When Milliseconds Matter: The Real Effects of High-Frequency Trading*

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Abstract

This paper examines how high-frequency trading affects corporate investment and financing. Using a unique Australian setting with broker-level HFT identifiers, we exploit the introduction of ASX-ITCH, a high-speed order-level market data feed that increased the speed of trading information, as plausibly exogenous variation in HFT presence. As HFT activity rises, firms experience sizable decline in investment and equity issuance. These effects are concentrated among firms that rely more heavily on external equity financing. We find consistent evidence using an alternative identification strategy based on the staggered global rollout of exchange co-location services. Overall, the findings show that financial market innovations can alter firms' financing capacity and investment decisions, providing a channel through which financial market structure may influence aggregate economic growth.

Keywords: Financial market innovation; High-frequency trading; Real firm decisions; External financing; Economic growth

JEL Codes: G23; G31; G32; O4

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1 Introduction

High-frequency trading (HFT), one of the most consequential financial market innovations of the past two decades, now accounts for a substantial share of trading volume in modern equity markets.[1] By design, HFT combines fast market data, automated decision rules, and low-latency execution to trade at horizons measured in milliseconds. A large literature studies how HFT affects market quality, but the empirical evidence remains mixed: many studies document improvements in liquidity and short-horizon price discovery (Hendershott, Jones, and Menkveld, 2011; Brogaard, Hendershott, and Riordan, 2014), whereas others show that faster trading can reduce incentives to acquire fundamental information (Weller, 2018) or amplify commonality and return comovement (Malceniece, Malcenieks, and Putniņš, 2019). Despite this active debate, comparatively little is known about whether HFT affects firms' real decisions—and, ultimately, the real economy. In this paper, we fill this gap by providing evidence on how HFT affects firms' financing and investment activities.

Conceptually, the sign of HFT's real effects is ambiguous. If HFT improves liquidity and lowers transaction costs, it can reduce firms' cost of external financing and, in turn, raise investment. Hendershott, Jones, and Menkveld (2011) provides evidence consistent with this mechanism by showing that algorithmic trading improves liquidity. However, the relation between speed and market quality need not be monotonic. When HFT increases return comovement and liquidity commonality (Malceniece, Malcenieks, and Putniņš, 2019), it can raise systematic risk exposures and potentially increase the cost of capital. Moreover, HFT liquidity provision can be fragile and may withdraw during periods of market stress, worsening effective liquidity and potentially increasing the cost of equity capital (Kirilenko, Kyle, Samadi, and Tuzun, 2017). Moreover, by shaping the informational content of prices, HFT can influence investment through feedback and learning channels emphasized in the

[1] For example, using message-level data from NASDAQ, Carrion (2013) identifies HFT participation directly. Using industry estimates, the Congressional Research Service reports that HFT accounted for as much as about two-thirds of U.S. equity trades between 2008 and 2011 and that this share declined to about one-half by 2012 (Miller and Shorter, 2014).

broader literature on the real effects of financial markets (Bond, Edmans, and Goldstein, 2012). More informative prices can guide managerial learning and improve the allocation of capital (Dow and Gorton, 1997; Chen, Goldstein, and Jiang, 2007), potentially reducing misinvestment; conversely, if HFT crowds out information acquisition in the longer term (Weller, 2018), it may weaken price signals and reduce investment efficiency. These competing mechanisms underscore the importance of clean empirical evidence on whether, and through which channels, HFT affects firms' real decisions.

Although there are early attempts to study the real effects of HFT and algorithmic trading, the evidence remains limited and the small set of existing findings is not fully consistent with one another (Zuo, Seo, Kim, and Oh, 2026; Aliyev, Huseynov, and Rzayev, 2025). Two related challenges make it difficult to estimate the causal effect of HFT on firm decisions. First, HFT activity and corporate investment are jointly determined by fundamentals and market conditions. Second, researchers rarely observe a direct and clean measure of HFT participation; instead, much of the literature relies on indirect proxies such as message-to-trade ratios, cancellations, or trade size, which can be noisy and difficult to interpret. Our setting overcomes these limitations. We use Australian data from the Securities Industry Research Centre of Asia-Pacific (SIRCA) that include broker identifiers, which are then classified into trader categories, allowing us to directly measure HFT order and trade activity. We further exploit an exchange technology upgrade—the introduction of ASX-ITCH—as plausibly exogenous variation in the feasibility and intensity of HFT. [2]

ASX-ITCH is an ultra-low-latency protocol that the ASX rolled out on April 2, 2012, to distribute market data to any participant willing to pay a monthly subscription fee. The ASX describes ITCH as a premium, ultra-low-latency protocol for accessing ASX price data.[3] Because the upgrade primarily relaxes technological constraints on data access, and the fastest

[2] Goldstein, Kwan, and Philip (2023) use the ASX-ITCH setting to study high-frequency trading strategies and market quality.

[3] See the ASX page "How to access ASX price data," which states that users can connect via the "premium ultra–low latency ASX ITCH protocol": https://www.asx.com.au/connectivity-and-data/information-services/price-data/how-to-access-asx-price-data.

strategies have the highest willingness to pay for incremental latency reductions, the introduction of ITCH provides a plausibly exogenous shock that should disproportionately benefit HFT. Goldstein, Kwan, and Philip (2023) show that HFT response times improve substantially after ITCH adoption, whereas the response times of slower participants are largely unchanged. Therefore, the rollout of ASX-ITCH provides a natural setting to estimate the causal effects of HFT on firms' real decisions.

To estimate the effect of HFT on firm investment, we first implement a difference-in-differences (DiD) design around the introduction of ASX-ITCH. The DiD compares firms with different levels of pre-ITCH exposure to HFT before versus after the ITCH rollout. Specifically, we measure this *ex-ante* exposure as the share of HFT-initiated trading volume in a firm's stock, scaled by total trading volume, averaged over the pre-ITCH period. We rank firms by this exposure in 2011 and assign the top tercile to the treated group; firms in the bottom tercile form the pool of potential controls. To mitigate concerns that low-exposure firms differ systematically from high-exposure firms, we use inverse-probability weighting (IPW): we estimate each firm's propensity to be treated using pre-event characteristics and weight observations by the inverse of this probability to balance covariates across groups. We then estimate IPW DiD regressions for capital expenditures and the change in property, plant, and equipment (PPE), a standard proxy for fixed-asset investment. As an alternative specification that does not rely on discrete treated/control assignment, we also estimate a continuous DiD by interacting the (continuous) HFT exposure measure with a post-ITCH indicator and obtain consistent results. Across specifications, we find that the introduction of ASX-ITCH leads to an economically meaningful decline in investment of about 3–6 percent. Equity issuance falls even more by roughly 9 percent, while debt issuance shows little change.

We further document that the declines in both investment and equity issuance are concentrated among firms that rely more heavily on equity financing. This pattern suggests that ASX-ITCH affects firm outcomes primarily through equity markets, rather than through broad balance-sheet constraints. The joint response of equity issuance and investment is

consistent with a financing-based mechanism in which a deterioration in equity market conditions reduces firms' ability or willingness to raise external equity and, in turn, curtails real investment (e.g., Bond, Edmans, and Goldstein 2012; Grullon, Michenaud, and Weston 2015). Consistent with this interpretation, we also find that firms' cost of equity increases following the introduction of ASX-ITCH. In contrast, we do not find a corresponding decline in debt issuance, suggesting limited substitution toward (or disruption of) debt financing in response to the shock. Finally, we find little evidence that HFT changes investment–q sensitivity, indicating that the primary impact of HFT is on the level of investment and external equity financing rather than on the allocation of investment across firms. We also find no change in ROA and a significant decline in sales growth, further weighing against an interpretation based on improved resource allocation.

Taken together, our findings are consistent with the introduction of ASX-ITCH worsening equity financing conditions. Firms appear to respond primarily by scaling back the level of fixed investment rather than by reallocating investment toward more efficient projects. In other words, our evidence suggests that a central consequence of HFT in our setting is fewer real projects being undertaken, particularly among firms that historically depend on equity issuance.

We also confirm these results using an alternative identification strategy based on the staggered rollout of exchange co-location services, which prior work uses to study algorithmic and high-frequency trading across markets (Boehmer, Fong, and Wu, 2021; Aitken, Cumming, and Zhan, 2015, 2023). Co-location lets traders place their servers near an exchange's matching engine, which reduces latency and makes speed more valuable. Showing that the same patterns emerge around co-location helps rule out the concern that our conclusions hinge on a single Australian technology change or other institutional features of the ASX.

Collectively, our evidence shows that financial market innovations that favor speed can have meaningful real consequences, including lower corporate investment and reduced access to external equity financing. These results have practical implications for regulators and

exchanges as they evaluate market design choices that affect the arms race for speed and as they assess the benefits and costs of HFT in an ongoing policy debate.

Our paper contributes to two strands of the literature. First, we contribute to the high-frequency trading and market microstructure literature by linking HFT and speed-related trading technology to real corporate outcomes. A large body of studies how HFT affects liquidity and price discovery (e.g., Carrion 2013; Hendershott, Jones, and Menkveld 2011; Brogaard, Hendershott, and Riordan 2014), information acquisition (e.g., Weller 2018), and market stability (e.g., Kirilenko, Kyle, Samadi, and Tuzun 2017), leaving unresolved whether the controversial effects of speed on market quality translate into meaningful changes in firms' financing and investment. We provide, to the best of our knowledge, the first causal evidence that HFT can reduce firms' real investment and we propose and test a concrete channel: HFT worsens equity financing conditions by increasing firms' cost of equity and reducing external equity issuance, with the real effects concentrated in equity-issuance-reliant firms.

