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THE SPEED PREMIUM: HIGH FREQUENCY TRADING AND THE COST OF CAPITAL

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ABSTRACT

When trading in financial markets reaches light speed, does the real economy slow down? Using co-location and latency improvement upgrades at NASDAQ as natural experiments, we find that, on average, high frequency trading (HFT) leads to higher cost of capital. However, the impact is not uniform. HFT raises the cost of capital for low-beta stocks by amplifying their systematic risk, as HFT's correlated trading strategies make these stocks more responsive to market-wide information. For the most liquid stocks, HFT reduces the cost of capital by lowering the liquidity premium required by investors. A complementary test using data from the unfragmented Hong Kong market shows that these causal effects are not due to market fragmentation and persist across countries and market structures. Our results demonstrate that HFT's real economic effects are heterogeneous across stock characteristics, with important implications for financial market regulation and policy design.

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1. INTRODUCTION

Technology has fundamentally transformed financial markets over the past two decades, with high-frequency trading (HFT) a dominant force. High-frequency traders (HFTs) invest substantial resources to gain microsecond advantages in market access, fundamentally changing how informed trading operates – speed, rather than superior information acquisition, has become the key competitive advantage (Budish et al., 2015; Menkveld, 2016; Foucault et al., 2017; Shkilko and Sokolov, 2020; Aquilina et al., 2022; Rzayev et al., 2023). With recent developments in artificial intelligence (AI), these technological capabilities are poised to accelerate even further, potentially reshaping the competitive landscape of financial markets once again.

Despite extensive research on HFT's effects on market quality, a significant gap remains: we know little about how these technological changes affect factors directly linked to the real economy, such as firms' cost of capital. This gap is concerning given that most retirement savings are invested in global capital markets, and job growth, incomes, and living standards depend on corporate investment financing that relies on well-functioning financial markets. Market quality, after all, is just a means to an end, and what policymakers and regulators are concerned about is how well markets are fulfilling their roles with regards to the real economy and contributing to welfare issues like the provision of capital to drive economic growth (Foucault et al., 2023). In this paper, we examine HFT's implications for the cost of capital, addressing this important but understudied connection between market microstructure innovations and real economic outcomes.

The impact of HFT on the cost of capital is theoretically ambiguous. Financial market innovations often have mixed effects – for instance, HFT is associated with narrower bid-ask spreads that benefit small traders (Hendershott et al., 2011) but also increases the tendency for extreme events, such as flash crashes (Easley et al., 2012; Rzayev and Ibikunle, 2021), and increases implementation shortfall of institutional traders by back-running them (Van Kervel and Menkveld, 2019; Yang and Zhu, 2020). Moreover, HFT's effects depend critically on whether speed advantages are adopted by liquidity providers or demanders (Brogaard et al., 2014), and HFT interacts with other market structure changes like fragmentation, including the growth of dark trading (Menkveld, 2016). Even when HFT improves market quality measures, this does not necessarily translate into better economic outcomes. Cochrane (2013) argues that *"it is especially hard to see why high-frequency trading is needed. Price discovery every millisecond does not seem necessary to guide corporate investment or individual risk sharing and hedging."* Thus, any change in market quality at ultra-high frequencies may not affect the endpoint – the real economy.

A key challenge in investigating the effects of HFT on financial markets is that HFT activity is endogenous to market quality characteristics and firm fundamentals. To address this endogeneity concern and establish causality, we exploit two technological shocks: co-location and latency improvement updates implemented by NASDAQ. These types of technological upgrades provide an ideal setting for a quasi-natural experiment because they directly lead to considerable reductions in trading latency and increased HFT activity (Chordia and Miao, 2020; Boehmer et al., 2021), while remaining orthogonal to firms' fundamentals. Similar shocks have also been employed in studies of other markets (Brogaard et al., 2015; Rzayev et al., 2023). We employ a difference-in-differences (DiD) framework, using NASDAQ-listed stocks as the treatment group and matched NYSE-listed stocks as the control group around the two technological shocks.

