS in Table 3. In Columns (1) and (2), we present the first-stage regression results. In the first-stage regressions, the two endogenous variables are *AT* and *RET* × *AT*, and the two instruments are *PRICE* and *RET* × *PRICE*. We find that *AT* and *RET* × *AT* are significantly associated with *PRICE* and *RET* × *PRICE*, satisfying the instrument relevance condition.[19] Column (3) displays results from the second-stage regression. We find that the coefficients on instrumented *AT* and instrumented *RET* × *AT* are negative at the 10% level and positive at the 5% level, respectively, consistent with the results in Table 2. These results alleviate the endogeneity concern that our results in Table 2 are confounded by omitted variable bias.

4.2. Cross-Sectional Tests

We conduct three sets of cross-sectional analyses to demonstrate that the effect of AT on the turnover-return sensitivity is greater in circumstances where theory predicts directors' learning to be more pronounced.

4.2.1 Firm Characteristics

We investigate whether the impact of AT on the sensitivity of turnover to returns varies with firm characteristics that are associated with the types of information directors are likely to glean from stock returns. Learning models posit that investors, collectively, possess information advantages in evaluating growth opportunities and industry factors such as product market competition (Bond et al. 2012; Goldstein et al. 2023). This information is valuable for

[19] The first-stage statistics from diagnostic tests are presented toward the bottom of the table. We find that the LM test rejects under-identification at the 1% significance level, and the first-stage F statistic (34.545) exceeds the Stock-Yogo weak IV test critical value corresponding to a 10% maximal IV size (7.03), indicating that the instrument easily passes the weak IV test (Stock and Yogo 2005; Wooldridge 2010).

directors in evaluating the CEO-firm match quality, especially in the context of evolving industry environments for the firm (Guay et al. 2015; Pan et al. 2015).[20] Moreover, because investors are geographically more dispersed, they may possess better local information than directors (Gao and Xiao 2022). Such local information serves as valuable signals in assessing the firm's future growth prospects (i.e., local product market competition and consumer demands).

To investigate whether the effect of AT varies with respect to the firm's growth option, we follow Peters and Taylor (2017) and employ a measure of the firm's intangible capital. This measure is based on the replacement cost of intangible capital and is estimated to be the sum of the firm's externally purchased intangible capital (i.e., goodwill) and internally created intangible capital. The replacement cost of internally created intangible capital is computed as the sum of knowledge capital (based on R&D spending) and organizational capital (based on SG&A expenses). We create an indicator variable (*HIGH INTCAP*) that equals one if a firm's intangible capital as of the beginning of period *t* is above the sample median, and zero otherwise. For the cross-sectional tests, we include partitioning indicator variables, *AT*, and *RET*, and our main variable of interest is the triple interaction term.

We present the estimation results in Columns (1) and (2) of Table 4. We find statistically significant and positive coefficients on the interaction term, *HIGH INTCAP* × *AT* × *RET* at the 5% level. This finding supports our inference of directors' learning from stock returns, as informed traders' information advantages lie in assessing growth opportunities rather than assets-in-place (Goldstein et al. 2023).

Second, we investigate whether the effect of AT varies with respect to the firm's competitive environment. We proxy for the firm's competitive environment using two

[20] Pan et al. (2015) find that the stock market's learning about CEO ability is stronger when firms operate in more competitive industries and introduce products more frequently (i.e., higher product obsolescence risk).

measures. First, we use the number of product market peers based on the Text-Based Network Industry (TNIC) classification (Hoberg and Phillps 2016; Jayaraman, Milbourn, Peters, and Seo 2021; Feichter, Moers, Timmermans 2022).[21] We create an indicator variable (*HIGH PMC*) that equals one if the number of product market peers as of the beginning of period *t* is above the sample median, and zero otherwise. Second, we use the number of new products introduced by the firm (Pan et al. 2015). Firms in more competitive industries face higher product obsolescence risks and thus introduce new products more frequently. We create an indicator variable (*HIGH PROD*) that equals one if the number of new products introduced by the firm over the past five years is above the sample median, and zero otherwise.

We present the estimation results in Columns (3) – (6) of Table 4. We find statistically significant and positive coefficients on *HIGH PMC* × *RET* × *AT* at the 1% significance level in Columns (3) and (4). The coefficients on *HIGH PROD* × *RET* × *AT* are also positive and significant at the 10% level in Columns (5) and (6). These findings further support the notion of directors' learning from stock returns, particularly about competition, which represents a form of uncertainty that the stock market is better at understanding by aggregating relevant information from diverse investors (Bond et al. 2012).

Third, we examine whether the effect of AT varies with the extent to which firms' investors are geographically dispersed. To proxy for the geographic dispersion of the firm's investor base, we use the variation in the locations of requests for the firm's filings on the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system. Prior studies find that such requests largely correspond to the firm's investor base given their significant explanatory power in explaining the firm's market reaction to earnings news (Drake, Roulstone, and Thornock 2015; Drake, Johnson, Roulstone, and Thornock 2020; Chen 2023). We

[21] We do not use industry concentration as a measure of product market competition because the relation between industry concentration and competition is conceptually ambiguous (Lang and Sul 2014).

construct a search-weighted Herfindahl-Hirschman Index (*GEODIV*) as the sum of the squares of each firm's number of non-robotic EDGAR searches by IP addresses from each state during the year, scaled by the number of all non-robotic EDGAR searches during the year. We create *HIGH GEODIV*, an indicator variable that equals one if the search-weighted HHI of the firm's geographic investor base is below the median during the year, and zero otherwise.

Columns (7) and (8) of Table 4 present the estimation results. Consistent with our prediction, we find statistically significant and positive coefficients on the interaction terms *HIGH GEODIV* × *RET* × *AT* at the 5% level in both columns. These findings indicate that the effect of AT on the turnover-return sensitivity is more pronounced among firms with a more geographically dispersed investor base. Overall, the results in Table 4 corroborate our argument that the effect of AT on the turnover-return sensitivity is driven by a decrease in directors' learning from stock returns.

4.2.2 Informed Trading Intensity

A key premise underlying the learning channel is that AT discourages investors' incentives to acquire and trade on private information about the CEO-firm match quality, which directors wish to glean from stock returns. Validating this premise is inherently challenging because such private information contained in stock returns is unobservable and existing measures of informed trading have been criticized (Collin-Dufresne and Fos 2015).

We overcome this issue by using a measure of informed trading intensity computed from machine learning models (*ITI*). Bogousslavsky et al. (2023) use Schedule 13D trades (i.e., observed informed trades) and train their algorithms to measure the intensity of unobservable informed trading on each trading day. They further decompose *ITI* into impatient *ITI* (*ITI_IMP*) and patient *ITI* (*ITI_P*), which capture the intensity of informed trading based on relatively short-horizon and long-horizon private information, respectively. For example, informed trading regarding the content of upcoming earnings announcements is likely based on short-horizon private information, whereas informed trading regarding the CEO-firm match quality is likely based on long-horizon private information.

We first examine the relation between AT and the extent of informed trading by regressing measures of informed trading intensity (*ITI*, *ITI_P*, or *ITI_IMP*) on algorithmic trading and control variables. Specifically, we modify Eq. (1) by replacing the dependent variable with the average of the informed trading intensity measure in period *t* and dropping *RET* × *AT* and interaction terms between *RET* and firm characteristics. We present the estimation results in Table OA.3 of the Online Appendix. In odd (even) columns, we use the continuous AT proxy, *ATPCA* (the decile-ranked AT proxy, *AT*). Apart from Column (6), where the dependent variable is *ITI_IMP*, we find statistically significant and negative associations between the informed trading intensity measure and AT proxies, validating the notion that AT discourages investors' incentives to acquire and trade on private information.

Next, we explore whether the effect of AT on the turnover-return sensitivity varies with the extent of informed trading. To create the conditioning variables, we first compute the averages of daily *ITI, ITI_P,* and *ITI_IMP* values between periods *t* and *t-1* consistent with the measurement of *AT* and *RET*. We lag the averages by two periods to create conditioning variables as of the beginning of period *t-1*, preceding the measurement window of *AT* and *RET*. We create indicator variables (*HIGH ITI*, *HIGH ITI_P*, and *HIGH ITI_IMP*) that equal one if the average values of *ITI*, *ITI_P*, and *ITI_IMP* are greater than the respective sample medians, and zero otherwise. We interact these indicator variables with *RET*, *AT*, and *RET* × *AT*.

The estimation results are reported in Table 5. We find statistically significant and positive coefficients on *HIGH ITI* × *RET* × *AT* at the 10% level in Columns (1) and (2) and on *HIGH ITI_P* × *RET* × *AT* at the 5% level in Columns (3) and (4). In contrast, interestingly, the coefficients on the interaction terms using impatient informed trading intensity (*HIGH ITI_IMP* × *RET* × *AT*) are insignificant, as shown in Columns (5) and (6). These findings suggest that boards rely more on stock returns in CEO turnover decisions when more investor information (particularly long-horizon information) is reflected in returns, and AT hinders directors' learning by deterring the incorporation of such information into stock returns.

4.2.3 Director Characteristics

We investigate whether the effect of AT on the turnover-return sensitivity varies with directors' expertise and information set. The learning channel suggests that directors can glean decision-relevant information from stock returns when making CEO turnover decisions. However, such a task is challenging as it requires directors to distinguish between price movements due to decision-relevant information and those due to noise trading. Thus, directors with expertise are more likely to learn from stock returns. Learning models posit that managers will rely more on investor information when their own information set is poor (Bai et al. 2016). Similarly, directors' ability and expertise to learn from stock returns may exhibit heterogeneity.

First, we examine the directors' expertise. We argue that directors with industry experience as CEOs are better able to glean decision-relevant information from stock returns. Consistent with heterogeneous director expertise, Dass, Kini, Nanda, Onal, and Wang (2014) find that directors from related industries bring valuable knowledge and help firms overcome information challenges, such as demand and supply shocks. In addition, CEOs remove the effect of noise trading on stock returns to extract useful information for their investment decisions (Jayaraman and Wu 2020). Therefore, directors with prior industry experience as CEOs are better able to glean information from stock returns and hence rely more on stock returns to assess the CEO-firm match quality. Thus, the effect of AT on the turnover-return sensitivity is predicted to be stronger for firms with such directors.

To test this prediction, we create an indicator variable (*HIGH INDEXP*) that equals one if the number of outside directors who have worked in the same industry as a CEO before joining the current firm divided by the total number of directors in period t is greater than the sample median, and zero otherwise. The results are reported in Columns (1) and (2) of Table 6. We find statistically significant and positive coefficients on the interaction term (*HIGH INDEXP* × *RET* × *AT*) at the 5% level. This finding is consistent with boards gleaning more investor information from stock returns when they have the expertise to do so, and AT deterring such boards' learning to a greater extent.

Next, we examine directors' information set. Specifically, we expect directors will look more to stock returns when the quality of their own information set is poor. A large body of literature examines the open market stock trading by outside directors to estimate the quality of information directors possess. Ravina and Sapienza (2010) find that outside directors earn substantial abnormal returns from trading the firm's stock. Cao, Dhaliwal, Li, and Yang (2015) find that outside directors with social ties to the CEO earn higher trading profits. Motivated by this line of research, we argue that when boards consist of more directors who are less likely to trade the stock of the firm and have lower insider trading profits, they are less likely to possess internal information about the CEO-firm match quality and thus will have more incentives to glean investor information from stock returns in CEO retention decisions.

To test this prediction, we create two variables that capture the quality of boards' information set.[22] First, we compute the percentage of the board that has traded the firm's stock at least once during the year. We create an indicator variable (*LOW INSTRADE*) that takes a value of one for boards with a below-median percentage of outside directors trading in the firm's stock during the year, and zero otherwise. Second, we estimate the average insider trading profits of outside directors during the year by following the method of Jagolinzer, Larcker, and Taylor (2011). Specifically, for every trade, we measure the trade profitability as the intercept (i.e., alpha) from the four-factor Fama and French (1993) and Carhart (1997)

[22] We restrict our analyses to open market sales and purchases since these trades are most likely to be information-driven, unlike option grants (Ravina and Sapienza 2010).

models estimated over 180 days following the trade. For sales transactions, we multiply by negative one to the alpha value. We take the mean alpha value if the director has multiple trades during the period. We create an indicator variable (*LOW INSPROFIT*) that takes a value of one for boards with a below-median average trading profit during the year, and zero otherwise.