Second, we contribute to the broader literature on the real effects of financial markets by showing that changes in trading technology and the microstructure of capital markets can affect firms' cost of capital and real investment (e.g., Bond, Edmans, and Goldstein 2012; Grullon, Michenaud, and Weston 2015; Deng, Gupta, Lipson, and Mortal 2023). Our evidence complements recent work studying how algorithmic trading shapes managerial learning and other real outcomes (Zuo, Seo, Kim, and Oh, 2026; Aliyev, Huseynov, and Rzayev, 2025) and highlights that market design choices that intensify the speed race can have first-order real effects.

The rest of the paper is organized as follows. Section 2 describes the data and sample construction. Section 3 presents the identification strategy and baseline results. Section 4 investigates the mechanisms through which high-frequency trading affects firms' financing and investment decisions. Section 5 studies how ITCH affects firms' operating performance. Section 6 presents an alternative identification strategy based on exchange co-location and corresponding results. Section 7 provides additional analyses and robustness checks. Sec-

tion 8 concludes.

2 Data and Sample

2.1 Data Sources

We obtain firm financial statement information from Compustat Global. To measure high-frequency trading (HFT) activity and obtain limit order book information, we use transaction and order book data from the Securities Industry Research Centre of Asia-Pacific (SIRCA). Our sample period spans 2000–2022.

SIRCA provides full order book event and trade data for the Australian Securities Exchange (ASX), a market that is relatively unfragmented and operates as a continuous limit order book with price–time priority (with opening and closing auctions). The data contain the stock symbol, millisecond time stamp, order price and size, an order identifier, event type (submit, trade, amend, cancel), and a broker identifier. The order identifier allows us to link amendments, executions, and cancellations to the original order and to reconstruct the limit order book. Broker identifiers are assigned to trader categories (including proprietary HFT firms, institutions, and retail), allowing us to quantify HFT activity directly. Using these broker identifiers and limit order information, we compute each stock's daily HFT trading volume share and then aggregate the resulting measures to the stock (firm)–year level. We provide a more detailed description of the SIRCA data in Online Appendix B.

We then merge the aggregated HFT measure with the Compustat Global sample as our final study sample. We exclude firms in financials and utilities and remove stocks with an annual average closing price below \$1.00. The resulting merged sample contains approximately 239 firms and 3,516 firm-year observations over 2000–2022.[4]

[4]Although the ASX lists more than 2,000 firms, many are very small or micro-cap; the firms in our sample collectively account for more than 90% of total Australian equity market capitalization.

2.2 Summary Statistics

Table 1 reports descriptive statistics for the Australian firm-year sample used in our ASX-ITCH analyses. The sample covers 2000–2022 and contains 3,516 firm-year observations with approximately 239 unique firms.

[Insert Table 1 about here]

The corporate investment variables exhibit substantial cross-sectional dispersion. Capital expenditures (*Capex*) average 9.56% of lagged assets, with a median of 4.41%, indicating a right-skewed distribution in which a subset of firms invests aggressively. The annual growth in property, plant, and equipment (ΔPPE) has a mean of 6.21% and a median of 0.99%, consistent with lumpy investment and heterogeneous growth opportunities across firms.

External financing activity is also sizable and highly variable. Equity issuance (*Equity Issues*) has a mean of 15.14 and a median near zero, implying that many firm-years involve little or no net equity issuance while issuance is large in the upper tail. In contrast, debt issuance (*Debt Issues*) is smaller on average (mean 2.65).

The HFT measure suggests that fast trading is economically meaningful for a nontrivial subset of Australian equities. The average HFT trading-volume share is 3.71% (median 3.15%), and it exceeds 10% at the 95th percentile, indicating that HFT activity is concentrated in a relatively small set of stocks. Consistent with this concentration, the treated-group indicator has a mean of 0.56, reflecting we have a balanced treated and control sample.

3 Identification Strategy: The Australian Market Setting

3.1 The Institutional Details of ASX and ASX-ITCH

ASX-ITCH is introduced by ASX on April 2, 2012. It is an ultralow-latency market-data protocol that provides message-level information on ASX trading activity and is available to

all market participants for a monthly fee. The designed goal of ITCH is about speed: relative to the ASX's prior premium data products, the ITCH feed materially reduces dissemination latency. Because subscription is optional and the ASX does not disclose the identities of subscribing brokers, we do not directly observe adoption; nonetheless, a natural assumption is that the traders with the strongest demand for speed adopt first.

This institutional change is central to our study because HFT is, in practice, implemented through rapid order submission, cancellation, and revision in the limit order book. The ITCH message stream (new orders, cancels, modifications, and executions) with millisecond timestamps allows us to reconstruct the order book and to measure HFT activity at a grangular level of detail. In addition, the ASX offers an unusually clean setting for studying HFT. Unlike many highly fragmented markets such as the US and European markets, Australian equities trade in a comparatively centralized environment with transparent price–time priority. This institutional structure reduces the extent to which our HFT measures are confounded by off-exchange internalization or cross-venue routing, and it makes it easier and less noisy to interpret and quantify changes in trading behavior through the lens of a single, observable order book. Finally, because ASX-ITCH represents a discrete change in the market's information and technology environment, it provides a clean empirical setting to study how fast trading activity evolves and how it influents firms' real corporate decisions in subsequent years.

3.2 The Identification and Empirical Results

To implement the ASX-ITCH setting, we estimate the following difference-in-differences regression specification:

$$Y_{i,t} = \alpha + \beta\, Treated_i + \theta\, Post_t + \gamma\,(Treated_i \times Post_t) + \delta' X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}, \qquad (1)$$

where $Y_{i,t}$ denotes our key variables of interest, $Capex_{i,t}$ and $\Delta PPE_{i,t}$, for company i in

year t. $Post_t$ is an indicator equal to one for observations after the year of ITCH introduction, 2012, and $Treated_i$ is an indicator for stocks with higher ex ante exposure to high-frequency trading. The vector $X_{i,t}$ captures the full set of time-varying firm controls, μ_i are firm fixed effects, and λ_t are year fixed effects. Because $Post_t$ is absorbed by year fixed effects and $Treated_i$ is absorbed by firm fixed effects, these main effects are not separately identified; the average treatment effect is captured by the interaction term $Treated_i \times Post_t$.

In addition, we include size-group $\times$ SIC2 fixed effects to flexibly absorb time-invariant differences across firms that operate in the same industry but fall into different size groups. This is particularly important in Australia, where there is substantial dispersion in firm size and related characteristics (e.g., financing capacity, analyst coverage, and institutional ownership). These interacted fixed effects help ensure that our estimates are not driven by persistent size- and industry-related heterogeneity. The control variables in $X_{i,t}$ include standard determinants of corporate investment and financing activity, such as firm size, profitability, cash flow, and leverage, as well as additional characteristics used throughout the paper (see Online Appendix A for the full list and detailed definitions).[5]

A key empirical task in implementing this difference-in-differences design is defining appropriate treated and control groups. Following the market microstructure literature, we sort firms based on their ex ante exposure to high-frequency trading (HFT). Specifically, we compute each stock's annual average HFT trading-volume share (HFT trading volume divided by total trading volume) in the period immediately preceding the introduction of ASX-ITCH, using 2010 and 2011. We use two pre-event years so that the exposure measure reflects persistent differences across firms rather than transitory fluctuations in trading activity. We then rank stocks by this pre-ITCH exposure measure and form terciles. Stocks in the top tercile are assigned to the treated group, while stocks in the bottom tercile form the control group.[6] The intuition is that ASX-ITCH primarily increases the value of speed and

[5]Following the literature, firm size, profitability, and leverage are lagged, while cash flow is measured contemporaneously.

[6]Our findings are not sensitive to the exact cutoff used to define treated and control groups.

low-latency market data; therefore, stocks with the highest pre-event HFT presence are the ones for which a further increase in speed should matter most, because these are precisely the stocks in which speed-sensitive strategies are already most active. Figure 1 provides visual evidence consistent with this identification strategy. For high-exposure (treated) stocks, the HFT trading-volume share increases from less than 7% prior to ASX-ITCH to approximately 10% after the introduction of ITCH, while low-exposure (control) stocks remain roughly flat at around 1%. This evidence supports the view that our treated group is the segment of the market most affected by the introduction of ASX-ITCH.

[Insert Figure 1 about here]

Table 2 presents our difference-in-differences estimates of the effect of ASX-ITCH on corporate investment. The key coefficient is γ on $Treated \times Post$, which captures the post-2012 change in investment for treated firms relative to control firms. In Columns (1)–(2), we estimate $\gamma = -2.362$ for Capex and $\gamma = -6.147$ for ΔPPE (both statistically significant). Using the pre-event sample means (Capex mean = 9.562 and ΔPPE mean = 6.213; Table 1), these magnitudes correspond to a decline of about 25% in Capex (2.362/9.562) and about 99% in ΔPPE (6.147/6.213) for treated firms relative to their pre-ITCH average levels, indicating that the estimated effect is economically large.

[Insert Table 2 about here]

To address concerns that treated and control firms may differ systematically in observable characteristics, we also report inverse probability weighting (IPW) DiD estimates in Columns (3)–(4). IPW reweights observations to balance covariates across groups and can improve comparability when treatment assignment is related to observables, while retaining the DiD identification based on within-firm changes over time (see, e.g., Abadie, 2005; Acemoglu, Naidu, Restrepo, and Robinson, 2019). The IPW estimates are similar in sign and significance to the baseline results, suggesting that our findings are not driven by observable differences between treated and control firms.