Our baseline results indicate that HFT increases the cost of capital. We investigate the economic mechanisms underlying this effect by testing two competing channels. The first channel we analyze is the systematic risk one. It posits that the correlated trading strategies employed by HFTs increase stocks' responsiveness to market-wide information (Chaboud et al., 2014; Boehmer et al., 2018), causing them to co-move more strongly with each other and with the overall market (Malceniece et al., 2019), thereby increasing systematic risk and the cost of capital. The second channel is linked to the liquidity premium. As HFTs generally increase market liquidity (Hendershott et al., 2011; Brogaard et al., 2015), they should lower the cost of capital since investors require lower returns to hold more liquid stocks (Amihud, 2002; Acharya and Pedersen, 2005). Our overall results indicate that the systematic risk channel dominates on average. However, we investigate both channels separately to understand their distinct impacts and find that focusing solely on the net effect masks important dynamics and can lead to misinterpretation of results and inappropriate policy implications.

We find evidence that both channels are important; however, their relevance varies across stock characteristics.

Consistent with the systematic risk channel, we find that HFT amplifies systematic risk in financial markets, with this effect being particularly pronounced among low-beta stocks ($\beta < 1$). This pattern is intuitive: low-beta stocks naturally co-move less with the market and are less responsive to market-wide information. The effect is stronger among illiquid stocks, as these are the ones where a positive shock to HFT is more likely to increase their correlation with the overall market. After all, liquid stocks, even if they have low beta, are more actively traded and followed by analysts, making them more likely to already reflect market-wide information (Malceniece et al., 2019; Glosten et al., 2021). For high-beta stocks, we do not find that HFT increases the cost of capital: these stocks are already highly responsive to market-wide information; hence, an increase in HFT does not appear to make a difference to their cost of capital.

Consistent with the liquidity channel, we find that HFTs reduce the cost of capital for the most liquid stocks, irrespective of their beta. This finding is in line with the fact that while HFTs increase liquidity on average, their liquidity-providing strategies are concentrated in the most liquid stocks (Brogaard et al., 2014), as market-making in illiquid stocks is less profitable and riskier. This is because high-frequency market making requires the ability to unload inventory positions very quickly, which is much more difficult in less liquid stocks (Menkveld and Zoican, 2017).

In financial markets, and especially in the US, HFT evolves with increased market fragmentation. Specifically, HFT facilitates the linking of multiple markets and allows investors to trade at the best available price, thereby increasing competition among trading venues (e.g., Menkveld, 2013). Hence it is important to examine whether our main results depend on the specific structure of the US market and if they would be different in a market where HFT exists independent of market fragmentation. To this end, we conduct a complementary analysis using data from the Stock Exchange of Hong Kong (SEHK), one of the largest yet essentially unfragmented financial market in the world. In this setting, we exploit a very similar shock as for our US sample: the introduction of the Orion Central Gateway (OCG) in 2014, a major technological upgrade that substantially reduced trading latency, as an exogenous shock to HFT activity. We construct a matched sample of firms listed on the Shanghai Stock Exchange (SSE), the largest exchange in the region and one unaffected by the OCG implementation, to serve as a control group. Using the same methodology as for our baseline specification, we find that our results hold in this alternative setting. Specifically, we continue to find that HFT increases the cost of capital, particularly for low-beta stocks, while reducing it for the most liquid stocks. Furthermore, the former channel dominates the latter when we investigate the overall impact.

This study makes two contributions to the literature. First, while the HFT literature has predominantly focused on the effects of HFT on traders and market participants (see Menkveld, 2016 for a survey), we shift the focus to issuers – the corporations that issue shares to raise capital for their investment activities. To the best of our knowledge, this is the first study to investigate the role of HFT in firms' cost of capital. Thus, our study straddles two traditionally distinct literature areas in financial economics, market microstructure and corporate finance, demonstrating how market microstructure innovations can have tangible implications for real economic outcomes. This cost of capital perspective is important because corporations rely on equity markets to raise capital for investment activities that drive economic growth and productivity. Thus, it is surprising that the impact of HFTs, which account for more than 50% of equity market trading volume, on the cost of capital has not been previously investigated.