The results for these cross-sectional tests are reported in Columns (3) – (6) of Table 6. We find statistically significant and positive coefficients on *LOW INSTRADE* × *RET* × *AT* at the 5% level in Columns (3) and (4) and on *LOW INSPROFIT* × *RET* × *AT* at the 10% level in Columns (5) and (6). More specifically, in Column (6), we find that the coefficient estimates on *RET* and *RET* × *AT* are equal to -0.147 and 0.063, indicating that the turnover-return sensitivity is reduced by approximately 42.9% when AT moves from the bottom to the top decile and insider trading profitability is higher than the sample median (-0.429 = 0.063/-0.147). However, the coefficient estimates on *LOW INSPROFIT* × *RET* and *LOW INSPROFIT* × *RET* × *AT* are equal to -0.032 and 0.072, respectively. These results suggest that, when insider trading profitability is lower than the sample median, the turnover-return sensitivity is reduced by approximately 75.4% when AT moves from the bottom to the top decile (-0.754 = (0.063+0.072)/(-0.147-0.032)). Overall, these findings suggest that AT deters learning to a greater extent for firms with informationally disadvantaged directors.

4.3. Falsification Tests of Board Monitoring

The results in Sections 4.1 and 4.2 are most consistent with the learning channel as opposed to the monitoring channel. Nonetheless, we further rule out the monitoring channel. Another explanation that could be consistent with the negative effect of AT on the turnover-sensitivity is that some boards may use the decreased informativeness of stock returns stemming from AT as an "excuse" for not dismissing CEOs in response to poor performance. To rule out these explanations, we conduct falsification tests by examining whether the effect of AT on the turnover-return sensitivity varies with the strength of corporate governance. Under both explanations, AT's effect will be stronger for firms with weak monitoring.

We measure the strength of firms' corporate governance with two proxies. First, we employ a measure of co-opted boards—the extent to which the board is comprised of directors who are appointed after the CEO took her office—as a proxy for the lack of effective board monitoring (Coles, Daniel, and Naveen 2014). Specifically, Coles et al. (2014) calculate the level of co-option as the fraction of the board comprised of directors who are appointed after the CEO joined the firm. They also calculate the level of tenure-weighted co-option, since the effect of co-opted directors on the board's monitoring effectiveness is more compromised as their tenure on the board increases. We present the results in Table 7. In Columns (1) and (2), we create an indicator variable (*HIGH MONITOR*) that equals one if the level of co-option in period *t* is below the sample median, and zero otherwise. We interact this indicator variable with *AT* and *RET*. We find that the coefficients on the interaction term *HIGH MONITOR* × *RET* × *AT* are statistically indifferent from zero. In Columns (3) and (4), we use the level of tenure-weighted co-option to create *HIGH MONITOR* and find similar results.

Second, we proxy for firms' corporate governance using institutional investors' ownership (e.g., Gillan and Starks 2000; Hartzell and Starks 2003). We construct the fraction of the number of outstanding shares owned by institutional investors (*IOR*) and institutional ownership concentration using the Herfindahl-Hirschman Index (HHI). We create *HIGH MONITOR* variable if institutional ownership as of the beginning of period *t* is greater than the sample median and zero otherwise. We interact this variable with *RET* and *AT*. We do not find significant coefficients on the interaction term, as shown in Columns (5) and (6). Using the HHI of institutional ownership to create *HIGH MONITOR* variable yields similar results, as shown in Columns (7) and (8). Overall, these findings help rule out board monitoring or the "captured" board as alternative explanations.

4.4. Do Boards Turn to Non-Market-Based Performance Measures?

To provide further support to the learning channel, we examine whether boards rely on other information sources when AT increases. Boards rely on both market and non-market signals in CEO turnover decisions, with the weights put on these two types of performance measures depending on the relative strength of signal versus noise (Engel et al. 2003).[23]

First, we examine whether the effect of AT on the sensitivity of turnover to accounting performance increases as AT decreases the turnover-return sensitivity. To test this prediction, we use industry-adjusted return on assets as the accounting performance measure (Dasgupta et al. 2018; Intintoli, Serfling, and Shaikh 2017). Return on assets is calculated as operating income before depreciation in period *t-1*, which excludes special items that are not under the CEO's control (e.g., Hayes, Lemmon, and Qiu 2012; Allen, Larson, and Sloan 2013), deflated by lagged total assets. We rank the industry-adjusted return on assets into deciles, ranging from 0 to 9, and scale it by 9 to create *ROA*. We augment Eq. (1) by adding *ROA* × *AT*. To mitigate endogeneity concerns, we estimate 2SLS regressions using the same instrument as in Table 3.

The results are presented in Table 8. The three endogenous variables are *AT*, *RET* × *AT*, and *ROA* × *AT* and the corresponding three instruments are *PRICE*, *RET* × *PRICE*, and *ROA* × *PRICE*, respectively. Three sets of the first-stage regressions are reported in Columns (1) – (3). We find that *PRICE* is significantly associated with *AT* in Column (1), *RET* × *AT* is significantly associated with *RET* × *PRICE* in Column (2), and *ROA* × *AT* is significantly associated with *ROA* × *PRICE* in Column (3). The first-stage statistics indicate that the model is identified and does not suffer from the weak instrument problem. Column (4) presents the second-stage regression results. We find that the coefficient on the instrumented interaction term (*RET* × *AT*) is positive at the 5% level, consistent with the results in Table 3. Importantly,

[23] An extensive body of literature also examines the relative importance of stock returns and earnings as performance measures for CEO compensation (Holmstrom 1979; Lambert and Larcker 1987; Baber, Kang, and Kumar 1998; Core, Guay, and Verrecchia 2003; Jayaraman and Milbourn 2012; Li and Wang 2016; Bettis, Bizjak, Coles, and Kalpathy 2018; Jayaraman, Ling, Wu, and Zhang 2021).

we document that the coefficient on the instrumented interaction term (*ROA* × *AT*) is significantly negative at the 10% level, suggesting that AT strengthens the sensitivity of forced CEO turnover to the accounting performance measure. Overall, these results are consistent with directors relying on accounting-based performance measures in CEO turnover decisions as AT increases, further supporting the learning channel.[24]

Another implication of AT's effect on board learning from stock returns is that boards may engage in more information collection and processing activities when AT increases. We use the number of special board meetings as a proxy for the intensity of information collection activities by boards. Boards typically hold regular meetings, but also special meetings as needed. We argue that when boards perceive lower investor information in stock returns due to higher AT, they are more likely to hold special meetings to discuss the CEO-firm match quality and its implications for firm value.

To count the number of special board meetings, we search for several keywords related to special meetings ("special meeting," "additional meeting," and "unscheduled meeting") in proxy statements and textually parse the number of special meetings held during the fiscal year from these filings. We define *BRDMEET* as the natural logarithm of one plus the number of special board meetings and regress *BRDMEET* on *AT* and a set of control variables as in Column (1) of Table 2. The results are presented in Column (1) of Table 9. We find the coefficient on *AT* is positive and significant at the 10% level, suggesting that boards engage in information acquisition through special board meetings when AT increases.[25]

We further conduct cross-sectional tests to examine whether special board meetings are held particularly when boards are likely to have more difficulty in evaluating the CEO-firm

[24] Prior research shows the negative effect of algorithmic trading on financial reporting quality (Ahmed, Li, and Xu, 2020). The negative relation suggests that, as AT increases, the sensitivity of CEO turnover to ROA will decrease. We find the opposite, suggesting that financial reporting quality is not a confounding factor.
[25] In Table OA.4 of the Online Appendix, we use the composite measure of algorithmic trading (*ATPCA*) and find consistent results.

match quality. The positive relation between AT and the frequency of special board meetings will be more pronounced when evaluating the CEO-firm match quality is costlier. Drawing on prior research, we use young CEOs and external CEOs to capture circumstances where boards incur higher costs to acquire private information about the CEO-firm match quality (Pan et al. 2015). Specifically, we create an indicator variable (*YOUNGCEO*) that equals one if the CEO is younger than 53 years old when starting her CEO position and zero otherwise (Pan et al. 2015). We create an indicator variable (*OUTSIDECEO*) that equals one if the CEO is hired outside of the firm, and zero otherwise. We interact these indicator variables with *AT*. The results presented in Columns (2) and (3) of Table 9 support our predictions. We find statistically significant and positive coefficients on *AT* × *YOUNGCEO* and *AT* × *OUTSIDECEO* at the 1% and 10% levels, respectively. These findings suggest that boards incur additional costs (i.e., more special meetings) to obtain information about the CEO-firm match quality when AT deters learning from stock returns.

Lastly, we examine whether boards place a higher weight on non-financial performance metrics in CEO pay contracts while decreasing weight on market-based performance metrics. Although our main interest lies in CEO turnover decisions, a similar argument can be made regarding the effect of AT on CEO compensation metrics. As AT deters the incorporation of investor information about the CEO-firm match quality into stock returns, boards may rely less on market-based performance metrics and increase weights in non-financial performance metrics. We identify performance metrics in CEO pay contracts from the Incentive Lab dataset. The results in Table OA.5 of the Online Appendix are consistent with boards increasing (decreasing) weights on non-financial (market-based) performance metrics when designing CEO pay contracts as AT increases, consistent with the learning channel.

4.5. Additional Analyses

We conduct additional analyses to assess the robustness of our results to alternative research designs. First, we combine all types of turnovers (forced, voluntary, and others such as retirement) and examine the effect of AT on the sensitivity of all types of turnovers with respect to stock returns. In conditional fixed-effects multinomial logit regressions, we find that the sensitivity of voluntary or other CEO turnovers to stock returns is not affected by AT, indicating that our findings are driven by CEO termination decisions by directors. We report the results in Table OA.2 of the Online Appendix. Second, we exploit a randomized field experiment conducted by the SEC, the Tick Size Pilot (TSP) program, which decreased algorithmic trading, to further mitigate endogeneity concerns.[26] In a generalized difference-in-differences design, we find that the turnover-return sensitivity for treatment firms significantly increases during the TSP program period compared to the pre-period. We report the results in Tables OA.6 and OA.7 of the Online Appendix.

5. Conclusion

We examine the effect of algorithmic trading on the extent to which corporate boards rely on stock returns in CEO turnover decisions. We find that the magnitude of the negative relation between the likelihood of forced CEO turnover and stock returns is reduced when algorithmic trading increases. This effect of algorithmic trading is more pronounced for growth firms, firms facing steeper competition, and firms with a geographically dispersed investor base. The effect is also more marked when there is more informed trading that AT dampens. Furthermore, the effect of AT on the turnover-return sensitivity is stronger when directors' expertise to extract decision-relevant information from stock returns is greater and when the

[26] Prior studies find that the TSP program is not only associated with AT but also related to various market-level and firm-level outcomes that could affect board monitoring and thus potentially the turnover-return sensitivity (e.g., Ahmed et al. 2020; Li and Xia 2021; Chen, Ng, Ofosu, Yang 2022; Hope and Liu 2023). Therefore, a caveat is that directors' learning may not be the sole channel through which the turnover-return sensitivity is affected by the TSP program.

quality of directors' own information set is poorer. Corroborating our inference, we find evidence that boards put a greater weight on the accounting performance measure in CEO turnover decisions and hold special meetings more frequently when AT increases. In sum, our paper provides evidence suggesting that directors learn from stock returns in the secondary financial markets, which aggregate information about the CEO-firm match quality from a long-term perspective, and that they use this investor information in CEO turnover decisions.

An interesting question to be addressed is whether boards make poorer forced CEO turnover decisions as algorithmic trading increases. For example, boards could dismiss CEOs too late or prematurely due to decreased investor information in stock returns. Our findings of increases in the turnover-accounting performance sensitivity and the frequency of special board meeting are consistent with boards taking adjustment actions for alternative information sources. We leave for future research whether such adjustments prevent inefficient turnover decisions fully or only partially.

References

Adams, R. B., Hermalin, B. E., & Weisbach, M. S. (2010). The role of boards of directors in corporate governance: A conceptual framework and survey. *Journal of Economic Literature*, *48*(1), 58-107.

Ahmed, A., Li, Y., & Xu, N. (2020). Tick size and financial reporting quality in small-cap firms: evidence from a natural experiment. *Journal of Accounting Research*, *58*(4), 869-914.

Ai, C., & Norton, E. C. (2003). Interaction terms in logit and probit models. *Economics Letters*, *80*(1), 123-129.

Allen, E. J., Larson, C. R., & Sloan, R. G. (2013). Accrual reversals, earnings and stock returns. *Journal of Accounting and Economics, 56*(1), 113-129.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, *5*(1), 31-56.

Armstrong, C. S., Guay, W. R. & Weber, J. P. (2010). The role of information and financial reporting in corporate governance and debt contracting. *Journal of Accounting and Economics*, *50*(2-3), 179-234.

Baber, W. R., Kang, S. H., & Kumar, K. R. (1998). Accounting earnings and executive compensation:: The role of earnings persistence. *Journal of Accounting and Economics*, *25*(2), 169-193.

Bai, J., Philippon, T., & Savov., A., (2016). Have financial markets become more informative? *Journal of Financial Economics 122*(3): 625-654.

Beaver, W., Lambert, R., & Morse, D. (1980). The information content of security prices. *Journal of Accounting and Economics, 2*(1), 3-28.