Columns (5)–(6) use a continuous treatment measure based on ex-ante HFT exposure (rather than a tercile-based treated indicator). This specification leverages the cross-sectional variation in pre-ITCH HFT intensity and avoids discretizing firms into treated and control groups, mitigating concerns about selection arising from the particular cutoff used to define treated and control groups. The results using continuous exposure are consistent with the baseline and IPW specifications, reinforcing the interpretation that the increase in HFT intensity induced by ASX-ITCH is associated with lower corporate investment.

Figure 2 provides complementary evidence on investment dynamics. The treated and control groups display similar pre-event trends in Capex and ΔPPE, supporting the parallel-trends assumption required for our DiD design. After the introduction of ASX-ITCH, investment declines more sharply for treated firms, and the average treated–control difference becomes more negative in the post period, consistent with the negative DiD coefficients in Table 2.

[Insert Figure 2 about here]

4 Underlying Mechanism: Reduced Equity Financing Capacity

We now turn to the question of what drives the decline in investment. We first focus on a financing-based mechanism in which the ITCH-induced increase in HFT activity reduces firms' effective access to external equity by raising the marginal cost of equity capital.

Table 3 presents the external financing regression results and documents a sharp decline in equity issuance following the introduction of ASX-ITCH. In the baseline specification, the DiD coefficient on $\textit{Treated} \times \textit{Post}$ is $\gamma = -9.778$ ($t = -3.73$) for Equity Issues, implying that treated firms reduce equity issuance by 9.778 percentage points more than control firms after ITCH. Relative to the pre-event mean equity issuance of 15.14 (Table 1), this estimate corresponds to a decline of roughly 65% (9.778/15.14), indicating a large contraction in equity

financing. In contrast, the corresponding estimate for Debt Issues is small and statistically insignificant ($\gamma = -0.871$, $t= -0.65$), suggesting that the financing response operates primarily through equity rather than debt markets. In the HFT-intensity specification, the coefficient on HFT Exposure×Post is also negative for Equity Issues (-1.386, $t= -4.31$), reinforcing the interpretation that higher HFT intensity is associated with a reduction in equity financing.

[Insert Table 3 about here]

Table 4 provides cross-sectional evidence consistent with this mechanism. We split firms based on equity-financing reliance, defined using a median cutoff on the ex-ante three-year average of equity issuance; *Equity Reliance* $= 1$ indicates firms above the median. The results show that the negative *Treated* $\times$ *Post* effects are concentrated among equity-reliant firms. In the high-reliance subsample, treated firms experience significantly larger declines in investment (Capex and ΔPPE) and equity issuance after ITCH, whereas the corresponding estimates for low-reliance firms are smaller in magnitude or insignificant. This pattern is consistent with ITCH tightening equity financing constraints primarily for firms that depend more heavily on external equity.

[Insert Table 4 about here]

The evidence in Tables 3 and 4 suggests a possible external financing-cost channel: treated firms reduce equity issuance, particularly among firms that are more reliant on equity markets. To formally examine this mechanism, we construct three implied cost-of-equity measures (r_{Gordon}, r_{OJ}, and r_{CT}), following Gordon and Gordon (1997), Ohlson and Juettner-Nauroth (2005) (as implemented by Gode and Mohanram (2003)), and Claus and Thomas (2001), respectively, and using the earnings-forecasting approach of Hou, van Dijk, and Zhang (2012) (see Online Appendix C for details). We then test whether ITCH is associated with a higher required return on equity capital for treated firms. Table 5 reports

the results. Across the three implied cost-of-equity measures, the *Treated* × *Post* coefficients are positive and statistically significant in the baseline specification: 0.043 (t= 3.06) for r_{Gordon}, 0.055 (t= 3.35) for r_{OJ}, and 0.031 (t= 2.12) for r_{CT}. The IPW estimates are similar, indicating that the increase in required returns is robust to reweighting treated and control observations. Taken together, these findings provide direct support for the cost-of-equity channel as a mechanism linking ITCH-induced HFT activity to lower corporate investment.

[Insert Table 5 about here]

Finally, we further probe the cost-of-equity channel by examining whether ITCH is associated with changes in the information environment of treated firms. Doing so helps us both shed light on a potential driver of the higher cost of equity and assess an alternative "allocation-efficiency" mechanism in which HFT improves price informativeness and thereby reduces financing frictions. Table 6 reports the results for such analysis. We consider (i) *Delay* following Hou and Moskowitz (2005), which captures the speed with which firm-specific information is incorporated into returns, and (ii) a return-comovement measure (market-model R^2) following Morck, Yeung, and Yu (2000) and Malceniece, Malcenieks, and Putniņš (2019), which captures the extent to which individual-stock returns move with common factors. The point estimates for *Delay* are statistically insignificant, providing no evidence of improved price informativeness for treated stocks after ITCH. In contrast, return comovement rises significantly for treated stocks in both the baseline and IPW specifications, consistent with prices reflecting relatively more common-factor variation and relatively less firm-specific information in the post-ITCH period.

[Insert Table 6 about here]

Overall, we find no evidence that ITCH improves price informativeness. The absence of a detectable improvement in price informativeness provides little support for an allocation-efficiency channel through which HFT would lower financing frictions and help firms reduce

overinvestment. The significant increase in return comovement implies that treated stocks load more heavily on common risk factors, which is consistent with an increase in systematic risk. All else equal, higher systematic risk raises the required return demanded by investors and can therefore contribute to the higher implied costs of equity reported in Table 5.

5 HFT and Operating Performance

To further understand the mechanisms underlying the investment response to ITCH, we next examine whether treated firms experience changes in operating performance. If the post-ITCH decline in investment reflected improved capital allocation or reduced overinvestment, one might expect to see stable or improved profitability and/or sales growth. Conversely, if higher HFT activity tightens financing conditions or increases systematic risk, the resulting investment pullback could be accompanied by weaker sales growth and operating outcomes.

Table 7 reports difference-in-differences estimates of the effect of ITCH on return on assets (ROA) and sales growth. In the baseline specification, the *Treated*$\times$ *Post* coefficient is economically small and statistically insignificant for ROA, indicating no change in accounting profitability for treated firms relative to controls. In contrast, the corresponding coefficient for sales growth is negative and statistically significant (-15.670, $t= -2.57$; Column 2), suggesting that treated firms experience approximately 16% slower revenue growth after ITCH. The estimates from the other two settings in Columns (3)–(6) show a similar pattern, with no meaningful effect on ROA and a negative (though insignificant) effect on sales growth.

[Insert Table 7 about here]

Taken together, the evidence in Table 7 suggests that the ITCH-induced increase in HFT is not associated with higher operating profitability, and may be associated with weaker sales growth. This pattern is consistent with a mechanism in which higher equity financing costs

and increased exposure to systematic risk reduce firms' capacity to fund growth opportunities, rather than a mechanism in which HFT improves informational efficiency and enhances real operating performance.

6 Alternative Setting: Exchange Co-location

Our main identification strategy exploits the introduction of ASX-ITCH within a single market. As an alternative setting, we examine the staggered rollout of exchange co-location services across markets. Co-location allows traders to place their servers in close physical proximity to an exchange's matching engine, reducing latency and increasing the value of speed. Because the introduction of co-location occurs at different times across exchanges, it provides additional variation that is distinct from the ASX-ITCH institutional setting.

We identify 15 co-location events during the sample period based on the dates reported in Boehmer, Fong, and Wu (2021), Aitken, Cumming, and Zhan (2015), and Aitken, Cumming, and Zhan (2023) (Online Appendix E lists the event dates).[7] We then estimate a staggered DiD specification in which the key regressor, *Co-location*, is an indicator equal to one for firm-year observations after the stock's listing exchange begins offering co-location services; we exclude observations in the event year to allow time for trading technology and market participation to adjust.

Table 8 reports the results. Consistent with the ASX-ITCH evidence, firms affected by co-location is associated with economically meaningful declines in both corporate investment and external equity financing. In Columns (1)–(2), which include firm and year fixed effects, the co-location coefficient is -2.442 for Capex ($t= -6.08$) and -4.205 for Equity Issues ($t= -8.50$). In Columns (3)–(4), which include year and country fixed effects, the estimates remain negative and statistically significant (Capex: -2.661, $t= -2.16$; Equity Issues: -5.677, $t= -6.45$). Overall, the results from this alternative setting further confirm

[7]When there is a discrepancy in the reported co-location dates, we use the date based on the official release from the exchange.

our main conclusion that speed-enhancing market structure changes are linked to reduced equity issuance capacity and lower real investment.

[Insert Table 8 about here]

7 Additional Analysis and Robustness

7.1 Alternative Explanation: Managerial Learning and Allocation Efficiency

One alternative interpretation of our finding is managerial learning (or allocation-efficiency) channel. In this view, the ITCH-induced increase in high-frequency trading (HFT) improves the information environment by accelerating the incorporation of firm- and market-level news into prices. Managers, boards, and other corporate decision-makers may then learn more from market prices and revise their beliefs about fundamentals and investment opportunities more quickly. A post-ITCH decline in average investment could therefore reflect improved investment discipline rather than tighter financing conditions: firms learn that some marginal projects have lower expected profitability than previously believed and optimally reduce capital expenditures. Under this hypothesis, investment falls, but investment efficiency improves.

This explanation has a clear empirical implication. If ITCH improves the information content of prices in a way that managers use to guide real decisions, then firms' investment should become more responsive to measures of investment opportunities. A standard benchmark is the sensitivity of investment to Tobin's q (or closely related proxies for growth opportunities). When learning improves and the mapping from fundamentals into prices strengthens, q should better summarize the payoff to marginal investment, and managers should allocate capital more strongly toward high-q states and away from low-q states. Accordingly, the investment–q sensitivity should increase after ITCH, especially for the treated

firms,those with greater ex ante exposure to HFT that experience the largest ITCH-related increase in speed-sensitive trading.