Second, we formally explore the economic channels driving the HFT-cost of capital relationship, identifying which channel dominates and under what conditions this dominance holds. By decomposing the net effect into systematic risk and liquidity channels, we provide a nuanced understanding of how HFT affects different types of firms, moving beyond aggregate effects that may mask important heterogeneity. By doing so, we contribute to the ongoing policy debate regarding the economic value of HFT. While this debate has captivated financial market stakeholders, including investors, intermediaries, policymakers, regulators, and researchers, empirical evidence on HFT's real economic effects has been limited. By providing novel evidence on the interactions between HFT and corporate cost of capital, we offer actionable insights for policy and regulation. Our findings suggest that the benefits and costs of HFT are not uniformly distributed across all stocks, raising important questions about whether access to HFT infrastructure should be differentiated based on stock characteristics rather than applied universally.

2. LINKING HFT TO THE COST OF CAPITAL

From a theoretical perspective, the impact of HFT on the cost of capital is unclear. On the one hand, given that HFTs are engaged in correlated trading strategies (Chaboud et al., 2014; Benos et al., 2017; Malceniece et al., 2019) as they incorporate marked-wide information into the price of every stock, HFT could increase systematic risk thereby increasing issuers' cost of capital. On the other hand, HFT enhancing liquidity in a given stock implies a reduction in the rate of return investors demand to hold the stock (Amihud, 2002; Menkveld, 2016).

Systematic risk, typically measured by a stock's beta, captures the sensitivity of a stock's return to aggregate market movements. Since the introduction of the Capital Asset Pricing Model (CAPM) (Sharpe, 1964), beta has been central to asset pricing models including extensions proposed by Fama and French (1993, 2015), which link higher exposure to systematic risk with higher required returns. Hence, any factor that increases a firm's exposure to market-wide risk is a natural candidate for explaining variation in the cost of capital.

A key feature of HFT strategies is their high degree of correlation. Chaboud et al. (2014) document substantial commonality in algorithmic traders' behavior, a by-product of automated responses to common market signals. While this pattern is not unique to HFTs, Benos et al. (2017) show that HFTs exhibit significantly higher trading correlation than other algorithmic participants, including investment banks. This suggests that HFTs amplify market-wide co-movements. Malceniece et al. (2019) test this hypothesis using the staggered entry of Chi-X Europe as a natural experiment and find that HFT activity increases return and liquidity co-movement, especially among small and mid-cap stocks. These findings point to a potential mechanism: HFTs may increase the cost of capital by amplifying systematic risk through increased correlation of individual stock returns with market movements, thereby raising their betas.

In addition to the systematic risk channel, HFT may also influence the cost of capital by directly impacting liquidity. A substantial stream of the market microstructure literature show that, on average, HFTs enhance market liquidity as they engage in market making (Menkveld, 2013, 2016). It is also well established in the literature that investors require higher returns for holding assets that are less liquid, translating into a higher cost of capital (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Chordia et al., 2011; Amihud and Levi, 2023). Hence, because of their activities which improve the liquidity of the underlying stocks, HFT can reduce issuer cost of capital.

However, HFTs tend to concentrate their market-making in the most liquid stocks (Brogaard et al., 2014). Liquidity provision involves significant risks, including adverse selection and inventory holding costs, which are easier to manage in liquid stocks where HFTs can more quickly unwind positions. In contrast, providing liquidity in illiquid stocks entails greater difficulty for HFTs due to limited trading volume. As a result, market-making HFTs typically avoid less liquid assets and focus on stocks with high baseline liquidity (Menkveld, 2013). This implication of this choice is that any reduction in the cost of capital due to improved liquidity from HFT activity will concentrate in the most liquid stocks.

3. DATA, MAIN VARIABLES AND DESCRIPTIVE STATISTICS

3.1. Cost of capital metrics

Given that the focus of our analysis is the effect of HFT on the cost of capital, we focus on the single component that they can directly influence, namely the cost of equity (COE). We use two quarterly COE measures. Our first measure, r^{CAPM}, is estimated using the CAPM. For each calendar quarter t, we estimate the following time-series regression for each individual stock i using all available daily excess returns: [1]

$$r_{i,d} - r_{f,d} = \alpha_{i,t} + \beta_{i,t}\left(r_{m,d} - r_{f,d}\right) + \varepsilon_{i,d} \quad (1),$$

where $r_{i,d}$ is the daily stock return obtained from the Center for Research in Security Prices (CRSP), $r_{f,d}$ is the daily risk-free rate proxied by the ten-year Treasury yield from the Federal Reserve Economic Data (FRED), and $r_{m,d}$ is the daily value-weighted market return obtained