Beaver, W. H., Lambert, R., & Ryan, S. (1987). The information content of security prices: A second look. *Journal of Accounting and Economics, 9*(2), 139-157.

Bennett, B., Stulz, R. & Wang. Z. (2020). Does the stock market make firms more productive? *Journal of Financial Economics*, *136*(2), 281–306.

Bettis, J. C., Bizjak, J., Coles, J. L., & Kalpathy, S. (2018). Performance-vesting provisions in executive compensation. *Journal of Accounting and Economics*, *66*(1), 194-221.

Bogousslavsky, V., Fos, V., & Muravyev, D. (2023). Informed trading intensity. *Journal of Finance*, Forthcoming.

Bond, P., Edmans, A., & Goldstein, I. (2012). The real effects of financial markets. *Annual Review Financial Economics*, *4*(1), 339-360.

Brockman, P., Subasi, M., Wang, J., & Zhang, E.X. (2024). Do credit rating agencies learn from the options market? *Management Science*, Forthcoming.

Brogaard, J., Hendershott, T., & Riordan, R. (2014). High-frequency trading and price discovery. *Review of Financial Studies*, *27*(8), 2267-2306.

Bushman, R., Dai, Z., & Wang, X. (2010). Risk and CEO turnover. *Journal of Financial Economics*, *96*(3), 381-398.

Cao, Y., Dhaliwal, D., Li, Z., & Yang, Y. G. (2015). Are all independent directors equally informed? Evidence based on their trading returns and social networks. *Management Science*, *61*(4), 795-813.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, *52*(1), 57-82.

Chakrabarty, B., Moulton, P.C., Wang, X. F. (2022). Attention: how high-frequency trading improve price efficiency following earnings announcements. *Journal of Financial Markets*, *57*, 100690

Chen, J. V. (2023). The wisdom of crowds and the market's response to earnings news: Evidence using the geographic dispersion of investors. *Journal of Accounting and Economics, 75*(2-3), 101567.

Chen, Q., Goldstein, I., & Jiang, W. (2007). Price informativeness and investment sensitivity to stock price. *Review of Financial Studies*, *20*(3), 619-650.

Chen, Y., Ng, J., Ofosu, E., & Yang, X. (2022). Investors' Information Acquisition and Firm Financing Decisions: Evidence from a Natural Experiment. *Available at SSRN 4074612*.

Chen, Y., Ng, J., & Yang, X. (2021). Talk less, learn more: Strategic disclosure in response to managerial learning from the options market. *Journal of Accounting Research*, *59*(5), 1609-1649.

Chordia, T., & Miao, B. (2020). Market efficiency in real time: Evidence from low latency activity around earnings announcements. *Journal of Accounting and Economics*, *70*(2-3), 101335.

Coles, J. L., Daniel, N. D., & Naveen, L. (2014). Co-opted boards. *Review of Financial Studies, 27*(6), 1751-1796.

Collin-Dufresne, P., & Fos, V. (2015). Do prices reveal the presence of informed trading. *Journal of Finance*, *70*(4), 1555-1582.
Collins, D. W., Kothari, S. P., & Rayburn, J. D. (1987). Firm size and the information content of prices with respect to earnings. *Journal of Accounting and Economics, 9*(2), 111-138.
Core, J. E., Guay, W. R., & Verrecchia, R. E. (2003). Price versus non-price performance measures in optimal CEO compensation contracts. *The Accounting Review*, *78*(4), 957-981.
Cornelli, F., Kominek, Z., & Ljungqvist, A. (2013). Monitoring managers: Does it matter? *Journal of Finance*, *68*(2), 431-481.
Dasgupta, S., Li, X., & Wang, A. Y. (2018). Product market competition shocks, firm performance, and forced CEO turnover. *Review of Financial Studies*, *31*(11), 4187-4231.
Dass, N., Kini, O., Nanda, V., Onal, B., & Wang, J. (2014). Board expertise: Do directors from related industries help bridge the information gap? *Review of Financial Studies*, *27*(5), 1533-1592.
Denis, D. J., Denis, D. K., & Sarin, A. (1997). Ownership structure and top executive turnover. *Journal of Financial Economics*, *45*(2), 193-221.
DeFond, M. L., & Hung, M. (2004). Investor protection and corporate governance: Evidence from worldwide CEO turnover. *Journal of Accounting Research*, *42*(2), 269-312.
De George, E. T., Donovan, J., Phillips, M., & Wittenberg Moerman, R. (2023). Lender Learning and the Public Equity Market. *Available at SSRN 4591443*.
Drake, M. S., Roulstone, D. T., & Thornock, J. R. (2015). The determinants and consequences of information acquisition via EDGAR. *Contemporary Accounting Research*, *32*(3), 1128-1161.
Drake, M. S., Johnson, B. A., Roulstone, D. T., & Thornock, J. R. (2020). Is there information content in information acquisition? *The Accounting Review*, *95*(2), 113-139.
Edmans, A., Jayaraman, S., & Schneemeier, J. (2017). The source of information in prices and investment-price sensitivity. *Journal of Financial Economics*, *126*(1), 74-96.
Eisfeldt, A. L., & Kuhnen, C. M. (2013). CEO turnover in a competitive assignment framework. *Journal of Financial Economics*, *109*(2), 351-372.
Engel, E., Hayes, R. M., & Wang, X. (2003). CEO turnover and properties of accounting information. *Journal of Accounting and Economics*, *36*(1-3), 197-226.
Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3-56.
Feichter, C., Moers, F., & Timmermans, O. (2022). Relative performance evaluation and competitive aggressiveness. *Journal of Accounting Research*, *60*(5), 1859-1913.
Feng, M, Li, C., & Luo, T. (2023). Do auditor learn from stock prices of their clients? Evidence from audit adjustments of re-audited earnings? Working Paper.
Gao, R., & Xiao, X. (2022) News from afar: The information role of nonlocal investors in guiding investment decisions. Working Paper.
Garmaise, M. J. (2011). Ties that truly bind: Noncompetition agreements, executive compensation, and firm investment. *Journal of Law, Economics, & Organization*, *27*(2), 376-425.
Gillan, S. L., & Starks, L. T. (2000). Corporate governance proposals and shareholder activism: The role of institutional investors. *Journal of Financial Economics*, *57*(2), 275-305.
Goldstein, I. (2023). Information in financial markets and its real effects. *Review of Finance, 27*(1), 1-32.
Goldstein, I., Yang, S., & Zuo, L. (2023). The real effects of modern information technologies: Evidence from the EDGAR implementation. *Journal of Accounting Research*, *61*(5), 1699-1733.
Guay, W. R., Taylor, D. J., & Xiao, J. J. (2015). Adapt or perish: Evidence of CEO adaptability to industry shocks. *Available at SSRN 2234886*.
Guo, L., & Masulis, R. W. (2015). Board structure and monitoring: New evidence from CEO turnovers. *Review of Financial Studies*, *28*(10), 2770-2811.
Han, J., Khapko, M., and Kyle, A. S. (2014). Liquidity with high-frequency market making. Research Paper, Swedish House of Finance.
Hartzell, J. C., & Starks, L. T. (2003). Institutional investors and executive compensation. *Journal of Finance*, *58*(6), 2351-2374.
Hayes, R. M., Lemmon, M., & Qiu, M. (2012). Stock options and managerial incentives for risk taking: Evidence from FAS 123R. *Journal of Financial Economics, 105*(1), 174-190.

Hayes, R. M., Tian, X., & Wang, X. (2023). Deregulation and Board Policies: Evidence from Performance and Risk Exposure Measures Used in Bank CEO Turnover Decisions. *The Accounting Review, 98*(3), 257-283.
Hendershott, T., Jones, C. M., & Menkveld, A. J. (2011). Does algorithmic trading improve liquidity?. *Journal of Finance*, *66*(1), 1-33.
Hermalin, B. E., & Weisbach, M. S. (1998). Endogenously chosen boards of directors and their monitoring of the CEO. *American Economic Review*, *88*(1), 96-118.
Hermalin, B., & Weisbach, M. (2003). Boards of directors as an endogenously determined institution: a survey of the economic literature. *Economic Policy Review*, *9*(Apr), 7-26.
Hoberg, G., & Phillips, G. (2016). Text-based network industries and endogenous product differentiation. *Journal of Political Economy, 124*(5), 1423-1465.
Holmstrom, B. (1979). Moral hazard and observability. *The Bell Journal of Economics*, 74-91.
Holmstrom, B. (2004). Pay without performance and the managerial power hypothesis: A comment. *Journal of Corporation Law, 30*(4), 703-716.
Holmstrom, B., & Milgrom, P. (1991). Multitask principal–agent analyses: Incentive contracts, asset ownership, and job design. *Journal of Law, Economics, & Organization, 7*(special_issue), 24-52.
Hope, O. K., & Liu, J. (2023). Does stock liquidity shape voluntary disclosure? Evidence from the SEC tick size pilot program. *Review of Accounting Studies*, *28*(4), 2233-2270.
Huson, M. R., Malatesta, P. H., & Parrino, R. (2004). Managerial succession and firm performance. *Journal of Financial Economics*, *74*(2), 237-275.
Intintoli, V. J., Serfling, M., & Shaikh, S. (2017). CEO turnovers and disruptions in customer–supplier relationships. *Journal of Financial and Quantitative Analysis*, *52*(6), 2565-2610.
Jagolinzer, A. D., Larcker, D. F., & Taylor, D. J. (2011). Corporate governance and the information content of insider trades. *Journal of Accounting Research*, *49*(5), 1249-1274.
Jayaraman, S., & Milbourn, T. T. (2012). The role of stock liquidity in executive compensation. *The Accounting Review*, *87*(2), 537-563.
Jayaraman, S., Milbourn, T., Peters, F., & Seo, H. (2021). Product market peers and relative performance evaluation. *The Accounting Review, 96*(4), 341-366.
Jayaraman, S., Ling, X., Wu, J. S., & Zhang, Y. (2021). The Role of Stock Returns in CEO Performance Evaluation: A New Interpretation. *Available at SSRN 3754022*.
Jayaraman, S., & Wu, J. S. (2020). Should I stay or should I grow? Using voluntary disclosure to elicit market feedback. *Review of Financial Studies, 33*(8), 3854-3888.
Jensen, M. C., & Ruback, R. S. (1983). The market for corporate control: The scientific evidence. *Journal of Financial Economics*, *11*(1-4), 5-50.
Jenter, D., & Kanaan, F. (2015). CEO turnover and relative performance evaluation. *Journal of Finance*, *70*(5), 2155-2184.
Jenter, D., & Lewellen, K. (2021). Performance-induced CEO turnover. *Review of Financial Studies*, *34*(2), 569-617.
Lambert, R. A., & Larcker, D. F. (1987). An analysis of the use of accounting and market measures of performance in executive compensation contracts. *Journal of Accounting Research*, 85-125.
Lang, M., & Sul, E. (2014). Linking industry concentration to proprietary costs and disclosure: Challenges and opportunities. *Journal of Accounting and Economics, 58*(2-3), 265-274.
Lee, C. M., & Watts, E. M. (2021). Tick size tolls: Can a trading slowdown improve earnings news discovery? *The Accounting Review*, *96*(3), 373-401.
Lee, C. M., So, E. C., & Wang, C. C. (2021). Evaluating firm-level expected-return proxies: implications for estimating treatment effects. *Review of Financial Studies*, *34*(4), 1907-1951.
Li, Z., & Wang, L. (2016). Executive compensation incentives contingent on long-term accounting performance. *Review of Financial Studies*, *29*(6), 1586-1633.
Li, D., & Xia, Y. (2021). Gauging the effects of stock liquidity on earnings management: evidence from the SEC tick size pilot test. *Journal of Corporate Finance, 67*, 101904.
Lin, Y., Peters, F., & Seo, H. (2022). Enforceability of Noncompetition Agreements and Forced Turnovers of Chief Executive Officers. *Journal of Law and Economics*, *65*(1), 177-209.
Luo, Y. (2005). Do insiders learn from outsiders? Evidence from mergers and acquisitions. *Journal of Finance*, *60*(4), 1951-1982.