We assess this possibility by combining our price-efficiency evidence with direct tests of investment efficiency. Our price-efficiency results in Table 6 speak to whether ITCH is associated with changes in the informational efficiency of prices, but we do not find supporting evidence. We therefore estimate regressions that explicitly test whether the investment–q relation changes differentially for treated firms after the introduction of ASX-ITCH. Specifically, we augment the baseline specifications to include Tobin's q and interact q with *Post* and treatment status, so that the slope on q can shift in the post-ITCH period for the treated group. If managerial learning is an important channel, the coefficients on these post-ITCH interaction terms should be positive and statistically significant.

Table F1 in the Online Appendix reports the results. Across specifications, we find no statistically significant changes in investment–q sensitivity following ITCH. The coefficients on the post-ITCH interaction terms are economically small and indistinguishable from zero, indicating that treated firms do not become more responsive to Tobin's q after the introduction of ASX-ITCH. Thus, while ITCH represents a discrete speed shock that increases HFT activity, we do not find evidence that it improves investment efficiency through a stronger investment–opportunity mapping.

Taken together with our price-efficiency results, these findings further rule out the managerial-learning explanation as the primary driver of our baseline effects. If ITCH materially improved the information content of prices in a way that managers used to make better investment decisions, we would expect to observe a steeper investment–q relation (higher investment–q sensitivity) in the treated group after ITCH. Instead, the combination of (i) weak or no improvement in price efficiency, and (ii) no detectable increase in investment–q sensitivity, suggests that the post-ITCH decline in investment is unlikely to be explained by improved learning and more efficient capital allocation. This pattern is more consistent with our financing-capacity mechanism, in which the ITCH-induced rise in HFT raises the

effective cost of equity or otherwise reduces firms' ability to access external equity financing.

7.2 Robustness

Our baseline ASX-ITCH analysis uses the full sample period and does not restrict to a narrow window around the April 2, 2012 ITCH introduction. While this approach maximizes statistical power, one concern is that long-horizon estimates could be influenced by slow-moving changes in the macroeconomic environment, market structure, or sample composition that happen to coincide with (but are not caused by) ITCH.

To address this concern, we re-estimate the main difference-in-differences specifications using symmetric event windows around ITCH. First, we restrict the sample to the five years before and after ITCH. Second, we consider a broader ten-year window before and after ITCH. In both cases, we confirm that the main conclusions are unchanged: treated firms continue to exhibit economically meaningful declines in investment and external equity issuance in the post-ITCH period relative to control firms.

The corresponding results are reported in Table F2 of the Online Appendix. The table shows that the estimated $Treated \times Post$ coefficients remain negative and similar in magnitude under both window restrictions, indicating that our baseline findings are not driven by sample period choice.

8 Conclusion

This paper studies the long-horizon real effects of high-frequency trading (HFT) through a sharp and plausibly exogenous change in HFT presence: the Australian Securities Exchange's introduction of ASX-ITCH on April 2, 2012. Using order-level data and broker identifiers to directly measure HFT activity and a difference-in-differences design, we show that the ITCH-driven increase in HFT is followed by economically large declines in real investment and external equity issuance. These effects are concentrated among firms that relied more

heavily on external equity financing prior to ITCH.

Our evidence points to a financing-based mechanism. Following ITCH, treated firms experience a pronounced contraction in equity issuance alongside an increase in implied costs of equity capital. In addition, return comovement rises, indicating greater exposure to systematic risk, which can rationalize higher required returns demanded by investors. By contrast, we find little support for an informational-efficiency channel in which faster trading improves price discovery and lowers financing frictions.

Our results speak directly to the ongoing debate about the controversial role of HFT in modern equity markets. Much of the discussion—both in academia and in policy circles—focuses on short-run market quality outcomes. Our evidence highlights a broader point: changes in trading speed and market technology can also affect firms by changing their access to equity financing and, in turn, their real investment decisions. We hope these findings provide useful guidance for regulators and exchanges as they evaluate market-data products and latency-reducing infrastructure, and as they weigh the benefits of faster trading against potential costs for capital formation and long-run economic growth.

Several open questions remain. Understanding which specific aspects of speed-based trading raise systematic risk exposure or increase the effective cost of external equity is an important direction for future research, as is identifying the firm characteristics and market environments under which speed improvements are most likely to benefit—rather than hinder—capital formation. As exchanges and regulators continue to innovate in market-data products and latency-reducing infrastructure, careful evaluation of these longer-run corporate outcomes should be an integral part of the assessment of modern market structure.

References

Abadie, A., 2005, "Semiparametric Difference-in-Differences Estimators," *Review of Economic Studies*, 72(1), 1–19.

Acemoglu, D., S. Naidu, P. Restrepo, and J. A. Robinson, 2019, "Democracy Does Cause Growth," *Journal of Political Economy*, 127(1), 47–100.

Aitken, M., D. Cumming, and F. Zhan, 2015, "High frequency trading and end-of-day price dislocation," *Journal of Banking & Finance*, 59, 330–349.

——— , 2023, "Algorithmic trading and market quality: International evidence of the impact of errors in colocation dates," *Journal of Banking & Finance*, 151, 106843.

Aliyev, N., F. Huseynov, and K. Rzayev, 2025, "The good and evil of algos: Investment-to-price sensitivity and the learning hypothesis," *Journal of Corporate Finance*, 94, 102834.

Boehmer, E., K. Fong, and J. J. Wu, 2021, "Algorithmic Trading and Market Quality: International Evidence," *Journal of Financial and Quantitative Analysis*, 56(8), 2659–2688.

Bond, P., A. Edmans, and I. Goldstein, 2012, "The Real Effects of Financial Markets," *Annual Review of Financial Economics*, 4(1), 339–360.

Brogaard, J., T. Hendershott, and R. Riordan, 2014, "High-Frequency Trading and Price Discovery," *The Review of Financial Studies*, 27(8), 2267–2306.

Carrion, A., 2013, "Very fast money: High-frequency trading on the NASDAQ," *Journal of Financial Markets*, 16(4), 680–711.

Chen, Q., I. Goldstein, and W. Jiang, 2007, "Price informativeness and investment sensitivity to stock price," *Journal of Financial Economics*, 86(2), 262–288.

Claus, J., and J. Thomas, 2001, "Equity Premia as Low as Three Percent? Evidence from Analysts' Earnings Forecasts for Domestic and International Stock Markets," *The Journal of Finance*, 56(5), 1629–1666.

Deng, X., V. K. Gupta, M. L. Lipson, and S. Mortal, 2023, "Short-Sale Constraints and Corporate Investment," *Journal of Financial and Quantitative Analysis*, p. 1–33.

Dow, J., and G. Gorton, 1997, "Stock Market Efficiency and Economic Efficiency: Is There a Connection?," *The Journal of Finance*, 52(3), 1087–1129.

Gode, D., and P. Mohanram, 2003, "Inferring the Cost of Capital Using the Ohlson–Juettner Model," *Review of Accounting Studies*, 8(4), 399–431.

Goldstein, M., A. Kwan, and R. Philip, 2023, "High-Frequency Trading Strategies," *Management Science*, 69(8), 4413–4434.

Gordon, J. R., and M. J. Gordon, 1997, "The Finite Horizon Expected Return Model," *Financial Analysts Journal*, 53(3), 52–61.

Grullon, G., S. Michenaud, and J. P. Weston, 2015, "The Real Effects of Short-Selling Constraints," *The Review of Financial Studies*, 28(6), 1737–1767.

Hendershott, T., C. M. Jones, and A. J. Menkveld, 2011, "Does Algorithmic Trading Improve Liquidity?," *The Journal of Finance*, 66(1), 1–33.

Hou, K., and T. J. Moskowitz, 2005, "Market Frictions, Price Delay, and the Cross-Section of Expected Returns," *The Review of Financial Studies*, 18(3), 981–1020.

Hou, K., M. A. van Dijk, and Y. Zhang, 2012, "The Implied Cost of Capital: A New Approach," *Journal of Accounting and Economics*, 53(3), 504–526.

Kirilenko, A. A., A. S. Kyle, M. Samadi, and T. Tuzun, 2017, "The Flash Crash: The Impact of High Frequency Trading on an Electronic Market," *The Journal of Finance*.

Malceniece, L., K. Malcenieks, and T. J. Putniņš, 2019, "High frequency trading and co-movement in financial markets," *Journal of Financial Economics*, 134(2), 381–399.

Miller, R. S., and G. Shorter, 2014, "High-Frequency Trading: Background, Concerns, and Regulatory Developments," working paper R43608, Congressional Research Service.

Morck, R., B. Yeung, and W. Yu, 2000, "The Information Content of Stock Markets: Why Do Emerging Markets Have Synchronous Stock Price Movements?," *Journal of Financial Economics*, 58(1–2), 215–260.

Ohlson, J. A., and B. E. Juettner-Nauroth, 2005, "Expected EPS and EPS Growth as Determinants of Value," *Review of Accounting Studies*, 10(2–3), 349–365.

Weller, B. M., 2018, "Does Algorithmic Trading Reduce Information Acquisition?," *The Review of Financial Studies*, 31(6), 2184–2226.

Zuo, L., H. Seo, J. Kim, and J. Oh, 2026, "Algorithmic Trading and Directors' Learning from Stock Prices: Evidence from CEO Turnover Decisions," *SSRN Working Paper*.