[1] For each quarterly estimation of beta, we require at least 30 valid observations of daily returns.

from Ken French's website. We winsorize daily stock returns at the 1% level in each tail to eliminate outliers. The quarterly cost of equity is then computed as:

$$r^{CAPM} = r_{f,t} + \hat{\beta}_{i,t} E_t\left(r_{m,t} - r_{f,t}\right) \quad (2),$$

where $\hat{\beta}_{i,t}$ is the estimated market beta from Equation (1), and $E_t\left(r_{m,t} - r_{f,t}\right)$ is the expected quarterly market excess return, calculated as the historical mean of quarterly market excess returns. We compute both the quarterly market excess return and risk-free rate using daily compounded values.

Our second measure, r^{FF-3}, extends the CAPM by incorporating the Fama and French (1993) three-factor model to capture additional sources of return variation. The model includes two additional factors: SMB (Small Minus Big), the return difference between portfolios of small and large market capitalization stocks; and HML (High Minus Low), the return difference between portfolios of high and low book-to-market stocks. In this model, we first estimate the following time-series regression using daily data:

$$r_{i,d} - r_{f,d} = \alpha_{i,t} + \beta_{i,t}\left(r_{m,d} - r_{f,d}\right) + s_{i,t} SMB_d + h_{i,t} HML_d + \varepsilon_{i,d} \quad (3),$$

where the daily SMB_d and HML_d are factors obtained from Ken French's website. Using the estimated factor loadings $\hat{\beta}_{i,t}$, $\hat{s}_{i,t}$ and $\hat{h}_{i,t}$, along with expected quarterly factor premiums calculated as historical averages, we compute:

$$r^{FF-3} = r_{f,t} + \hat{\beta}_{i,t} E_t\left(r_{m,t} - r_{f,t}\right) + \hat{s}_{i,t} E_t[SMB_t] + \hat{h}_{i,t} E_t[HML_t] \quad (4).$$

We employ both COE measures to ensure robustness in our analysis. The Fama-French three-factor model captures additional sources of return variation beyond the market factor that help explain cross-sectional differences in stock returns (Fama and French, 1993). However, higher-dimensional factor models can introduce potential estimation issues, such as extreme value estimates, due to their increased complexity and sensitivity to factor exposures (Fama and French, 2018; Lee et al., 2021). Therefore, we use both measures as complementary proxies.

3.2. Liquidity proxies

We construct two inverse measures of liquidity using intraday trading data from CRSP to capture different dimensions of market liquidity. Our first measure is the relative quoted spread, defined as:

$$Relative\ Qspread_{i,d} = 100\,\frac{Ask_{i,d} - Bid_{i,d}}{(Ask_{i,d} + Bid_{i,d})/2} \quad (5),$$

where $Ask_{i,d}$ and $Bid_{i,d}$ correspond to the last ask and bid quotes for stock i on day d. Daily estimates are averaged across each quarter to obtain the quarterly measure $Relative\ Qspread_{i,t}$. The second measure is the quarterly Amihud price impact ratio, computed as:

$$ILLIQ_{i,t} = 10^6\,\frac{1}{D}\sum_{d=1}^{D}\frac{|R_{i,d}|}{V_{i,d}} \quad (6),$$

where D is the number of trading days in quarter t, $R_{i,d}$ is the return on day d and $V_{i,d}$ is the trading volume in US dollars on day d. Following Amihud et al. (2015), observations with daily volume below \$100 are excluded.

These two measures capture complementary dimensions of market liquidity. $Relative\ Qspread_{i,t}$ is the most used proxy for transaction costs and can be interpreted as the immediate roundtrip cost of a small trade. $ILLIQ_{i,t}$, while also well-established in the literature, captures price impact and is particularly suitable for the lower-frequency context of our analysis, as it reflects how much prices move in response to trading volume over longer periods.