Mauboussin, M., & Rappaport, A. (2021). *Expectations Investing: Reading Stock Prices for Better Returns, Revised and Updated.* Columbia University Press.
Menkveld, A. J. (2016). The economics of high-frequency trading: Taking stock. *Annual Review of Financial Economics*, 8, 1-24.
Neyman, J., & Scott, E. L. (1948). Consistent estimates based on partially consistent observations. *Econometrica: Journal of the Econometric Society*, *16*(1), 1-32.
Pan, Y., Wang, T. Y., & Weisbach, M. S. (2015). Learning about CEO ability and stock return volatility. *Review of Financial Studies*, *28*(6), 1623-1666.
Parrino, R. (1997). CEO turnover and outside succession a cross-sectional analysis. *Journal of Financial Economics*, *46*(2), 165-197.
Peters, R. H., & Taylor, L. A. (2017). Intangible capital and the investment-q relation. *Journal of Financial Economics*, *123*(2), 251-272.
Pinto, J. (2023). Mandatory disclosure and learning from external market participants: Evidence from the JOBS act. *Journal of Accounting and Economics*, *75*(1), 101528.
Rappaport, A. (1987). Linking competitive strategy and shareholder value analysis. *Journal of Business Strategy*, 7(4), 58-67.
Ravina, E., & Sapienza, P. (2010). What do independent directors know? Evidence from their trading. *Review of Financial Studies*, *23*(3), 962-1003.
Shleifer, A., & Vishny, R. W. (1997). A survey of corporate governance. *Journal of Finance*, *52*(2), 737-783.
Stiglitz, J. E. (2014). Tapping the brakes: Are less active markets safer and better for the economy? Presented at the Federal Reserve Bank of Atlanta 2014 Financial Markets Conference
Stock, J. H., & Yogo, M. (2002). Testing for weak instruments in linear IV regression. Identification and inference for econometric models: Essays in honor of Thomas Rothenberg.
Suk, I., Lee, S., & Kross, W. (2021). CEO turnover and accounting earnings: The role of earnings persistence. *Management Science*, *67*(5), 3195-3218.
Taylor, L. A. (2010). Why are CEOs rarely fired? Evidence from structural estimation. *Journal of Finance*, *65*(6), 2051-2087.
Weisbach, M. S. (1988). Outside directors and CEO turnover. *Journal of Financial Economics*, *20*, 431-460.
Weller, B. M. (2018). Does algorithmic trading reduce information acquisition? *Review of Financial Studies*, *31*(6), 2184-2226.
Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*. MIT press.
Ye, M., Zheng, M. Y., & Zhu, W. (2023). The effect of tick size on managerial learning from stock prices. *Journal of Accounting and Economics*, *75*(1), 101515.
Zhang, S.S. (2017). Need for speed: an empirical analysis of hard and soft information in a high frequency world. Working Paper.
Zuo, L. (2016). The informational feedback effect of stock prices on management forecasts. *Journal of Accounting and Economics*, *61*(2-3), 391-413.

Appendix A Variable Definitions

Variable	Description
FORCED	*FORCED* is an indicator variable equal to one if forced CEO turnover occurs in period *t*, and zero otherwise. Forced CEO turnover is classified using the Parrino (1997) algorithm.
RETURN	*RETURN* is the industry-adjusted stock returns for firm *i* measured over periods *t* and *t-1*.
RET	*RET* is the decile-ranked industry-adjusted stock returns. To create *RET*, we rank the continuous return variable (*RETURN*) into deciles, ranging from 0 to 9, and scale it by 9.
ATPCA	*ATPCA* is a composite measure of algorithmic trading obtained from the Principal Component Analysis using the four proxies for AT activity: Odd Lot Ratio, Cancel-to-Trade Ratio, Trade-to-Order Ratio, and Average Trade Size. Algorithmic trading proxies are measured over periods *t* and *t-1*.
AT	*AT* is the decile-ranked algorithmic trading proxy. To create *AT*, we rank the composite measure of algorithmic trading (*ATPCA*) into deciles, ranging from 0 to 9, and scale it by 9.
OLR	*OLR* is the natural logarithm of the equal-weighted average of the daily odd lot ratio, measured over periods *t* and *t-1.* The odd lot ratio is computed as the sum of all odd lot trade volume (*oddlotvol*) divided by the sum of all trade volume (*litvol*).
CTR	*CTR* is the natural logarithm of the equal-weighted average of the daily cancel-to-trade ratio, measured over periods *t* and *t-1.* The cancel-to-trade ratio is computed as the count of all canceled orders (*cancels*) divided by the count of all trades (*littrades*).
TTOR	*TTOR* is the natural logarithm of the equal-weighted average of the daily trade-to-order ratio, measured over periods *t* and *t-1.* The trade-to-order ratio is calculated as the sum of all trade volume (*litvol*) divided by the sum of all order volume (*ordervol*).
ATS	*ATS* is the equal-weighted average of the daily average trade size, measured over periods *t* and *t-1*. The average trade size is computed as the sum of all trading volume (*litvol*) divided by the count of all trades (*littrades*).
SIZE	*Size* is the natural logarithm of the market value of equity for firm *i* at the beginning of period *t*.
BTM	*BTM* is the book-to-market of equity for firm *i* at the beginning of period *t*.
VOL	*VOL* is the standard deviation of daily market-adjusted returns for firm *i* in period *t-1*.
EARNVOL	*EARNVOL* is the standard deviation of the return on assets over the prior 10-year period.
AIM	*AIM* is the natural logarithm of one plus the average of the daily AIM for firm *i*, measured over periods *t* and *t-1*. Daily AIM is measured as the ratio of absolute stock return to dollar volume [10,000,000 × absolute *ret* ÷ (*prc* × *vol*)].
EARN	*EARN* is the return on assets for firm *i* in period *t-1*.
ROA	*ROA* is the decile-ranked return on assets for firm *i* in period *t-1*. To create *ROA*, we rank the earnings variable (*EARN*) into deciles, ranging from 0 to 9, and scale it by 9.
ANALYST	*ANALYST* is the natural logarithm of one plus the number of financial analysts following firm *i* at the beginning of period *t*.
IOR	*IOR* is the level of institutional ownership for firm *i* as of the beginning of period *t*.
DIV	*DIV* is an indicator variable equal to one if the firm pays dividends in period *t-1*, and zero otherwise.
DUALITY	*DUALITY* is an indicator variable equal to one if the CEO is the chairman of the board at the beginning of period *t*, and zero otherwise.
OWN	*OWN* is the percentage of shares owned by the CEO at the beginning of period *t*.
AGE	*AGE* is the natural logarithm of CEO age in years.
TENURE	*TENURE* is the natural logarithm of CEO tenure in years.
INTCAP	*INTCAP* is the replacement cost of intangible capital (Peters and Taylor 2017). The replacement cost of intangible capital is estimated as the sum of the firm's externally purchased intangible capital, i.e., goodwill, and internally created intangible capital. The

	replacement cost of internally created intangible capital is computed as the sum of knowledge capital (based on R&D spending) and organizational capital (based on SG&A expenses).
GEODIV	*GEODIV* is the sum of the squares of the number of non-robotic EDGAR searches by IP addresses from each state during the year, scaled by the number of all non-robotic EDGAR searches during the year (i.e., a search-weighted concentration index). A larger value of *GEODIV* indicates a more geographically concentrated investor base.
ITI	*ITI* is the measure of informed trading derived from machine learning techniques that evaluate the market conditions and informed trading intensity around the Schedule 13D filing window (Bogousslavsky et al. 2023).
ITI_P	*ITI_P* is a measure of patient informed trading intensity based on *ITI* trained on the first 40 days of the 60-day Schedule 13D filing window (Bogousslavsky et al. 2023).
ITI_IMP	*ITI_IMP* is a measure of impatient informed trading intensity based on *ITI* trained on the last 20 days of the 60-day Schedule 13D filing window (Bogousslavsky et al. 2023).
PMC	*PMC* is the number of product market peers in the Text-Based Network Industry Classification (Hoberg and Phillips 2016).
PROD	*PROD* is the number of new products introduced by the firm over the past five years. New product introductions are the total number of articles identified using RavenPack press releases classified as "product release" using their classification algorithm.
INDEXP	*INDEXP* is the number of outside directors who have worked in the same industry as a CEO prior to joining the current firm, divided by the total number of directors.
INSTRADE	*INSTRADE* is the percentage of outside directors that have traded the firm's stock at least once during the year.
INSPROFIT	*INSPROFIT* is the average insider trading profit during the year made by outside directors. For every trade, we first measure the trade profitability as the intercept (i.e., alpha) from the four-factor Fama and French (1993) and Carhart (1997) model estimated over 180 days following the trade. For sales transactions, we multiply negative one to the alpha value. We use the mean alpha value if the director has multiple trades during the period.
BRDMEET	*BRDMEET* is the natural logarithm of one plus the number of special board meetings held by the firm, disclosed in the firm's yearly proxy statements. We search for keywords related to special meetings and textually parse the number of special meetings held by the board during the fiscal year from these filings using regular expressions preceding the following phrases: *special meeting*, *additional meeting*, *unscheduled meeting*.
YOUNGCEO	*YOUNGCEO* is an indicator variable equal to one if the CEO is younger than 53 years old when starting their CEO position, and zero otherwise (Pan et al. 2015).
OUTSIDECEO	*OUTSIDECEO* is an indicator variable equal to one if the CEO is hired from outside of the firm, and zero otherwise.

Appendix B Algorithmic Trading and Firm Characteristics

	ATPCA	*OLR*	*CTR*	*TOR*	*ATS*
	(1)	(2)	(3)	(4)	(5)
SIZE	0.280***	0.166***	-0.026**	-0.020*	-0.081***
	(0.034)	(0.016)	(0.012)	(0.011)	(0.008)
BTM	-0.292***	-0.091***	-0.096***	0.113***	0.049***
	(0.056)	(0.029)	(0.018)	(0.017)	(0.015)
VOL	-28.387***	-10.861***	-7.061***	6.865***	5.190***
	(2.686)	(1.185)	(0.945)	(0.818)	(0.628)
EARNVOL	0.921*	0.657**	-0.292	0.028	-0.528***
	(0.495)	(0.258)	(0.201)	(0.165)	(0.126)
AIM	0.772***	0.355***	0.630***	0.011	0.182***
	(0.185)	(0.063)	(0.063)	(0.048)	(0.037)
RET	0.152***	0.047***	0.065***	-0.058***	-0.008
	(0.024)	(0.011)	(0.009)	(0.008)	(0.006)
ROA	0.147***	0.073***	0.074***	-0.056***	-0.014
	(0.045)	(0.020)	(0.018)	(0.016)	(0.010)
ANALYST	-0.063*	-0.051***	0.004	0.005	0.018**
	(0.034)	(0.014)	(0.013)	(0.011)	(0.007)
IOR	0.306***	0.063	0.122***	-0.135***	-0.027
	(0.100)	(0.047)	(0.034)	(0.027)	(0.025)
DIV	-0.070	-0.004	-0.016	0.024	0.007
	(0.044)	(0.019)	(0.017)	(0.016)	(0.010)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	11,828	11,828	11,828	11,828	11,828
Adjusted R^2	0.869	0.907	0.781	0.802	0.889

This table presents the estimation results from the regression of algorithmic trading proxies on firm characteristics. *ATPCA* is a composite measure of algorithmic trading (*ATPCA*) obtained from a principal component analysis using four algorithmic trading proxies: Odd Lot Ratio (*OLR*), Cancel-to-Trade Ratio (*CTR*), Trade-to-Order Ratio (*TTOR)*, and Average Trade Size (*ATS*). All other variables are defined in Appendix A. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.

Table 1 Descriptive Statistics

Panel A Descriptive Statistics

	N	Mean	STD	Q1	Median	Q3
FORCED	11,828	0.036	0.186	0.000	0.000	0.000
ATPCA	11,828	0.000	1.429	-0.874	-0.052	0.842
OLR	11,828	2.652	0.714	2.192	2.706	3.176
CTR	11,828	3.270	0.446	2.967	3.209	3.488
TTOR	11,828	0.968	0.428	0.703	1.016	1.280
ATS	11,828	2.360	0.367	2.098	2.338	2.601
RETURN	11,828	0.063	0.435	-0.200	-0.003	0.236
SIZE	11,828	7.927	1.631	6.800	7.780	8.994
BTM	11,828	0.528	0.404	0.250	0.449	0.735
VOL	11,828	0.018	0.008	0.012	0.016	0.022
EARNVOL	11,828	0.043	0.051	0.013	0.027	0.052
AIM	11,828	0.056	0.195	0.002	0.007	0.027
EARN	11,828	0.049	0.123	-0.010	0.018	0.081
ANALYST	11,828	2.198	0.784	1.609	2.303	2.833
IOR	11,828	0.772	0.232	0.693	0.837	0.930
DIV	11,828	0.609	0.488	0.000	1.000	1.000
DUALITY	11,828	0.448	0.497	0.000	0.000	1.000
OWN	11,828	0.021	0.068	0.001	0.003	0.011
AGE	11,828	4.040	0.124	3.970	4.043	4.111
TENURE	11,828	1.919	0.820	1.338	1.946	2.532
BRDMEET	11,828	0.073	0.333	0.000	0.000	0.000

Panel B Pairwise Correlations Among AT Proxies

		(1)	(2)	(3)	(4)
(1)	*ATPCA*				
(2)	*OLR*	**0.851**			
(3)	*CTR*	**0.697**	**0.302**		
(4)	*TTOR*	**-0.684**	**-0.277**	**-0.812**	
(5)	*ATS*	**-0.737**	**-0.931**	**-0.101**	**0.115**

This table presents descriptive statistics for our sample during the sample period between 2012 and 2019. Panel A presents summary statistics for the variables used in our analyses. To mitigate the influence of extreme values, all continuous variables are winsorized at the 1st and 99th percentiles. Panel B presents pairwise correlations among the algorithmic trading proxies. The significance level at 1% is bolded. All variables are defined in Appendix A.