Table 1
Descriptive statistics

This table reports descriptive statistics for the Australian sample used in the ASX-ITCH analysis. The sample consists of firm-year observations for 2000–2022. All variables are defined in Online Appendix A.

Variable	N	Mean	Median	SD	P5	P95
Capex	3,516	9.562	4.412	14.01	0.373	44.10
ΔPPE	3,223	6.213	0.991	18.73	-10.27	47.06
Equity Issues	3,516	15.14	0.041	50.57	0.000	83.04
Debt Issues	3,515	2.651	0.000	11.61	-13.01	30.69
Treated	2,374	0.559	1.000	0.497	0.000	1.000
HFT Volume (%)	3,516	3.707	3.152	3.089	0.199	10.27
Market Cap	3,336	1,518	685.6	1,592	23.75	4,035
Cash Flow	3,406	6.330	10.57	26.56	-31.93	30.76
Size	3,516	5.367	5.556	1.843	1.888	7.510
Past Profitability	3,508	8.856	13.36	27.51	-34.23	33.56
Leverage	3,514	23.20	21.37	20.62	0.000	61.35

Table 2
ASX-ITCH and Corporate Investment

This table reports difference-in-differences (DiD) estimates of the effect of high-frequency trading (HFT) on corporate investment around the introduction of ASX-ITCH. The dependent variables are capital expenditure (Capex) and the annual growth in property, plant, and equipment (ΔPPE), as indicated in the column headings. Columns (1)–(2) report baseline DiD estimates, Columns (3)–(4) report inverse probability weighting (IPW) DiD estimates, and Columns (5)–(6) use a continuous ex-ante HFT exposure treatment measure, defined as the average HFT volume share prior to the introduction of ASX-ITCH. All variables are defined in Online Appendix A. Regressions include firm and year fixed effects, as well as Size Group × SIC2 fixed effects. *t*-statistics based on standard errors adjusted for clustering at the firm and year level are in parentheses below each coefficient. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Baseline		IPW		HFT Intensity	
	(1) Capex	(2) Δ PPE	(3) Capex	(4) Δ PPE	(5) Capex	(6) Δ PPE
Treated × Post	-2.362**	-6.147***	-2.943**	-6.052**		
	(-2.18)	(-3.30)	(-2.25)	(-2.80)		
HFT Exposure × Post					-0.323**	-0.771***
					(-2.21)	(-3.35)
Size	-3.134***	-4.817***	-2.354**	-3.013***	-3.400***	-5.341***
	(-3.85)	(-7.81)	(-2.33)	(-4.91)	(-4.96)	(-7.07)
Cash flow	0.100*	0.235**	0.128*	0.165*	0.020	0.077
	(1.77)	(2.40)	(1.86)	(1.73)	(0.38)	(0.77)
Past profitability	-0.136*	-0.210*	-0.037	-0.088	-0.058	-0.027
	(-1.81)	(-1.91)	(-0.46)	(-0.72)	(-0.87)	(-0.25)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Size Group × SIC2	Yes	Yes	Yes	Yes	Yes	Yes
N	1972	1994	1972	1994	2849	2894
Adj. R^2	0.503	0.216	0.495	0.199	0.511	0.202

Table 3
ASX-ITCH and External Financing

This table reports difference-in-differences (DiD) estimates of the effect of high-frequency trading (HFT) on firms' external financing around the introduction of ASX-ITCH. The dependent variables are equity issues (Equity Issues) and debt issues (Debt Issues), as indicated in the column headings. Columns (1)–(2) report baseline DiD estimates, Columns (3)–(4) report inverse probability weighting (IPW) DiD estimates, and Columns (5)–(6) use a continuous ex-ante HFT exposure treatment measure, defined as the average HFT volume share prior to the introduction of ASX-ITCH. All variables are defined in Online Appendix A. Regressions include firm and year fixed effects, as well as Size Group × SIC2 fixed effects. *t*-statistics based on standard errors adjusted for clustering at the firm and year level are in parentheses below each coefficient. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Baseline		IPW		HFT Intensity	
	(1) Equity Issue	(2) Debt Issue	(3) Equity Issue	(4) Debt Issue	(5) Equity Issue	(6) Debt Issue
Treated × Post	-9.778***	-0.871	-12.504***	-0.526		
	(-3.73)	(-0.65)	(-3.61)	(-0.29)		
HFT Exposure × Post					-1.386***	-0.109
					(-4.31)	(-0.66)
Size	-7.942***	-1.178**	-6.342**	-0.668	-8.656***	-0.854**
	(-3.02)	(-2.47)	(-2.11)	(-0.80)	(-3.60)	(-2.70)
Cash Flow	0.289	-0.055	0.239	-0.097	-0.054	-0.047
	(1.35)	(-0.63)	(1.59)	(-0.92)	(-0.26)	(-0.84)
Past Profitability	-1.141***	0.077	-0.485**	0.202	-0.705***	0.046
	(-5.10)	(0.81)	(-2.42)	(1.50)	(-3.11)	(0.78)
Leverage	0.001	-0.189***	0.187*	-0.202***	-0.002	-0.202***
	(0.01)	(-8.28)	(1.98)	(-7.05)	(-0.03)	(-8.90)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Size Group × SIC2	Yes	Yes	Yes	Yes	Yes	Yes
N	1,978	1,994	1,978	1,994	2,860	2,894
Adj. R^2	0.429	0.102	0.191	0.154	0.417	0.098

Table 4
Cross-sectional Results by Equity Financing Reliance

This table reports difference-in-differences (DiD) estimates examining cross-sectional heterogeneity in the effect of high-frequency trading (HFT) around the introduction of ASX-ITCH. The dependent variables are capital expenditure (Capex), the annual growth in property, plant, and equipment (ΔPPE), and equity issues (Equity Issues), as indicated in the column headings. Columns (1)–(3) and Columns (4)–(6) report results for subsamples with high versus low equity financing reliance. All variables are defined in Online Appendix A. Regressions include firm and year fixed effects, as well as Size Group × SIC2 fixed effects. *t*-statistics based on standard errors adjusted for clustering at the firm and year level are in parentheses below each coefficient. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	High Equity Reliance			Low Equity Reliance		
	(1) Capex	(2) ΔPPE	(3) Equity Issues	(4) Capex	(5) ΔPPE	(6) Equity Issues
Treated × Post	-3.577**	-6.620*	-15.510***	-1.384	-4.970**	0.012
	(-2.31)	(-2.01)	(-3.56)	(-0.92)	(-2.43)	(0.01)
Size	-2.444**	-4.448***	-7.217*	-4.342***	-4.948***	-6.679***
	(-2.54)	(-7.01)	(-2.06)	(-3.88)	(-3.40)	(-3.80)
Cash Flow	0.137**	0.263**	0.445**	-0.026	0.172	-0.022
	(2.76)	(2.61)	(2.29)	(-0.25)	(1.47)	(-0.19)
Past Profitability	-0.212***	-0.274**	-1.382***	0.111	0.066	-0.160
	(-3.71)	(-2.64)	(-8.11)	(1.23)	(0.43)	(-1.08)
Leverage			0.015			-0.024
			(0.12)			(-0.79)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Size Group x SIC2	Yes	Yes	Yes	Yes	Yes	Yes
N	1,012	1,031	1,017	960	963	961
Adj. R^2	0.460	0.216	0.449	0.595	0.196	0.185

Table 5
ASX-ITCH and Implied Cost of Equity

This table reports difference-in-differences (DiD) estimates of the effect of high-frequency trading (HFT) around the introduction of ASX-ITCH on firms' implied cost of equity. The dependent variables are r_{Gordon}, r_{OJ}, and r_{CT}, as indicated in the column headings. All variables are defined in Online Appendix A. Columns (1)–(3) report baseline DiD estimates, Columns (4)–(6) report inverse probability weighting (IPW) DiD estimates. Regressions include firm and year fixed effects, as well as Size Group × SIC2 fixed effects. *t*-statistics based on standard errors adjusted for clustering at the firm and year level are in parentheses below each coefficient. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Baseline			IPW		
	(1)	(2)	(3)	(4)	(5)	(6)
	r_{Gordon}	r_{OJ}	r_{CT}	r_{Gordon}	r_{OJ}	r_{CT}
Treated × Post	0.043***	0.055***	0.031**	0.033*	0.053***	0.030*
	(3.06)	(3.35)	(2.12)	(1.94)	(3.16)	(1.76)
Size	0.009**	0.014	0.009	0.009	0.035**	0.004
	(2.16)	(1.74)	(1.25)	(1.14)	(2.51)	(0.33)
Cash Flow	0.002**	0.002*	0.000	0.002	0.002	0.000
	(2.82)	(1.93)	(0.45)	(1.70)	(1.54)	(0.07)
Past Profitability	-0.001	-0.001	-0.001	-0.000	-0.000	-0.002*
	(-1.44)	(-0.86)	(-1.59)	(-0.65)	(-0.34)	(-1.94)
Leverage	0.000*	0.000*	0.000	0.000	0.001	0.000
	(1.78)	(1.80)	(0.33)	(1.56)	(1.43)	(1.33)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Size Group x SIC2	Yes	Yes	Yes	Yes	Yes	Yes
N	1,168	643	677	1,168	643	677
Adj. R^2	0.397	0.364	0.495	0.508	0.474	0.506