3.3. Other variables

We obtain accounting information from Compustat to construct nine quarterly firm-level control variables that capture key dimensions of firm characteristics including size, profitability, investment, leverage, and valuation. $SIZE$ is measured as the logarithm of total assets. IK, investment-to-capital ratio, is calculated as investment expenditure divided by total net property, plant, and equipment. We include two profitability metrics: return on assets (ROA), computed as operating income before depreciation divided by the average total assets over the most recent two years; and return on equity (ROE), calculated as income before extraordinary items divided by the average equity market value over the most recent two years. BM is the book value of equity divided by the market value of equity. $Lever$ is total debt divided by total assets. Cash ratio ($Cash$) is cash and short-term equivalents divided by total assets. Gross profit margin (GP) is the difference between sales and cost of goods sold divided by sales. PPE is net property, plant, and equipment divided by total sales. Detailed variable definitions are provided in Appendix Table A.

3.4. Summary statistics

Table 1 presents descriptive statistics for our main variables across NASDAQ and NYSE samples. Given that the co-location shock occurred around 2005Q2 and the latency improvement occurred around 2010Q2, the sample encompasses data from 2004 to 2011 in Table 1. The cost of capital measures show that NYSE firms have slightly higher average financing costs than NASDAQ firms. The mean $r_{i,t}^{CAPM}$ is 3.085% for NASDAQ versus 3.419% for NYSE, while the $r_{i,t}^{FF-3}$ yields higher estimates of 3.437% and 3.871%, respectively. Market betas are comparable across exchanges, with means of 1.013 for NASDAQ and 1.176 for NYSE.

Firm characteristics show notable differences between the two exchanges. NYSE firms are substantially larger, with mean $SIZE$ (the logarithm of total assets) of 8 compared to 5.7 for NASDAQ firms. NASDAQ firms exhibit higher investment rates (17.5% versus 12.4% for NYSE) and maintain significantly higher cash ratios (24.2% versus 10.3% for NYSE firms). NYSE firms show higher profitability, with mean ROA of 3.2% compared to 0.6% for NASDAQ. NASDAQ firms display higher book-to-market ratios (0.668 versus 0.584) and

Table 1. Descriptive statistics

This table presents descriptive statistics for all variables employed in the analysis. The statistics include the mean, standard deviation (σ), 25th percentile (first quartile), median, and 75th percentile (third quartile) for each variable. $r_{i,t}^{CAPM}$ and $r_{i,t}^{FF-3}$ are the cost of capital measures calculated using the CAPM and Fama and French (1993) models, respectively. β_{it} is the systematic risk measure estimated by regressing stock returns on market returns. Firm characteristics are $SIZE_{it}$ (the natural logarithm of total assets), $IK_{i,t}$ (ratio of investment expenditure), ROA_i and ROE_i (returns on average total assets and common equity, respectively), $Lever_i$ (ratio of current liabilities and long-term debt to total assets), $Cash_i$ (ratio of cash and short-term equivalents to total assets), GP_i (gross profit margin), and PPE_i (ratio of gross value of property and equipment to total revenue). Liquidity measures are $ILLIQ_{i,t}$ (Amihud's illiquidity measure) and $Relative\ Qspread_{i,t}$ (relative quoted spread). Variable definitions are provided in Appendix A. All variables are winsorized at the 1% level in both tails of the distribution. The sample period extends from January 1, 2004, to December 31, 2011, encompassing the timeframe surrounding two technological infrastructure upgrades examined in this study: the co-location upgrade implemented in Q2 2005 and the latency reduction upgrade implemented in Q2 2010.