Table 2 Algorithmic Trading and Forced CEO Turnover

	FORCED		
	(1)	(2)	(3)
RET	**-0.058*****	**-0.100*****	**-0.151****
	(0.007)	**(0.014)**	**(0.075)**
AT	-0.050***	-0.094***	-0.092***
	(0.016)	(0.022)	(0.023)
RET × AT		**0.089*****	**0.085*****
		(0.021)	**(0.024)**
SIZE	0.003	0.004	0.003
	(0.007)	(0.007)	(0.009)
BTM	0.043***	0.040***	0.038**
	(0.014)	(0.014)	(0.019)
VOL	-0.821	-0.755	-2.037**
	(0.611)	(0.613)	(0.955)
EARNVOL	0.275**	0.253**	0.396***
	(0.127)	(0.126)	(0.152)
AIM	-0.012	-0.009	0.018
	(0.017)	(0.018)	(0.029)
ROA	-0.035***	-0.034***	-0.069***
	(0.012)	(0.012)	(0.021)
ANALYST	-0.007	-0.007	-0.003
	(0.007)	(0.007)	(0.011)
IOR	0.002	0.003	0.001
	(0.018)	(0.018)	(0.026)
DIV	-0.000	-0.000	-0.006
	(0.010)	(0.010)	(0.015)
DUALITY	-0.043***	-0.042***	-0.042***
	(0.010)	(0.010)	(0.010)
OWN	-0.077	-0.084	-0.086*
	(0.051)	(0.052)	(0.052)
AGE	-0.130***	-0.129***	-0.129***
	(0.047)	(0.047)	(0.047)
TENURE	0.069***	0.069***	0.069***
	(0.006)	(0.006)	(0.006)
RET × SIZE			-0.001
			(0.008)
RET × BTM			0.004
			(0.020)
RET × VOL			2.455**
			(1.128)
RET × EARNVOL			-0.241*
			(0.128)
RET × AIM			-0.056*
			(0.033)
RET × ROA			0.068***
			(0.025)
RET × ANALYST			-0.007
			(0.012)
RET × IOR			0.003
			(0.030)
RET × DIV			0.009
			(0.016)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	11,828	11,828	11,828
Adjusted R^2	0.078	0.080	0.081

This table presents the estimation results from the regression of an indicator variable for forced CEO turnover on algorithmic trading and control variables. *FORCED* is an indicator variable equal to one if forced CEO turnover occurs in period *t*, and zero otherwise. *RET* is the decile-ranked industry-adjusted stock returns. To create *RET*, we rank the industry-adjusted stock returns measured over periods *t* and *t-1* (*RETURN)* into deciles, ranging from 0 to 9, and scale it by 9. *AT* is the decile-ranked composite measure of algorithmic trading (*ATPCA*) obtained from a principal component analysis using four algorithmic trading proxies: Odd Lot Ratio, Cancel-to-Trade Ratio, Trade-to-Order Ratio, and Average Trade Size. Algorithmic trading proxies are measured over the same performance measurement window as *RET*. To create *AT*, we rank the composite measure into deciles, ranging from 0 to 9, and scale it by 9. All other variables are defined in Appendix A. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.

Table 3 Instrumental Variable Approach

	AT	*RET × AT*	*FORCED*
	(1)	(2)	(3)
	1st Stage Result		2nd Stage Result
RET × PRICE	0.119***	0.511***	
	(0.017)	(0.023)	
PRICE	0.075***	-0.186***	
	(0.018)	(0.016)	
RET × AT			**0.137****
			(0.060)
AT			-0.237*
			(0.140)
RET	-0.000	0.270***	-0.120***
	(0.010)	(0.015)	(0.027)
SIZE	0.060***	0.023***	0.012
	(0.007)	(0.005)	(0.011)
BTM	-0.084***	-0.013*	0.028
	(0.012)	(0.008)	(0.019)
VOL	-5.357***	-3.087***	-1.478*
	(0.567)	(0.415)	(0.885)
EARNVOL	0.253**	0.270***	0.248*
	(0.121)	(0.092)	(0.129)
AIM	0.151***	0.039*	0.009
	(0.035)	(0.022)	(0.027)
ROA	0.029***	0.019**	-0.029**
	(0.011)	(0.008)	(0.013)
ANALYST	-0.022***	-0.013**	-0.011
	(0.008)	(0.005)	(0.008)
IOR	0.031	0.007	0.005
	(0.021)	(0.013)	(0.019)
DIV	-0.022**	-0.010	-0.002
	(0.010)	(0.008)	(0.011)
DUALITY	-0.001	-0.008	-0.042***
	(0.007)	(0.005)	(0.010)
OWN	0.351***	0.269***	-0.050
	(0.109)	(0.071)	(0.071)
AGE	-0.068**	-0.028	-0.139***
	(0.033)	(0.024)	(0.048)
TENURE	0.010**	0.001	0.070***
	(0.004)	(0.003)	(0.006)
First-Stage Diagnostics			
Kleibergen-Paap *rk* LM statistic		61.432***	
Kleibergen-Paap rk Wald *F* statistic		34.545	
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	11,602	11,602	11,602
Adjusted R^2	0.858	0.837	0.037

This table presents the results from the instrumental variable estimation. Columns (1) and (2) present the first-stage results. In the first-stage estimation, two endogenous variables, *AT* and *RET × AT*, are instrumented using *PRICE* and *RET × PRICE*. The first and second stages are estimated simultaneously. *AT* is the decile-ranked composite measure of algorithmic trading measured over periods *t* and *t-1*. *RET* is the decile-ranked industry-adjusted stock returns measured over periods *t* and *t-1*. The instrument, *PRICE*, is measured as the decile-ranked average stock price in period *t-2*. Column (3) reports the second-stage result from the regression of *FORCED*, an indicator variable equal to one if forced CEO turnover occurs in period *t*, and zero otherwise. All other variables are defined in Appendix A. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.

Table 4 Cross-Sectional Tests – Firm Characteristics

	FORCED							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RET	-0.081***	-0.130*	-0.071***	-0.108	-0.065***	-0.162**	-0.053**	-0.130
	(0.018)	(0.077)	(0.020)	(0.077)	(0.020)	(0.082)	(0.021)	(0.084)
AT	-0.054**	-0.052*	-0.041	-0.034	-0.063**	-0.060**	-0.068**	-0.066**
	(0.026)	(0.027)	(0.028)	(0.029)	(0.027)	(0.027)	(0.030)	(0.031)
RET × AT	0.050*	0.044	0.021	0.007	0.043	0.036	0.026	0.023
	(0.026)	(0.029)	(0.030)	(0.032)	(0.030)	(0.030)	(0.032)	(0.035)
HIGH INTCAP	0.064**	0.061**						
	(0.025)	(0.027)						
HIGH INTCAP × RET	-0.045*	-0.038						
	(0.027)	(0.031)						
HIGH INTCAP × AT	-0.099***	-0.099**						
	(0.038)	(0.038)						
HIGH INTCAP × RET × AT	**0.105****	**0.107****						
	(0.044)	**(0.044)**						
HIGH PMC			0.051**	0.053**				
			(0.021)	(0.021)				
HIGH PMC × RET			-0.049*	-0.053*				
			(0.027)	(0.027)				
HIGH PMC × AT			-0.098***	-0.102***				
			(0.036)	(0.036)				
HIGH PMC × RET × AT			**0.127*****	**0.134*****				
			(0.044)	**(0.044)**				
HIGH PROD					0.040*	0.047**		
					(0.021)	(0.022)		
HIGH PROD × RET					-0.065**	-0.079***		
					(0.029)	(0.031)		
HIGH PROD × AT					-0.060*	-0.058*		
					(0.035)	(0.035)		
HIGH PROD × RET × AT					**0.088***	**0.087***		
					(0.046)	**(0.046)**		
HIGH GEODIV							0.031	0.036*
							(0.022)	(0.022)
HIGH GEODIV × RET							-0.050	-0.060**
							(0.030)	(0.030)

HIGH GEODIV × AT							-0.083**	-0.089**
							(0.035)	(0.035)
HIGH GEODIV × RET × AT							**0.098****	**0.110****
							(0.048)	**(0.047)**
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Characteristics × *RET*	No	Yes	No	Yes	No	Yes	No	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,828	11,828	11,087	11,087	10,031	10,031	8,790	8,790
Adjusted R^2	0.081	0.082	0.081	0.082	0.063	0.064	0.093	0.093

This table presents the cross-sectional tests in settings where boards actively learn from stock returns. *FORCED* is an indicator variable equal to one if forced CEO turnover occurs in period *t* and zero otherwise. *AT* is the decile-ranked composite measure of algorithmic trading measured over periods *t* and *t-1*. *RET* is the decile-ranked industry-adjusted stock returns measured over periods *t* and *t-1*. *HIGH INTCAP* is an indicator variable equal to one if a firm's replacement costs of intangible capital (*INTCAP*) are above the sample median, and zero otherwise. *HIGH PMC* is an indicator variable equal to one if the number of product market peers in the Text-Based Network Industry Classification (Hoberg and Phillips 2016) is greater than the sample median, and zero otherwise. *HIGH PROD* is an indicator variable equal to one if the number of new products introduced by the firm over the past five years (*PROD*) is greater than the sample median, and zero otherwise. New product introductions are the total number of articles identified using RavenPack press releases classified as "product release" using their classification algorithm. *HIGH GEODIV* is equal to one if the extent of a firm's investors' geographic diversity concentration (*GEODIV*) is below the sample median, and zero otherwise. Investors' geographic diversity concentration is measured as the sum of the squares of the number of non-robotic EDGAR searches by IP addresses from each state during the year, scaled by the number of all non-robotic EDGAR searches during the year. A lower value of *GEODIV* indicates more geographic dispersion of the firm's investor base. All variables are defined in Appendix A. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.

Table 5 Cross-Sectional Tests – Informed Trading Intensity

	FORCED					
	(1)	(2)	(3)	(4)	(5)	(6)
RET	-0.078***	-0.184**	-0.070***	-0.158*	-0.073***	-0.210***
	(0.020)	(0.082)	(0.020)	(0.081)	(0.020)	(0.081)
AT	-0.077***	-0.078***	-0.067**	-0.068**	-0.075***	-0.078***
	(0.026)	(0.028)	(0.027)	(0.028)	(0.026)	(0.027)
RET × AT	0.055*	0.056*	0.047	0.047	0.058**	0.062**
	(0.029)	(0.032)	(0.030)	(0.032)	(0.029)	(0.031)
HIGH ITI	0.012	0.013				
	(0.019)	(0.019)				
HIGH ITI × RET	-0.046	-0.049*				
	(0.028)	(0.028)				
HIGH ITI × AT	-0.044	-0.042				
	(0.031)	(0.031)				
HIGH ITI × RET × AT	**0.080***	**0.077***				
	(0.043)	**(0.044)**				
HIGH ITI_P			0.034*	0.037*		
			(0.019)	(0.019)		
HIGH ITI_P × RET			-0.062**	-0.069**		
			(0.027)	(0.027)		
HIGH ITI_P × AT			-0.056*	-0.056*		
			(0.030)	(0.030)		
HIGH ITI_P × RET × AT			**0.090****	**0.090****		
			(0.042)	**(0.042)**		
HIGH ITI_IMP					0.029	0.034*
					(0.019)	(0.019)
HIGH ITI_IMP × RET					-0.058**	-0.068**
					(0.029)	(0.028)
HIGH ITI_IMP × AT					-0.041	-0.039
					(0.031)	(0.031)
HIGH ITI_IMP × RET × AT					**0.071**	**0.069**
					(0.045)	**(0.045)**
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm Characteristics × *RET*	No	Yes	No	Yes	No	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,292	11,292	11,292	11,292	11,292	11,292
Adjusted R^2	0.085	0.087	0.085	0.087	0.085	0.087

This table presents the cross-sectional tests in settings where ex-ante informed trading intensity is greater. *FORCED* is an indicator variable equal to one if forced CEO turnover occurs in period *t* and zero otherwise. *AT* is the decile-ranked composite measure of algorithmic trading measured over periods *t* and *t-1*. *RET* is the decile-ranked industry-adjusted stock returns measured over periods *t* and *t-1*. *HIGH ITI* is an indicator variable equal to one if the average insider trading intensity (*ITI*) measured over the two-year periods preceding the measurement periods of *AT* and *RET* is greater than the sample median, and zero otherwise. *ITI* is a measure of informed trading derived from machine learning techniques that evaluate the market conditions and informed trading intensity around the Schedule 13D filing window (Bogousslavsky et al. 2023). *ITI* is decomposed into patient informed trading intensity (*ITI_P*) and impatient informed trading intensity (*ITI_IMP*); the former captures the intensity of informed trading based on relatively long-term private information, whereas the latter captures the intensity of informed trading based on relatively short-term private information. *HIGH ITI_P* (*HIGH ITI_IMP*) is an indicator variable equal to one if the average of *ITI_P* (*ITI_IMP*) is greater than the sample median, and zero otherwise. All variables are defined in Appendix A. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.