Table 6
Price Informativeness and Returns Comovement

This table reports difference-in-differences (DiD) estimates examining the effect of high-frequency trading (HFT) around the introduction of ASX-ITCH on price informativeness and return comovement. The dependent variables are *Delay* (Hou and Moskowitz, 2005) and *Return Comovement* (Morck, Yeung, and Yu, 2000; Malceniece, Malcenieks, and Putniņš, 2019), as indicated in the column headings. Columns (1)–(2) report baseline DiD estimates, Columns (3)–(4) report inverse probability weighting (IPW) DiD estimates, and Columns (5)–(6) use a continuous ex-ante HFT exposure treatment measure. All variables are defined in Online Appendix A. Regressions include stock and year fixed effects, as well as Size Group × SIC2 fixed effects. *t*-statistics based on standard errors adjusted for clustering at the firm and year level are in parentheses below each coefficient. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Baseline		IPW		HFT Intensity	
	(1) Delay	(2) Comovement	(3) Delay	(4) Comovement	(5) Delay	(6) Comovement
Treated × Post	-0.021	0.229**	-0.041	0.371**		
	(-0.47)	(2.51)	(-0.85)	(2.63)		
HFT Exposure × Post					-0.005	0.032*
					(-0.81)	(2.26)
Ln(Market Cap)	-0.021	0.064	-0.096**	0.154	-0.022	0.050
	(-0.62)	(0.85)	(-2.92)	(1.06)	(-0.83)	(0.79)
Ln(Price)	-0.032	0.207	-0.020	0.216	-0.020	0.185
	(-1.04)	(1.57)	(-0.39)	(1.55)	(-0.66)	(1.47)
Volatility	1.445*	0.080	1.038	6.560	0.407	1.195
	(2.24)	(0.02)	(0.61)	(0.74)	(0.49)	(0.22)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Size Group x SIC2	Yes	Yes	Yes	Yes	Yes	Yes
N	960	956	960	956	1,339	1,334
Adj. R^2	0.230	0.424	0.157	0.307	0.214	0.381

Table 7
ASX-ITCH and Firm Operating Performance

This table reports difference-in-differences (DiD) estimates of the effect of high-frequency trading (HFT) around the introduction of ASX-ITCH on firm operating performance. The dependent variables are return on assets (ROA) and sales growth, as indicated in the column headings. Columns (1)–(2) report baseline DiD estimates, Columns (3)–(4) report inverse probability weighting (IPW) DiD estimates, and Columns (5)–(6) use a continuous ex-ante HFT exposure treatment measure. All variables are defined in Online Appendix A. Regressions include firm and year fixed effects, as well as Size Group × SIC2 fixed effects. *t*-statistics based on standard errors adjusted for clustering at the firm and year level are in parentheses below each coefficient. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Baseline		IPW		HFT Intensity	
	(1) ROA	(2) Sales Growth	(3) ROA	(4) Sales Growth	(5) ROA	(6) Sales Growth
Treated × Post	0.061	-15.670**	0.096	-9.726		
	(0.17)	(-2.57)	(0.25)	(-1.30)		
HFT Exposure × Post					0.036	-0.780
					(0.67)	(-0.83)
Size	-0.914***	-31.488***	-0.786**	-21.827***	-0.429	-31.136***
	(-6.05)	(-4.50)	(-2.69)	(-3.36)	(-1.41)	(-5.22)
Cash Flow	0.962***	0.766	0.985***	-0.120	0.980***	0.346
	(56.06)	(1.11)	(31.99)	(-0.53)	(78.38)	(0.66)
Past Profitability	-0.018	0.610	-0.055	1.585***	-0.023	0.766
	(-0.92)	(0.86)	(-1.39)	(4.22)	(-1.67)	(1.38)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Size Group x SIC2	Yes	Yes	Yes	Yes	Yes	Yes
N	1,965	1,942	1,965	1,942	2,854	2,798
Adj. R^2	0.984	0.214	0.980	0.308	0.978	0.201

Table 8
Staggered DiD Results from Co-location Setting

This table presents staggered DiD estimates of the effect of exchange co-location on corporate investment and external equity financing. The dependent variables are capital expenditure (Capex) and equity issues (Equity Issues), as indicated in the column headings. The results are from OLS regressions using firm-year observations from 2002 to 2017. All variables are defined in Online Appendix A. Columns (1)–(2) include firm and year fixed effects, and Columns (3)–(4) include year and country fixed effects. *t*-statistics based on standard errors clustered at the firm level are in parentheses below each coefficient. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) Capex	(2) Equity Issues	(3) Capex	(4) Equity Issues
Co-location	-2.442***	-4.205***	-2.661**	-5.677***
	(-6.08)	(-8.50)	(-2.16)	(-6.45)
Size	-1.637***	-13.168***	-0.190***	-4.468***
	(-42.84)	(-46.82)	(-4.01)	(-8.09)
Cash Flow	0.016***	-0.063**	0.013	-0.203***
	(5.19)	(-2.56)	(1.00)	(-5.19)
Past Profits	0.049***	-0.391***	0.054	-0.435***
	(13.66)	(-13.92)	(1.36)	(-5.88)
Leverage		0.123***		0.038*
		(12.98)		(1.80)
GDP Growth	0.048***	-0.322***	0.077*	-0.273
	(3.79)	(-3.24)	(1.95)	(-0.77)
Firm FE	Yes	Yes		
Year FE	Yes	Yes	Yes	Yes
Country FE			Yes	Yes
N	169,366	93,595	169,366	93,595
Adj. R^2	0.512	0.497	0.098	0.358

Figure 1. HFT Activity around ASX-ITCH Introduction

This figure plots the monthly equal-weighted HFT trade volume share for treated and control groups over the period January 2012 to December 2012. The treated group consists of stocks in the top tercile of HFT exposure, and the control group consists of stocks in the bottom tercile, based on the average HFT trading volume scaled by total trading volume during 2010–2011.The dashed vertical line indicates April 2012, which is the month ASX introduced the ITCH protocol.The shaded area represents the gap between the two groups.

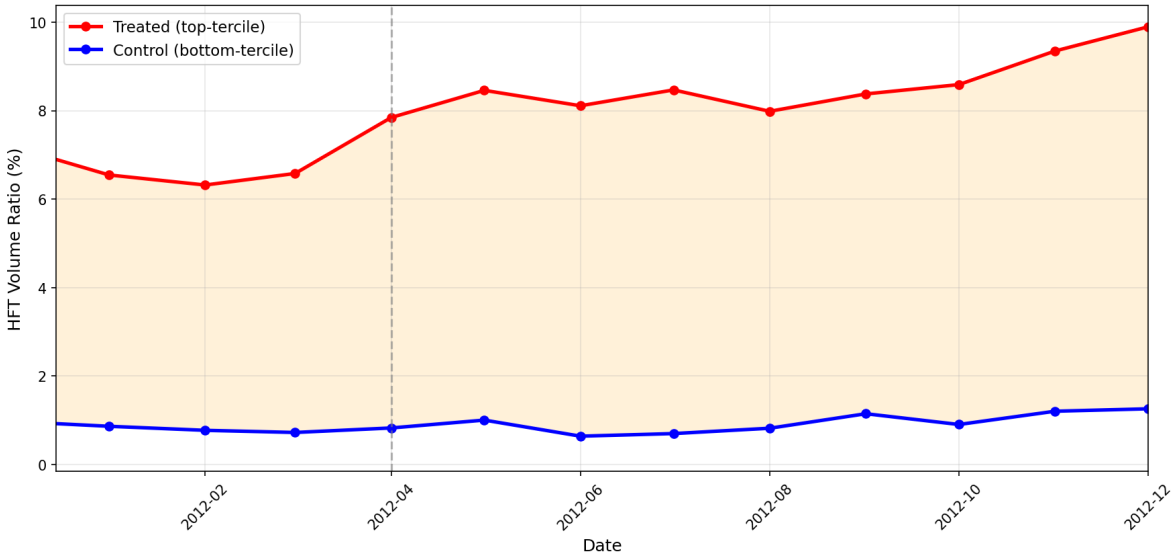
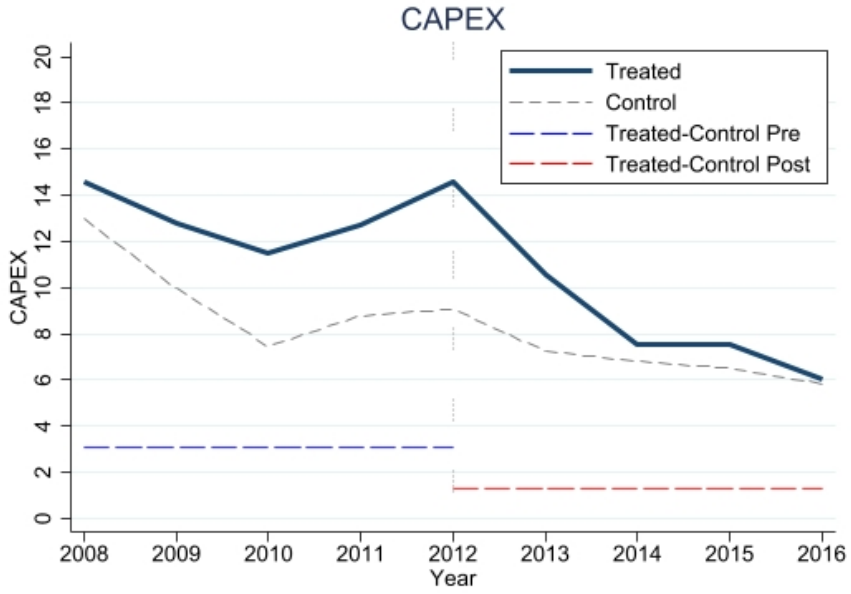
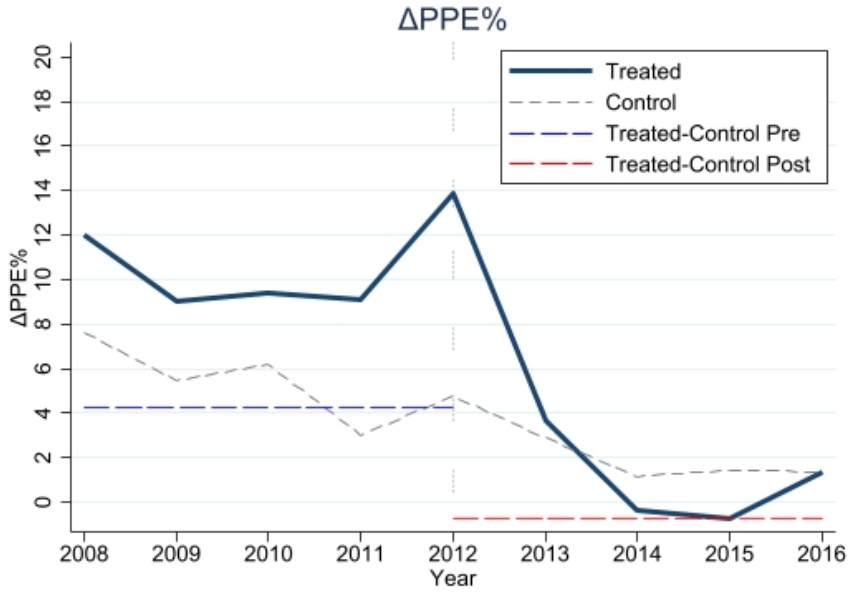