	NASDAQ					NYSE				
	Mean	σ	25th	Median	75th	Mean	σ	25th	Median	75th
Cost of capital metrics										
$r_{i,t}^{CAPM}$ (%)	3.085	1.534	1.933	2.978	4.030	3.419	1.166	2.602	3.292	4.105
$r_{i,t}^{FF-3}$ (%)	3.437	2.247	1.846	3.052	4.536	3.871	2.033	2.476	3.543	4.851
β_{it} (%)	1.013	0.725	0.465	0.975	1.468	1.176	0.566	0.777	1.111	1.508
Firm characteristics										
$SIZE_{it}$ (ln assets, \$M)	5.704	1.670	4.550	5.717	6.796	7.999	1.638	6.814	7.824	9.015
IK_{it}	0.175	0.173	0.050	0.117	0.242	0.124	0.111	0.046	0.091	0.166
ROA_{it}	0.006	0.062	0.001	0.012	0.036	0.032	0.026	0.017	0.030	0.045
ROE_{it}	-0.009	0.050	-0.006	0.004	0.008	0.001	0.036	0.003	0.007	0.010
BM_{it}	0.668	0.646	0.295	0.516	0.826	0.584	0.499	0.307	0.497	0.739
$Lever_{it}$	0.160	0.202	0.000	0.092	0.235	0.264	0.194	0.118	0.243	0.370
$Cash_{it}$	0.242	0.253	0.038	0.136	0.389	0.103	0.120	0.023	0.058	0.139
GP_{it}	-0.295	5.341	0.246	0.442	0.629	0.354	0.220	0.204	0.319	0.489
PPE_{it}	1.861	5.587	0.268	0.618	1.290	2.080	3.297	0.406	0.796	1.936
Liquidity										
$ILLIQ_{i,t}$	78.912	227.234	0.422	2.907	32.243	1.716	8.073	0.028	0.102	0.435
$Relative\ Qspread_{i,d}$ (bps)	118.160	192.536	17.400	40.192	127.833	20.271	31.296	7.723	12.495	21.182

lower leverage (16.0% versus 26.4%). The liquidity measures also highlight stark differences between the two exchanges. NASDAQ stocks are substantially less liquid, with a mean $ILLIQ$ of 78.9 compared to 1.7 for NYSE. Similarly, $Relative\ Qspread$ averages 118 basis points for NASDAQ versus 20 basis points for NYSE. Overall, the differences in fundamentals and liquidity dynamics clearly show that there are significant differences between firms listed on NYSE and NASDAQ. Therefore, in the next section, where we investigate the impact of HFT on the cost of capital using the technological shocks implemented on NASDAQ, we use a matched sample approach.

4. THE IMPACT OF HFT ON THE COST OF CAPITAL

HFT activity and market quality are jointly determined, creating an endogeneity problem. We address this using a DiD framework that exploits two technological shocks affecting HFT activity. The first shock is NASDAQ's introduction of co-location hosting services in 2005 (Boehmer et al., 2021), and the second is the 2010 introduction of NASDAQ's technological upgrade that reduces order submission and processing latency (Chordia and Miao, 2020). In this section, we discuss these technological upgrades, describe our sample matching procedure, and estimate the impact of HFT on the cost of capital around the shocks.

4.1. Technological shocks

Using technological upgrades in financial markets to investigate the role of HFTs in market quality is common. One frequently used technological change is the introduction of co-location services (Brogaard et al., 2015; Boehmer et al., 2021). Co-location allows fast traders to minimize data turnaround time by physically locating their computer hardware close to the stock exchange's hardware. This proximity reduces the physical distance that electronic signals must travel, cutting latency from milliseconds to microseconds – a significant advantage when trading decisions occur in fractions of a second. The service typically involves traders renting space in the same data center as the exchange's matching engines. Many financial markets have introduced co-location to facilitate HFT activity, recognizing that even nanosecond advantages can translate into substantial profits for HFTs. We use NASDAQ's introduction of co-location services around 2005Q2 as in Boehmer et al. (2021).[2] NASDAQ's co-location service was among the first comprehensive offerings by a major U.S. exchange, providing a clean setting to examine how enhanced speed advantages affect market outcomes.

The second shock we take advantage of is NASDAQ's improvement in data and order dissemination technology in 2010Q2. Ye et al. (2013) document a significant decrease in trading latency for order cancellation and execution on NASDAQ in April and May 2010. This improvement was partly driven by NASDAQ's installation of the Nehalem engine. As a result, order submission and processing latency decreased from microseconds to nanoseconds. This technological upgrade not only affected order execution but also improved the dissemination of market data, allowing traders to receive price updates and trade confirmations with substantially reduced latency. Given the importance of this event, Chordia and Miao (2020) use it to examine HFT's effect on market efficiency around earnings announcements, finding that the enhanced speed facilitates more rapid price discovery during information-intensive periods.