Table 6 Cross-Sectional Tests – Board Characteristics

	FORCED					
	(1)	(2)	(3)	(4)	(5)	(6)
RET	-0.087***	-0.132*	-0.084***	-0.138*	-0.090***	-0.147**
	(0.017)	(0.076)	(0.017)	(0.075)	(0.016)	(0.075)
AT	-0.071***	-0.070***	-0.077***	-0.074***	-0.077***	-0.076***
	(0.025)	(0.026)	(0.024)	(0.025)	(0.024)	(0.025)
RET × AT	0.057**	0.054*	0.053**	0.048*	0.067***	0.063**
	(0.027)	(0.028)	(0.026)	(0.028)	(0.025)	(0.027)
HIGH INDEXP	0.023	0.022				
	(0.024)	(0.024)				
HIGH INDEXP × RET	-0.034	-0.032				
	(0.028)	(0.029)				
HIGH INDEXP × AT	-0.064*	-0.063*				
	(0.037)	(0.037)				
HIGH INDEXP × RET × AT	**0.089****	**0.087****				
	(0.043)	**(0.044)**				
LOW INSTRADE			0.016	0.016		
			(0.019)	(0.019)		
LOW INSTRADE × RET			-0.049*	-0.048*		
			(0.027)	(0.028)		
LOW INSTRADE × AT			-0.050*	-0.051*		
			(0.029)	(0.029)		
LOW INSTRADE × RET × AT			**0.107****	**0.108****		
			(0.043)	**(0.043)**		
LOW INSPROFIT					0.028	0.026
					(0.020)	(0.020)
LOW INSPROFIT × RET					-0.035	-0.032
					(0.028)	(0.028)
LOW INSPROFIT × AT					-0.058*	-0.057*
					(0.031)	(0.031)
LOW INSPROFIT × RET × AT					**0.074***	**0.072***
					(0.043)	**(0.043)**
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm Characteristics × *RET*	No	Yes	No	Yes	No	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,828	11,828	11,828	11,828	11,828	11,828
Adjusted R^2	0.081	0.082	0.081	0.082	0.080	0.082

This table presents the cross-sectional tests in settings where boards have greater ability or incentive to learn from stock returns. *FORCED* is an indicator variable equal to one if forced CEO turnover occurs in period *t* and zero otherwise. *AT* is the decile-ranked composite measure of algorithmic trading measured over periods *t* and *t-1*. *RET* is the decile-ranked industry-adjusted stock returns measured over periods *t* and *t-1*. *HIGH INDEXP* is an indicator equal to one if the extent of outside directors' industry experience (*INDEXP*) is greater than the sample median, and zero otherwise. *LOW INSTRADE* is an indicator variable equal to one if the percentage of the board engaging in insider trading (*INSTRADE*) is less than the sample median, and zero otherwise. *LOW INSPROFIT* is an indicator variable equal to one if the average insider trading profit by directors (*INSPROFIT*) is less than the sample median, and zero otherwise. All variables are defined in Appendix A. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.

Table 7 Forced CEO Turnover-Return Sensitivity and Board Monitoring

	FORCED							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Co-option		*Tenure-weighted Co-option*		*Inst. Own.*		*HHI of Inst. Own*	
RET	-0.122***	-0.155	-0.119***	-0.154	-0.095***	-0.151**	-0.105***	-0.151**
	(0.030)	(0.102)	(0.030)	(0.101)	(0.018)	(0.076)	(0.018)	(0.075)
AT	-0.114***	-0.116***	-0.110***	-0.112***	-0.099***	-0.098***	-0.096***	-0.092***
	(0.035)	(0.036)	(0.035)	(0.036)	(0.026)	(0.027)	(0.027)	(0.028)
RET × AT	0.124***	0.122***	0.127***	0.125***	0.081***	0.077***	0.109***	0.101***
	(0.043)	(0.045)	(0.043)	(0.045)	(0.028)	(0.029)	(0.029)	(0.030)
HIGH MONITOR	-0.070***	-0.072***	-0.060**	-0.063**	-0.005	-0.000	0.012	0.019
	(0.026)	(0.026)	(0.025)	(0.025)	(0.022)	(0.024)	(0.019)	(0.021)
HIGH MONITOR × RET	0.033	0.036	0.031	0.034	-0.014	-0.023	0.011	-0.002
	(0.037)	(0.037)	(0.038)	(0.038)	(0.027)	(0.030)	(0.025)	(0.028)
HIGH MONITOR × AT	0.085**	0.089**	0.074*	0.079**	0.009	0.010	0.001	-0.002
	(0.042)	(0.042)	(0.040)	(0.040)	(0.034)	(0.034)	(0.031)	(0.031)
HIGH MONITOR × RET × AT	**-0.049**	**-0.054**	**-0.059**	**-0.066**	**0.022**	**0.019**	**-0.038**	**-0.031**
	(0.056)	**(0.056)**	**(0.056)**	**(0.056)**	**(0.042)**	**(0.042)**	**(0.041)**	**(0.040)**
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Characteristics × *RET*	No	Yes	No	Yes	No	Yes	No	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,649	7,649	7,649	7,649	11,828	11,828	11,828	11,828
Adjusted R^2	0.108	0.109	0.108	0.109	0.080	0.081	0.080	0.082

This table presents the cross-sectional tests conditional on monitoring intensity. *FORCED* is an indicator variable equal to one if forced CEO turnover occurs in period *t* and zero otherwise. *AT* is the decile-ranked composite measure of algorithmic trading measured over periods *t* and *t-1*. *RET* is the decile-ranked industry-adjusted stock returns measured over periods *t* and *t-1*. In Columns (1) and (2), *HIGH MONITOR* is an indicator variable equal to one if the fraction of co-opted directors is lower than the sample median, and zero otherwise. In Columns (3) and (4), *HIGH MONITOR* is an indicator variable equal to one if the extent of tenure-weighted co-option is lower than the sample median, and zero otherwise. In Columns (5) and (6), *HIGH MONITOR* is an indicator variable equal to one if the level of institutional ownership is greater than the sample median, and zero otherwise. In Columns (7) and (8), *HIGH MONITOR* is an indicator variable equal to one if the extent of institutional ownership concentration (HHI) is greater than the sample median, and zero otherwise. All variables are defined in Appendix A. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.

Table 8 Algorithmic Trading and CEO Turnover – Accounting Performance Sensitivity

	AT	*RET × AT*	*ROA × AT*	*FORCED*
	(1)	(2)	(3)	(4)
		1st Stage Result		2nd Stage Result
RET × PRICE	0.117***	0.511***	0.084***	
	(0.017)	(0.023)	(0.011)	
ROA × PRICE	0.057*	-0.004	0.407***	
	(0.030)	(0.022)	(0.026)	
PRICE	0.045*	-0.184***	-0.142***	
	(0.025)	(0.020)	(0.015)	
RET × AT				**0.133****
				(0.061)
ROA × AT				**-0.186***
				(0.102)
AT				-0.071
				(0.194)
RET	0.001	0.270***	-0.002	-0.120***
	(0.010)	(0.015)	(0.006)	(0.027)
ROA	0.004	0.020	0.272***	0.049
	(0.017)	(0.013)	(0.017)	(0.042)
SIZE	0.060***	0.023***	0.021***	0.006
	(0.007)	(0.005)	(0.005)	(0.013)
BTM	-0.084***	-0.013*	-0.038***	0.035*
	(0.012)	(0.008)	(0.007)	(0.020)
VOL	-5.385***	-3.085***	-2.046***	-0.941
	(0.566)	(0.415)	(0.359)	(0.998)
EARNVOL	0.244**	0.270***	0.304***	0.275**
	(0.121)	(0.092)	(0.103)	(0.130)
AIM	0.148***	0.040*	0.002	-0.011
	(0.035)	(0.022)	(0.016)	(0.031)
ANALYST	-0.022***	-0.013**	-0.009**	-0.009
	(0.008)	(0.005)	(0.004)	(0.008)
IOR	0.032	0.007	-0.001	-0.001
	(0.021)	(0.013)	(0.012)	(0.019)
DIV	-0.021**	-0.010	-0.009	-0.001
	(0.010)	(0.008)	(0.006)	(0.011)
DUALITY	-0.001	-0.008	-0.001	-0.042***
	(0.007)	(0.005)	(0.005)	(0.010)
OWN	0.350***	0.269***	0.161***	-0.077
	(0.109)	(0.071)	(0.059)	(0.071)
AGE	-0.069**	-0.028	-0.031	-0.132***
	(0.033)	(0.024)	(0.022)	(0.049)
TENURE	0.010**	0.001	0.001	0.069***
	(0.004)	(0.003)	(0.003)	(0.006)
First-Stage Diagnostics				
Kleibergen-Paap *rk* LM statistic		44.643***		
Kleibergen-Paap rk Wald *F* statistic		16.058		
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	11,602	11,602	11,602	11,602
Adjusted R^2	0.858	0.837	0.895	0.038

This table presents the results from instrumental variable estimation. Columns (1), (2), and (3) present the first-stage results. In the first-stage estimation, three endogenous variables, *AT*, *RET* × *AT*, and *ROA* × *AT* are instrumented using *PRICE*, *RET* × *PRICE*, and *ROA* × *PRICE*. The first and second stages are estimated simultaneously. *AT* is the decile-ranked composite measure of algorithmic trading measured over periods *t* and *t*-

1. *RET* is the decile-ranked industry-adjusted stock returns measured over periods *t* and *t-1*. *ROA* is a decile-ranked variable of industry-adjusted return on assets in period *t-1*. The instrument, *PRICE*, is measured as the decile-ranked average stock price in period *t-2*. Column (4) demonstrates the second-stage result from the regression of *FORCED*, an indicator variable equal to one if forced CEO turnover occurs in period *t*, and zero otherwise. All other variables are defined in Appendix A. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.

Table 9 Algorithmic Trading and Special Board Meeting Frequency

	BRDMEET		
	(1)	(2)	(3)
AT	**0.040***	**-0.002**	**0.015**
	(0.024)	**(0.027)**	**(0.027)**
YOUNGCEO		0.004	
		(0.019)	
AT* × *YOUNGCEO		**0.061*****	
		(0.023)	
OUTSIDECEO			-0.022
			(0.020)
AT* × *OUTSIDECEO			**0.049***
			(0.030)
RET	-0.003	-0.003	-0.004
	(0.009)	(0.009)	(0.009)
SIZE	0.003	0.003	0.003
	(0.010)	(0.010)	(0.010)
BTM	0.017	0.017	0.017
	(0.018)	(0.018)	(0.018)
VOL	0.230	0.230	0.235
	(0.796)	(0.796)	(0.799)
EARNVOL	0.051	0.051	0.051
	(0.123)	(0.123)	(0.124)
AIM	-0.030	-0.030	-0.031
	(0.020)	(0.020)	(0.020)
ROA	-0.027**	-0.027**	-0.027**
	(0.012)	(0.012)	(0.012)
ANALYST	-0.000	-0.000	-0.001
	(0.010)	(0.010)	(0.010)
IOR	-0.043*	-0.043*	-0.044*
	(0.024)	(0.024)	(0.024)
DIV	-0.005	-0.005	-0.005
	(0.013)	(0.013)	(0.013)
DUALITY	0.018	0.018	0.018
	(0.013)	(0.013)	(0.013)
OWN	0.014	0.014	0.006
	(0.094)	(0.094)	(0.093)
AGE	-0.030	-0.030	-0.029
	(0.055)	(0.055)	(0.056)
TENURE	-0.001	-0.001	-0.002
	(0.006)	(0.006)	(0.006)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	11,828	11,828	11,828
Adjusted R^2	0.521	0.521	0.521

This table presents the estimation results from the regression of the number of special board meetings on algorithmic trading and control variables. *BRDMEET* is the natural logarithm of one plus the number of special board meetings held by the firm, disclosed in the firm's yearly proxy statements. *AT* is the decile-ranked composite measure of algorithmic trading measured over periods *t* and *t-1*. In Columns (2) and (3), we examine the cross-sectional variation using two proxies capturing circumstances where boards incur higher costs to acquire private information specific to the CEO-firm match quality. In Column (2), *YOUNGCEO* is an indicator variable equal to one if the CEO is younger than 53 years old when starting her CEO position, and zero otherwise (Pan et al. 2015). In Column (3), *OUTSIDECEO* is an indicator variable equal to one if the CEO is hired from outside of the firm, and zero otherwise. All other variables are defined in Appendix A. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.