Figure 2. Corporate Investment around ASX-ITCH Introduction

This figure plots yearly mean Capex and ΔPPE for treated and control firms around the introduction of ASX-ITCH. The treated group consists of stocks in the top tercile of pre-ITCH HFT exposure, and the control group consists of stocks in the bottom tercile. For each variable, we also report the average treated–control difference in the pre period and in the post period to summarize how the gap changes after ASX-ITCH.





Online Appendix for "When Milliseconds Matter: The "Long-Term" Real Effects of High-Frequency Trading"

A. Variable Definitions

Variables	Definitions
Capex	Capital expenditure divided by lagged assets, multiplied by 100.
ΔPPE	Annual growth in property, plant, and equipment (PPE), in percent.
HFT Volume (%)	High-frequency trading activity measured as HFT volume share (percent).
HFT Exposure	Ex-ante HFT exposure defined as average HFT volume share prior to ASX-ITCH.
Treated	Indicator equal to one for firms in the ASX-ITCH treated group.
Post	Indicator equal to one for years after ASX-ITCH introduction.
Colocation	Indicator for years after a stock exchange allows colocation.
Cash Flow	Net income before extraordinary items plus depreciation, scaled by lagged assets and multiplied by 100.
Equity Issues	Change in total shareholder equity minus net income divided by lagged equity, multiplied by 100.
Debt Issues	Change in total debt scaled by lagged total assets, multiplied by 100.
Market Cap	Market capitalization in millions.
Price	Fiscal year-end stock price.
Volatility	Annual average daily high-low volatility.
Delay	Price delay measure following Hou and Moskowitz (2005).
Size	Natural log of total assets in millions.
Return Comovement	Logit transformation of R^2 from the market model following (Morck, Yeung, and Yu, 2000; Malceniece, Malcenieks, and Putniņš, 2019).
ROA	Return on assets.
Sales Growth	Annual growth of sales (percent).
Leverage	Total debt scaled by total assets, multiplied by 100.
Past Profitability	Operating income divided by total assets, multiplied by 100.
Q	Tobin's q: market value of assets divided by book value of assets.
r_{Gordon}	Implied cost of equity from the Gordon and Gordon (1997) model.
r_{OJ}	Implied cost of equity from the Ohlson and Juettner-Nauroth (2005) model.
r_{CT}	Implied cost of equity from the Claus and Thomas (2001) model.

B. SIRCA Order-Level Data

Our intraday data come from the Securities Industry Research Centre of Asia-Pacific (SIRCA). The dataset provides complete order-level records for all securities traded on the Australian Securities Exchange (ASX), including order entries, amendments, and cancellations. Each record contains the instrument identifier, date, timestamp, order type, price, volume, and unique order identifiers (Bid ID or Ask ID). Crucially, every order record includes a *Buyer Broker ID* and a *Seller Broker ID*, which are numeric codes assigned by the ASX to each registered broker. These broker identifiers allow us to trace each order and trade to a specific broker and, using the broker-level classifications, we can categorize trading activity by trader type (e.g., high-frequency trader, institutional, or retail). Figure 3 displays a sample of the raw data.

Figure 3. Sample of SIRCA Order-Level Data

Notes: This figure displays a subset of the raw SIRCA order-level data for illustration. Each row represents an individual order entry on the ASX. The last two columns—Buyer Broker ID and Seller Broker ID—are numeric codes that uniquely identify the broker behind each side of the order, enabling classification of trading activity by trader type.

#	#Instrument	Date	Time	Record Type	Price	Volume	Undisclosed Volume	Value	Qualifiers	Trans ID	Bid ID	Ask ID	Bid/Ask	Entry Time	Old Price	Old Volume	Buyer Broker ID	Seller Broker ID
1	AAC	20090701	00:00:00.000	ENTER	1.250	2,000	0	2,500		0	8,731,207,287,894,064,986		B				140	
2	AAC	20090701	00:00:00.000	ENTER	1.310	2,000	0	2,620		0	13,794,766,320,232,688,926		B				140	
3	AAC	20090701	00:00:00.000	ENTER	1.890	5,600	0	10,584		0		9,661,681,926,936,620,350	A					638
4	AAC	20090701	00:00:00.000	ENTER	1.240	12,000	0	14,880		0	4,380,369,974,567,319,199		B				238	
5	AAC	20090701	00:00:00.000	ENTER	1.395	2,970	0	4,143.15		0		2,469,874,737,067,806,307	A					140
6	AAC	20090701	00:00:00.000	ENTER	1.500	5,000	0	7,500		0		2,330,697,264,823,065,825	A					140
7	AAC	20090701	00:00:00.000	ENTER	2.000	5,000	0	10,000		0		16,265,744,095,415,229,378	A					406
8	AAC	20090701	00:00:00.000	ENTER	1.250	8,000	0	10,000		0	12,547,711,480,154,805,976		B				140	
9	AAC	20090701	00:00:00.000	ENTER	1.195	2,000	0	2,390		0	13,295,032,936,119,190,080		B				105	
10	AAC	20090701	00:00:00.000	ENTER	1.525	2,180	0	3,324.5		0		9,639,953,771,750,948,903	A					140
11	AAC	20090701	00:00:00.000	ENTER	1.870	1,850	0	3,459.5		0		11,707,757,566,189,275,770	A					144
12	AAC	20090701	00:00:00.000	ENTER	1.300	4,000	0	5,200		0	14,646,001,332,497,746,733		B				105	
13	AAC	20090701	00:00:00.000	ENTER	1.320	5,000	0	6,600		0	7,278,416,486,959,282,254		B				140	
14	AAC	20090701	00:00:00.000	ENTER	1.310	1,500	0	1,965		0	12,428,783,834,700,880,279		B				140	
15	AAC	20090701	00:00:00.000	ENTER	1.610	10,416	0	16,769.76		0		2,443,021,378,870,614,725	A					606
16	AAC	20090701	00:00:00.000	ENTER	1.260	800	0	1,008		0	3,980,296,868,089,774,903		B				140	
17	AAC	20090701	00:00:00.000	ENTER	1.570	10,640	0	16,704.8		0		3,019,473,372,611,958,729	A					606
18	AAC	20090701	00:00:00.000	ENTER	1.085	461	0	500.185		0	9,617,392,236,442,234,685		B				606	
19	AAC	20090701	00:00:00.000	ENTER	1.845	1,000	0	1,845		0		15,087,888,697,205,409,711	A					140
20	AAC	20090701	00:00:00.000	ENTER	1.320	5,000	0	6,600		0	14,165,957,609,012,303,084		B				606	
21	AAC	20090701	00:00:00.000	ENTER	1.300	2,000	0	2,600		0	11,563,661,767,927,919,676		B				140	

C. Implied Cost of Capital Estimation

We estimate the implied cost of equity capital (ICC) using three models: Claus and Thomas (2001), Ohlson and Juettner-Nauroth (2005) as implemented by Gode and Mohanram (2003), and Gordon and Gordon (1997). To generate the required earnings forecasts, we follow the cross-sectional approach of Hou, van Dijk, and Zhang (2012), which replaces analyst consensus forecasts with model-based expectations and substantially expands sample coverage. For each country and year, we estimate a pooled cross-sectional regression of future earnings on current firm characteristics (total assets, dividends, a dividend payer dummy, earnings, a negative earnings dummy, and accruals) using a rolling 10-year window. We estimate the model separately for each country to avoid mixing different currency units. The estimated coefficients are then applied to current-year characteristics to generate out-of-sample earnings forecasts $\hat{E}_{i,t+\tau}$ for $\tau = 1, \ldots, 5$ years ahead.

We compute the ICC at the end of June of year t, using financial statements with fiscal year-ends from April of year $t-1$ through March of year t to ensure a minimum three-month reporting lag. Let P_t denote the stock price, $\hat{e}_{t+\tau}$ the per-share forecasted earnings, and $\hat{d}_{t+1} = \hat{e}_{t+1} \times k$ the expected per-share dividend, where k is the payout ratio.

Model 1: CT (Claus and Thomas (2001)). The Claus and Thomas (2001) model is a residual income model with a five-year explicit forecast horizon and a perpetuity terminal value. Let B_t denote book value of equity and $\widehat{ROE}_{t+\tau} = \hat{E}_{t+\tau}/B_{t+\tau-1}$. The implied cost of capital r_{CT} solves:

$$M_t = B_t + \sum_{\tau=1}^{5} \frac{(\widehat{ROE}_{t+\tau} - r_{CT}) \cdot B_{t+\tau-1}}{(1+r_{CT})^{\tau}} + \frac{(\widehat{ROE}_{t+5} - r_{CT}) \cdot B_{t+5} \cdot (1+g_{ae})}{(r_{CT} - g_{ae}) \cdot (1+r_{CT})^{5}} \tag{2}$$

where M_t is total market capitalization, $g_{ae} = \max(r_f - 0.03,\ 0)$ is the long-run abnormal earnings growth rate, and r_f is the country-specific 10-year government bond yield. Book values evolve via the clean surplus relation: $B_{t+\tau} = B_{t+\tau-1} + \hat{E}_{t+\tau} - \hat{D}_{t+\tau}$.

Model 2: OJ (Ohlson and Juettner-Nauroth (2005); Gode and Mohanram (2003)). The Ohlson and Juettner-Nauroth (2005) model, as implemented by Gode and Mohanram (2003), prices the firm based on expected near-term abnormal earnings growth:

$$r_{OJ} = A + \sqrt{A^2 + \frac{\hat{e}_{t+1}}{P_t}\big(\hat{g}_{st} - (\gamma - 1)\big)} \tag{3}$$

where $A = \frac{1}{2}\big[(\gamma - 1) + \hat{d}_{t+1}/P_t\big]$, $\gamma - 1 = \max(r_f - 0.03,\ 0)$ is the perpetual earnings growth rate, and $\hat{g}_{st}$ is the short-term earnings growth rate:

$$\hat{g}_{st} = \frac{1}{2}\left[\frac{\hat{e}_{t+3} - \hat{e}_{t+2}}{\hat{e}_{t+2}} + \frac{\hat{e}_{t+5} - \hat{e}_{t+4}}{\hat{e}_{t+4}}\right]$$

Model 3: Gordon (Gordon and Gordon (1997)). The Gordon and Gordon (1997) finite-horizon expected return model simplifies to a pure earnings yield:

$$r_{Gordon} = \frac{\hat{e}_{t+1}}{P_t} \tag{4}$$

This assumes that all growth beyond the forecast horizon is value-neutral (i.e., incremental investments earn exactly the cost of capital).

D. Price Delay and Return Comovement

Price delay. We measure the speed of price adjustment using the price delay measure of Hou and Moskowitz (2005). For each firm i in year t, we estimate the following two regressions using weekly returns:

$$r_{i,w} = \alpha_i + \beta_i \, r_{m,w} + \varepsilon_{i,w} \tag{5}$$

$$r_{i,w} = \alpha_i + \beta_{i,0} \, r_{m,w} + \sum_{k=1}^{4} \beta_{i,k} \, r_{m,w-k} + \varepsilon_{i,w} \tag{6}$$

where $r_{i,w}$ is firm i's return in week w and $r_{m,w}$ is the market return, defined as the equal-weighted average return of all other stocks in the same country excluding firm i itself. Price delay is then defined as:

$$D_i = 1 - \frac{R^2_{\text{restricted}}}{R^2_{\text{unrestricted}}} \tag{7}$$

where $R^2_{\text{restricted}}$ and $R^2_{\text{unrestricted}}$ are from equations (5) and (6), respectively. Higher values of D_i indicate slower incorporation of market-wide information into the stock price. We require a minimum of 26 weekly observations per firm-year.

Return comovement. We measure return comovement using the R^2 from a market model regression. For each firm i in year t, we estimate:

$$r_{i,w} = \alpha_i + \beta_{i,0} \, r_{m,w} + \beta_{i,1} \, r_{m,w-1} + \beta_{i,2} \, r_{m,w+1} + \varepsilon_{i,w} \tag{8}$$

where $r_{m,w}$ is the equal-weighted market return (excluding firm i), and $r_{m,w-1}$ and $r_{m,w+1}$ are the one-week lagged and leading market returns, respectively. The inclusion of lead and lag terms follows Morck, Yeung, and Yu (2000) and accounts for nonsynchronous trading. The R^2 from this regression captures the fraction of a stock's return variation explained by market-wide factors. Higher R^2 indicates greater return comovement and less firm-specific information in prices. We require a minimum of 30 weekly observations per firm-year.

E. The List of Colocation Events

The List of Colocation Events

This table lists the adoption date of colocation services for exchanges in our sample. These dates are based on those reported in Boehmer, Fong, and Wu (2021) and Aitken, Cumming, and Zhan (2015, 2023).

Stock Exchange	Country	Date
Toronto Stock Exchange	CAN	Apr 2008
Bombay	IND	Feb 2010
National Market	IND	Jan 2010
NYSE Euronext Brussels	BEL	Apr 2008
SWX Swiss Exchange	CHE	Apr 2012
Hong Kong Stock Exchange	HKG	Oct 2012
London Stock Exchange	GBR	Sep 2009
Osaka	JPN	Nov 2008
Oslo	NOR	Apr 2010
BM and F Bovespa	BRA	Jun 2009
Singapore	SGP	Jul 2011
Stockholm	SWE	Mar 2011
Taipei	TWN	Oct 2010
Tokyo	JPN	Jan 2010
NYSE Euronext Paris	FIN	Apr 2008
NYSE Euronext Paris	FRA	Apr 2008
NYSE Euronext Paris	ISR	Apr 2008
NYSE Euronext Paris	ITA	Apr 2008
NYSE Euronext Paris	NLD	Apr 2008
NYSE Euronext Paris	NOR	Apr 2008
NYSE Euronext Paris	ESP	Apr 2008

F. Supplementary Analysis

Table F1
ASX-ITCH and investment-to-Q sensitivity

This table reports investment–q sensitivity regression results in the ASX-ITCH setting. The dependent variables are investment outcomes (Capex and ΔPPE), as indicated in the column headings. The key variable of interest is *Treated* × *Post* × Q, which captures how the sensitivity of investment to Tobin's q changes after the introduction of ASX-ITCH for treated firms relative to control firms. Columns (1)–(2) report baseline OLS estimates and Columns (3)–(4) report inverse-probability-weighted (IPW) estimates. All variables are defined in Online Appendix Section A. All regressions include firm and year fixed effects and Size Group × SIC2 fixed effects. t-statistics based on standard errors clustered at the firm level are in parentheses below each coefficient. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Baseline		IPW	
	(1) Capex	(2) ΔPPE	(3) Capex	(4) ΔPPE
Treated × Post × Q	0.496	0.520	0.480	0.766
	(1.69)	(1.27)	(1.12)	(1.61)
Treated × Post	-3.057*	-6.271***	-2.431	-6.860**
	(-1.91)	(-3.14)	(-1.09)	(-2.73)
Treated × Q	-0.392	0.161	0.001	-0.066
	(-1.36)	(0.33)	(0.00)	(-0.11)
Post × Q	-0.515**	-0.863***	-0.662**	-0.820**
	(-2.72)	(-3.02)	(-2.34)	(-2.54)
Q	1.089***	1.391***	1.070***	1.272***
	(4.41)	(3.57)	(3.00)	(3.29)
Cash Flow × Treated × Post	0.071	0.138	-0.049	0.087
	(0.86)	(1.31)	(-0.48)	(0.71)
With Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Size Group x SIC2	Yes	Yes	Yes	Yes
N	1,876	1,894	1,876	1,894
Adj. R^2	0.553	0.265	0.563	0.270

Table F2
ITCH DiD Results with Restricted Event Windows

This table reports ASX-ITCH difference-in-differences (DiD) estimates using the baseline specification but restricting the sample to observations within symmetric event windows around the ASX-ITCH introduction. Columns (1)–(3) use a $[-5, +5]$ window and Columns (4)–(6) use a $[-10, +10]$ window, where year 0 (2012) is excluded. The dependent variables are investment (Capex and ΔPPE) and external equity financing (Equity Issues), as indicated in the column headings. All variables are defined in Online Appendix Section A. All regressions include firm and year fixed effects and Size Group × SIC2 fixed effects. *t*-statistics based on standard errors clustered at the firm level are in parentheses below each coefficient. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	[-5, 5] Window			[-10, 10] Window		
	(1) Capex	(2) ΔPPE	(3) Equity Issues	(4) Capex	(5) ΔPPE	(6) Equity Issues
Treated × Post	-1.851	-5.088***	-8.766**	-2.332**	-6.192***	-10.301***
	(-1.36)	(-3.63)	(-3.13)	(-2.25)	(-3.26)	(-3.75)
Size	-3.517***	-5.914***	-9.655**	-3.563***	-5.124***	-9.060***
	(-4.52)	(-3.45)	(-2.28)	(-4.66)	(-7.34)	(-3.25)
Cash Flow	0.084	0.215*	-0.267	0.106*	0.253**	0.284
	(1.49)	(2.19)	(-1.43)	(1.82)	(2.65)	(1.27)
Past Profitability	-0.186**	-0.241	-0.756**	-0.139*	-0.229**	-1.141***
	(-2.57)	(-1.78)	(-3.20)	(-1.82)	(-2.13)	(-5.01)
Leverage			0.116			-0.007
			(1.25)			(-0.07)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Size Group x SIC2	Yes	Yes	Yes	Yes	Yes	Yes
N	994	1,002	996	1,896	1,918	1,902
Adj. R^2	0.626	0.266	0.519	0.518	0.225	0.444