Online Appendix for

Does Algorithmic Trading Affect Forced CEO Turnover?

Table OA.1 AT and Forced CEO Turnover-Return Sensitivity using Raw Returns

	FORCED		
	(1)	(2)	(3)
RETURN	**-0.044*****	**-0.066*****	**-0.161*****
	(0.005)	**(0.009)**	**(0.047)**
AT	-0.051***	-0.055***	-0.053***
	(0.016)	(0.016)	(0.017)
RETURN × AT		**0.050*****	**0.056*****
		(0.015)	**(0.016)**
SIZE	0.003	0.004	0.002
	(0.007)	(0.007)	(0.008)
BTM	0.042***	0.041***	0.039***
	(0.014)	(0.014)	(0.014)
VOL	-0.706	-0.643	-0.976
	(0.613)	(0.615)	(0.640)
EARNVOL	0.278**	0.256**	0.305**
	(0.127)	(0.126)	(0.128)
AIM	-0.011	-0.009	-0.008
	(0.017)	(0.018)	(0.019)
ROA	-0.033***	-0.032***	-0.040***
	(0.012)	(0.012)	(0.013)
ANALYST	-0.008	-0.008	-0.007
	(0.007)	(0.007)	(0.007)
IOR	0.002	0.004	0.002
	(0.018)	(0.018)	(0.018)
DIV	0.000	-0.000	-0.002
	(0.010)	(0.010)	(0.010)
DUALITY	-0.043***	-0.043***	-0.043***
	(0.010)	(0.010)	(0.010)
OWN	-0.076	-0.080	-0.083
	(0.052)	(0.053)	(0.052)
AGE	-0.131***	-0.130***	-0.130***
	(0.047)	(0.047)	(0.047)
TENURE	0.069***	0.069***	0.069***
	(0.006)	(0.006)	(0.006)
RET × SIZE			0.002
			(0.006)
RET × BTM			-0.002
			(0.014)
RET × VOL			2.433***
			(0.701)
RET × EARNVOL			-0.072
			(0.073)
RET × AIM			-0.010
			(0.019)
RET × ROA			0.050***
			(0.017)
RET × ANALYST			-0.008
			(0.008)
RET × IOR			0.015
			(0.020)
RET × DIV			0.006
			(0.011)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	11,828	11,828	11,828
Adjusted R^2	0.079	0.080	0.082

This table presents the estimation results from the regression of an indicator variable for forced CEO turnover on algorithmic trading and control variables. *FORCED* is an indicator variable equal to one if forced CEO turnover occurs in period *t*, and zero otherwise. *RETURN* is the industry-adjusted stock returns measured over periods *t* and *t-1*. *AT* is the decile-ranked composite measure of algorithmic trading (*ATPCA*) obtained from a principal component analysis using four algorithmic trading proxies: Odd Lot Ratio, Cancel-to-Trade Ratio, Trade-to-Order Ratio, and Average Trade Size. Algorithmic trading proxies are measured over the same performance measurement window as *RETURN*. To create *AT*, we rank the composite measure into deciles, ranging from 0 to 9, and scale it by 9. All other variables are defined in Appendix A. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.

Table OA.2 Algorithmic Trading and All CEO Turnovers

Panel A Descriptive Statistics

	All Turnover	Forced (=1)	Voluntary (=2)	Other (=3)
Frequency	1,596	425	786	385
Percentage	100.00%	26.63%	49.25%	24.12%

Panel B Conditional Fixed-Effects Multinomial Regression Result

	FORCED	*VOLUNTARY*	*OTHER*
	(1)	(2)	(3)
RET	-4.488*	-0.113	-2.609
	(2.552)	(1.739)	(2.519)
AT	-2.661***	-0.407	-1.275
	(0.638)	(0.636)	(1.049)
RET × AT	**1.817****	**0.053**	**1.092**
	(0.806)	**(0.614)**	**(0.995)**
SIZE	0.187	0.111	0.031
	(0.230)	(0.260)	(0.316)
BTM	0.619**	-0.141	-0.912
	(0.313)	(0.401)	(0.626)
VOL	-40.138*	24.262	-33.547
	(21.310)	(25.015)	(29.587)
EARNVOL	6.547*	-3.091	-11.610**
	(3.821)	(4.684)	(5.233)
AIM	-0.315	-0.080	-1.870
	(0.746)	(1.357)	(1.650)
ROA	-1.531***	-1.112**	-0.030
	(0.479)	(0.494)	(0.677)
ANALYST	-0.382	0.004	0.002
	(0.265)	(0.291)	(0.356)
IOR	-0.214	0.902	-1.185
	(0.600)	(0.854)	(0.844)
DIV	0.171	-0.063	-0.317
	(0.343)	(0.379)	(0.437)
DUALITY	-0.694**	0.943***	0.180
	(0.295)	(0.275)	(0.451)
OWN	-6.765	-3.148	0.985
	(4.338)	(3.455)	(6.693)
AGE	0.785	19.988***	12.832***
	(1.297)	(2.635)	(2.161)
TENURE	2.096***	2.094***	0.011
	(0.234)	(0.239)	(0.216)
RET × SIZE	-0.015	-0.021	0.183
	(0.271)	(0.174)	(0.267)
RET × BTM	0.501	0.520	1.009
	(0.513)	(0.436)	(0.716)
RET × VOL	86.188***	0.980	-0.492
	(33.431)	(30.745)	(33.713)
RET × EARNVOL	-6.151*	5.582	-0.112
	(3.482)	(4.219)	(5.156)
RET × AIM	-1.657	-0.787	1.268
	(1.206)	(1.234)	(1.272)
RET × ROA	1.012	0.966*	-1.786**
	(0.766)	(0.564)	(0.886)
RET × ANALYST	-0.015	-0.188	0.147
	(0.423)	(0.311)	(0.532)
RET × IOR	0.295	-0.992	0.324
	(0.873)	(0.933)	(1.222)
RET × DIV	-0.620	0.145	0.708

	(0.576)	(0.396)	(0.555)
Log-pseudolikelihood		-1714.88	
Number of Observations		8,034	
Number of Groups (Firms)		1,186	
Wald Chi-squared		604.36***	

This table presents the estimation results from the conditional fixed-effects multinomial regression where the dependent variable is equal to one if forced CEO turnover occurs in period *t*, two if a voluntary CEO turnover occurs in period *t*, three if any other CEO turnover occurs in period *t*, and zero otherwise. *RET* is the decile-ranked industry-adjusted stock returns. To create *RET*, we rank the industry-adjusted stock returns measured over periods *t* and *t-1* (*RETURN)* into deciles, ranging from 0 to 9, and scale it by 9. *AT* is a decile-ranked variable based on a composite measure of algorithmic trading (*ATPCA*) obtained from a principal component analysis using four algorithmic trading proxies: Odd Lot Ratio, Cancel-to-Trade Ratio, Trade-to-Order Ratio, and Average Trade Size. Algorithmic trading proxies are measured over the same performance measurement window as *RET*. To create *AT*, we rank the composite measure into deciles, ranging from 0 to 9, and scale it by 9. Firm and year fixed effects are included. In estimation, 553 groups (3,794 firm-year observations) are omitted because they exhibit no variation in the outcome variable over time. All other variables are defined in Appendix A. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.

Table OA.3 Algorithmic Trading and Informed Trading Intensity

	ITI		*ITI_P*		*ITI_IMP*	
	(1)	(2)	(3)	(4)	(5)	(6)
ATPCA	**-0.007*****		**-0.008*****		**-0.002****	
	(0.001)		**(0.001)**		**(0.001)**	
AT		**-0.018*****		**-0.024*****		**-0.001**
		(0.004)		**(0.003)**		**(0.003)**
RET	-0.020***	-0.020***	-0.015***	-0.016***	0.002	0.002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
SIZE	0.009***	0.008***	0.008***	0.008***	0.002	0.002
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
BTM	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.007***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
VOL	-0.922***	-0.851***	-0.541***	-0.471***	-1.157***	-1.116***
	(0.131)	(0.130)	(0.117)	(0.116)	(0.120)	(0.120)
EARNVOL	0.160***	0.160***	0.123***	0.123***	0.178***	0.177***
	(0.029)	(0.029)	(0.025)	(0.025)	(0.026)	(0.026)
AIM	0.032***	0.029***	0.011	0.008	0.011*	0.010
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
ROA	0.006**	0.005*	0.003	0.003	0.004*	0.004
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
ANALYST	-0.001	-0.001	-0.005***	-0.005***	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
IOR	-0.013***	-0.013***	-0.014***	-0.015***	-0.011***	-0.012***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
DIV	-0.001	-0.001	-0.001	-0.001	-0.004**	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
DUALITY	0.000	0.000	0.002	0.002	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
OWN	-0.009	-0.013	-0.017	-0.021	0.003	0.000
	(0.029)	(0.028)	(0.023)	(0.023)	(0.022)	(0.022)
AGE	-0.023***	-0.022***	-0.015**	-0.014**	-0.021***	-0.021***
	(0.008)	(0.008)	(0.006)	(0.006)	(0.007)	(0.007)
TENURE	0.003**	0.002**	0.001	0.001	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,443	11,443	11,443	11,443	11,443	11,443
Adjusted R^2	0.238	0.235	0.212	0.209	0.242	0.242

This table presents the estimation results from the regression of informed trading intensity on algorithmic trading and control variables. Informed trading intensity (*ITI*) is a measure of informed trading derived from machine learning techniques that evaluate the market conditions and informed trading intensity around the Schedule 13D filing window (Bogousslavsky et al. 2023), averaged over the period *t*. *ITI* is decomposed into patient informed trading intensity (*ITI_P*) in Columns (3) and (4) and impatient informed trading intensity (*ITI_IMP*) in Columns (5) and (6). All variables are defined in Appendix A. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.

Table OA.4 Using Composite AT Measure in the Board Meeting Frequency Test

	BRDMEET		
	(1)	(2)	(3)
ATPCA	**0.013****		
	(0.006)		
YOUNGCEO		0.033**	
		(0.015)	
ATPCA* × *YOUNGCEO		**0.011****	
		(0.004)	
OUTSIDECEO			0.003
			(0.013)
ATPCA* × *OUTSIDECEO			**0.016****
			(0.008)
RET	-0.004	-0.004	-0.005
	(0.009)	(0.009)	(0.009)
SIZE	0.002	0.001	0.001
	(0.010)	(0.010)	(0.010)
BTM	0.018	0.016	0.016
	(0.018)	(0.018)	(0.018)
VOL	0.369	0.295	0.382
	(0.793)	(0.789)	(0.797)
EARNVOL	0.050	0.053	0.058
	(0.123)	(0.124)	(0.124)
AIM	-0.033*	-0.034*	-0.035*
	(0.020)	(0.020)	(0.020)
ROA	-0.028**	-0.026**	-0.027**
	(0.012)	(0.012)	(0.012)
ANALYST	-0.000	-0.000	-0.000
	(0.010)	(0.010)	(0.010)
IOR	-0.046*	-0.044*	-0.047*
	(0.024)	(0.024)	(0.025)
DIV	-0.005	-0.005	-0.005
	(0.013)	(0.013)	(0.013)
DUALITY	0.018	0.018	0.017
	(0.013)	(0.013)	(0.013)
OWN	0.005	0.001	-0.005
	(0.095)	(0.095)	(0.093)
AGE	-0.028	0.059	-0.029
	(0.055)	(0.078)	(0.055)
TENURE	-0.001	-0.012	-0.002
	(0.006)	(0.008)	(0.006)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	11,828	11,828	11,828
Adjusted R^2	0.521	0.521	0.521

This table presents the estimation results from the regression of the number of special board meetings on algorithmic trading and control variables. *BRDMEET* is the natural logarithm of one plus the number of special board meetings held by the firm, disclosed in the firm's yearly proxy statements. *ATPCA* is the first principal component of the four algorithmic trading proxies: Odd Lot Ratio, Cancel-to-Trade Ratio, Trade-to-Order Ratio, and Average Trade Size. In Columns (2) and (3), we examine the cross-sectional variation using two proxies capturing circumstances where boards incur higher costs to acquire private information specific to the CEO-firm match quality. In Column (2), *YOUNGCEO* is an indicator variable equal to one if the CEO is younger than 53 years old when starting her CEO position, and zero otherwise (Pan et al. 2015). In Column (3), *OUTSIDECEO* is an indicator variable equal to one if the CEO is hired from outside of the firm, and zero otherwise. All other variables are defined in Appendix A. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.

Table OA.5 Performance Metrics in CEO Pay Contracts

Panel A Descriptive Statistics

Performance Metric	Frequency	Percent
Accounting	22,412	55.4%
Other	**9,947**	**24.6%**
Earnings/Profit-related	2,429	6.0%
Stock Price	1,298	3.2%
Non-Financial	**1,221**	**3.0%**
Revenue-related	968	2.4%
Financial/Investment return ratios	579	1.4%
Cash Flow	395	1.0%
Market-related	345	0.9%
Social	**344**	**0.9%**
Liquidity/Solvency-related	144	0.4%
Activity-related	**110**	**0.3%**
Environment	**92**	**0.2%**
Economic Value	65	0.2%
Balance Sheet-related	63	0.2%
CSR	**29**	**0.1%**
NA	29	0.1%
Total Number of Metrics	40,470	100.0%

Table OA.5 Performance Metrics in CEO Pay Contracts, continued

Panel B Regression Results

	NONFIN		*MKT*	
	(1)	(2)	(3)	(4)
ATPCA	**0.012***		**-0.010****	
	(0.007)		**(0.005)**	
AT		**0.053****		**-0.032***
		(0.026)		**(0.017)**
RET	-0.013	-0.013	0.002	0.001
	(0.008)	(0.008)	(0.007)	(0.007)
SIZE	-0.015*	-0.015*	-0.004	-0.005
	(0.009)	(0.009)	(0.009)	(0.009)
BTM	-0.012	-0.011	0.020	0.020
	(0.016)	(0.016)	(0.017)	(0.017)
VOL	1.117	1.060	-0.119	-0.007
	(0.880)	(0.881)	(0.852)	(0.866)
EARNVOL	-0.035	-0.036	-0.039	-0.040
	(0.178)	(0.178)	(0.168)	(0.167)
AIM	-0.010	-0.010	-0.119	-0.125
	(0.136)	(0.136)	(0.110)	(0.109)
ROA	-0.029*	-0.029*	-0.001	-0.001
	(0.017)	(0.017)	(0.014)	(0.013)
ANALYST	-0.016	-0.016	0.001	0.001
	(0.011)	(0.011)	(0.010)	(0.010)
IOR	-0.014	-0.011	-0.036*	-0.038*
	(0.025)	(0.024)	(0.020)	(0.020)
DIV	-0.006	-0.006	0.008	0.008
	(0.015)	(0.015)	(0.011)	(0.011)
DUALITY	-0.008	-0.009	0.004	0.004
	(0.011)	(0.011)	(0.008)	(0.008)
OWN	-0.185**	-0.186**	-0.002	-0.006
	(0.088)	(0.088)	(0.046)	(0.046)
AGE	-0.070	-0.070	-0.000	0.001
	(0.053)	(0.053)	(0.045)	(0.045)
TENURE	0.011*	0.011*	-0.007	-0.007
	(0.006)	(0.006)	(0.006)	(0.006)
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	5,868	5,868	5,868	5,868
Adjusted R^2	0.599	0.599	0.544	0.543

This table examines the relation between CEO performance metrics and algorithmic trading. Panel A presents the descriptive statistics of performance metrics in CEO pay contracts. Panel B presents the estimation results from the regression of various performance metrics on algorithmic trading and control variables. In Columns (1) and (2), the dependent variable is *NONFIN*, defined as the average percentage of the use of non-financial performance metrics in period *t*. For each grant, we count the number of non-financial performance metrics (highlighted in Panel A of Table OA.5) and scale it by the total number of performance metrics specified in the pay contract. Since CEOs typically have multiple grants each year, we compute the average percentage for each CEO to define *NONFIN*. In Columns (3) and (4), *MKT* is defined as the average percentage of the use of "Stock Price" or "Market-related" performance metrics in period *t*.

Table OA.6 Algorithmic Trading and the Tick Size Pilot Program

Panel A Difference-in-Differences Estimation

	FORCED			
	(1)	(2)	(3)	(4)
TREAT	-0.064**	-0.058**		
	(0.026)	(0.026)		
POST	-0.060**	-0.054*		
	(0.027)	(0.027)		
TREAT × *POST*	0.110***	0.104***	0.098***	0.099***
	(0.035)	(0.035)	(0.036)	(0.037)
RET	-0.123***	-0.116***	-0.084***	-0.283
	(0.030)	(0.030)	(0.031)	(0.241)
RET × *TREAT*	0.092**	0.084**	0.071*	0.071*
	(0.036)	(0.036)	(0.040)	(0.040)
RET × *POST*	0.087**	0.079**	0.065*	0.059
	(0.039)	(0.039)	(0.038)	(0.041)
RET* × *TREAT* × *POST	**-0.159*** **	**-0.147*** **	**-0.150*** **	**-0.158*** **
	(0.051)	**(0.051)**	**(0.054)**	**(0.055)**
SIZE		-0.008	-0.000	-0.014
		(0.007)	(0.023)	(0.030)
BTM		0.017	0.037	0.048
		(0.016)	(0.047)	(0.055)
VOL		0.331	-0.431	-1.748
		(0.680)	(1.522)	(2.124)
EARNVOL		0.153	0.069	0.423
		(0.113)	(0.252)	(0.270)
AIM		-0.038	-0.013	-0.077
		(0.027)	(0.038)	(0.077)
ROA		0.015	0.017	-0.033
		(0.017)	(0.031)	(0.049)
ANALYST		-0.006	-0.007	-0.002
		(0.007)	(0.018)	(0.027)
IOR		0.009	-0.034	-0.027
		(0.021)	(0.064)	(0.095)
DIV		-0.011	-0.004	0.014
		(0.009)	(0.031)	(0.039)
DUALITY		0.000	0.000	0.001
		(0.009)	(0.031)	(0.030)
OWN		-0.029	-0.066	-0.056
		(0.028)	(0.233)	(0.230)
AGE		0.029	-0.257**	-0.244*
		(0.031)	(0.126)	(0.126)
TENURE		-0.008	0.099***	0.098***
		(0.005)	(0.019)	(0.019)
RET × *SIZE*				0.026
				(0.028)
RET × *BTM*				-0.045
				(0.045)
RET × *VOL*				3.173
				(2.383)
RET × *EARNVOL*				-0.593**
				(0.269)
RET × *AIM*				0.150
				(0.114)
RET × *ROA*				0.087
				(0.060)
RET × *ANALYST*				-0.009
				(0.031)

RET × IOR				-0.016
				(0.084)
RET × DIV				-0.035
				(0.036)
Firm Fixed Effects	No	No	Yes	Yes
Year Fixed Effects	No	No	Yes	Yes
Observations	2,503	2,503	2,503	2,503
Adjusted R^2	0.022	0.026	0.107	0.110

Panel B Falsification Test

	FORCED			
	(1)	(2)	(3)	(4)
TREAT	-0.008	-0.005		
	(0.025)	(0.024)		
PSEUDO POST	-0.037	-0.036		
	(0.024)	(0.023)		
TREAT × PSEUDO POST	0.012	0.012	0.038	0.044
	(0.033)	(0.033)	(0.034)	(0.034)
RET	-0.074***	-0.070***	-0.032	-0.002
	(0.024)	(0.024)	(0.027)	(0.170)
RET × TREAT	0.009	0.005	0.016	0.020
	(0.035)	(0.034)	(0.037)	(0.037)
RET × PSEUDO POST	0.050	0.052	0.050	0.068*
	(0.037)	(0.036)	(0.038)	(0.041)
RET × TREAT × PSEUDO POST	**-0.015**	**-0.014**	**-0.063**	**-0.072**
	(0.050)	**(0.050)**	**(0.052)**	**(0.051)**
Control Variables	No	Yes	Yes	Yes
Firm Characteristics × *RET*	No	No	No	Yes
Firm Fixed Effects	No	No	Yes	Yes
Year Fixed Effects	No	No	Yes	Yes
Observations	2,272	2,272	2,272	2,272
Adjusted R^2	0.008	0.020	0.098	0.099

This table presents the results from the difference-in-differences estimation of forced CEO turnover. *FORCED* is an indicator variable equal to one if forced CEO turnover occurs in period *t* and zero otherwise. *RET* is a decile-ranked industry-adjusted stock return variable measured over periods *t* and *t-1*. *TREAT* is a dummy variable equal to one for treatment firms, and zero for control firms in the Tick Size Pilot Program. In Panel A, the sample period is between 2015 and 2018, and *POST* is a dummy variable equal to one for the fiscal years of 2017 and 2018, and zero for the fiscal years of 2015 and 2016. In Panel B, the sample period is between 2011 and 2014, and *PSUEDO POST* is a dummy variable equal to one for the fiscal years of 2013 and 2014, and zero for the fiscal years of 2011 and 2012. All variables are defined in Appendix A. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.

Table OA.7 Algorithmic Trading and the Tick Size Pilot Program: Extended Period

	FORCED			
	(1)	(2)	(3)	(4)
TREAT	-0.096**	-0.092**		
	(0.041)	(0.040)		
POST	-0.098**	-0.086**		
	(0.039)	(0.039)		
TREAT × POST	0.142***	0.135***	0.118**	0.116**
	(0.047)	(0.047)	(0.047)	(0.047)
RET	-0.175***	-0.162***	-0.134***	-0.129
	(0.048)	(0.047)	(0.045)	(0.166)
RET × TREAT	0.131**	0.126**	0.125**	0.119**
	(0.055)	(0.054)	(0.055)	(0.054)
RET × POST	0.139**	0.124**	0.111**	0.096*
	(0.055)	(0.054)	(0.053)	(0.054)
RET × TREAT × POST	**-0.198*** **	**-0.185*** **	**-0.168** **	**-0.167** **
	(0.066)	**(0.066)**	**(0.067)**	**(0.067)**
POST AFTER TSP	-0.091**	-0.084**		
	(0.040)	(0.039)		
TREAT × POST AFTER TSP	0.099**	0.095**	0.082*	0.082*
	(0.048)	(0.047)	(0.046)	(0.046)
RET × POST AFTER TSP	0.120**	0.116**	0.055	0.048
	(0.057)	(0.056)	(0.055)	(0.056)
RET × TREAT × POST AFTER TSP	**-0.138** **	**-0.132** **	**-0.092**	**-0.094**
	(0.067)	**(0.065)**	**(0.068)**	**(0.068)**
SIZE		-0.002	0.022	0.013
		(0.006)	(0.017)	(0.022)
BTM		0.022	0.069**	0.090***
		(0.014)	(0.028)	(0.033)
VOL		-0.189	-1.393	-2.564
		(0.516)	(1.132)	(1.684)
EARNVOL		0.220*	0.283	0.509
		(0.117)	(0.275)	(0.316)
AIM		0.021	0.061	0.094
		(0.026)	(0.044)	(0.062)
ROA		0.022	0.025	0.023
		(0.014)	(0.026)	(0.042)
ANALYST		0.000	-0.020	0.004
		(0.006)	(0.016)	(0.022)
IOR		0.015	-0.010	-0.027
		(0.016)	(0.024)	(0.048)
DIV		-0.014	-0.014	-0.002
		(0.009)	(0.026)	(0.036)
DUALITY		-0.003	-0.012	-0.011
		(0.008)	(0.028)	(0.027)
OWN		-0.022	-0.133	-0.120
		(0.025)	(0.109)	(0.108)
AGE		0.033	-0.151	-0.156
		(0.028)	(0.123)	(0.123)
TENURE		-0.008*	0.081***	0.082***
		(0.004)	(0.014)	(0.015)
RET × SIZE				0.012
				(0.021)
RET × BTM				-0.067*
				(0.040)
RET × VOL				2.223
				(1.761)
RET × EARNVOL				-0.551**

				(0.253)
RET × AIM				-0.048
				(0.093)
RET × ROA				-0.007
				(0.053)
RET × ANALYST				-0.048**
				(0.023)
RET × IOR				0.044
				(0.067)
RET × DIV				-0.025
				(0.033)
Firm Fixed Effects	No	No	Yes	Yes
Year Fixed Effects	No	No	Yes	Yes
Observations	3,044	3,043	3,042	3,042
Adjusted R^2	0.024	0.032	0.137	0.140

This table presents the results from the difference-in-differences estimation of forced CEO turnover using the extended sample period between 2015 and 2020. *FORCED* is an indicator variable equal to one if forced CEO turnover occurs in period *t* and zero otherwise. *RET* is a decile-ranked industry-adjusted stock return variable measured over periods *t* and *t-1*. *TREAT* is a dummy variable equal to one for treatment firms, and zero for control firms in the Tick Size Pilot Program. *POST* is a dummy variable equal to one for the fiscal years of 2017 and 2018, and zero otherwise. *POST AFTER TSP* is a dummy variable equal to one for the fiscal years of 2019 and 2020, and zero otherwise. All variables are defined in Appendix A. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.