4.2. Sample matching

The two technological shocks occur on NASDAQ. Therefore, we designate NASDAQ-listed stocks as our treatment group and NYSE-listed stocks as the corresponding control group in the DiD analysis. However, stocks listed on these two exchanges differ fundamentally with

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[2] There is a debate in the literature on the correct timing of NASDAQ's introduction of co-location services for the first time. Boehmer et al. (2021) use April 2005 as NASDAQ's co-location introduction date, while Aitken et al. (2023) use March 2007. We carried out an extensive search and concluded that 2005Q2 is much more likely to be the correct date. NASDAQ introduced co-location well before 2007, as evidenced by a document available on the SEC website announcing the existence of a co-location agreement in December 2005: https://www.sec.gov/Archives/edgar/data/1120193/000119312505242699/dex994.htm. It is plausible that NASDAQ introduced co-location in April 2005 and later increased capacity or upgraded its technological features in 2007.

regards to certain characteristics (see Table 1); hence, to mitigate potential biases, we match NYSE and NASDAQ stocks. For each HFT shock event, we obtain a matched sample using propensity score matching (PSM), which constructs balanced treatment and control groups by matching firms with similar characteristics, thereby isolating the effects of the technological upgrades from confounding factors (Dai et al., 2020; Francis et al., 2021). Specifically, ahead of each technological shock at quarter t, we estimate the following pre-match probit regression using cross-sectional observations at quarter $t-4$:

$$NASDAQ_i = \alpha + \beta_1 X_i + \delta_n + \varepsilon_i \qquad (7),$$

where $NASDAQ_i$ is a dummy variable equaling one if firm i is listed on NASDAQ and zero if listed on NYSE, and δ_n corresponds to industry fixed effects. X_{it} is a vector of firm controls relevant to firm i's cost of capital, including $SIZE_{it}$ (the natural logarithm of total assets), IK_i (ratio of investment expenditure), ROA_i and ROE_i (returns on average total assets and common equity, respectively), $Lever_i$ (ratio of current liabilities and long-term debt to total assets), $Cash_i$ (ratio of cash and short-term equivalents to total assets), GP_i (gross profit margin), and PPE_i (ratio of gross value of property and equipment to total revenue). Appendix A defines all variables and their sources. All variables are winsorized at the 1% level. Standard errors are double-clustered by firm and quarter.

The fitted value of $\widehat{NASDAQ_i}$ for firm i serves as its propensity score and is used to match each NASDAQ firm to a corresponding NYSE firm.[3] Following Francis et al. (2021), we require that the difference in a matched pair's $\widehat{NASDAQ_i}$ value be less than 0.01. This

[3] We implement a nearest neighbor matching (NNM) algorithm without replacement to match firms with similar propensity scores across both platforms. The NNM algorithm calculates the distance between covariate patterns to identify the "closest" neighbors, minimizing the disparity between matched units while avoiding duplicates. This approach ensures that each treated firm is paired with the most comparable control firm, enhancing the validity of the matching process. By prioritizing similarity in key covariates, NNM reduces potential bias in estimating treatment effects, providing a robust framework for causal inference.

Table 2. Propensity score matching results

This table reports results from propensity score matching (PSM) of firms listed on NASDAQ (treatment group) with those listed on NYSE (control group). The pre-match probit regression is estimated using cross-sectional observations at quarter t-4, four quarters prior to the implementation of technological upgrades: co-location hosting service on NASDAQ in Q2 2005 and latency upgrade technology in Q2 2010, as documented in Boehmer et al. (2021) and Chordia and Miao (2020), respectively. The probit regression specification is:

$$NASDAQ_i = \alpha + \beta_1 \boldsymbol{X_i} + \delta_n + \varepsilon_i,$$

where $NASDAQ_{i,t}$ is a dummy variable equaling one if firm i is listed on NASDAQ and zero if listed on NYSE, and δ_n corresponds to industry fixed effects. X_{it} is a vector of firm controls relevant to firm i's cost of capital, including $SIZE_{it}$ (the natural logarithm of total assets), $IK_{i,t}$ (ratio of investment expenditure), ROA_i and ROE_i (returns on average total assets and common equity, respectively), $Lever_i$ (ratio of current liabilities and long-term debt to total assets), $Cash_i$ (ratio of cash and short-term equivalents to total assets), GP_i (gross profit margin), and PPE_i (ratio of gross value of property and equipment to total revenue). Appendix A defines all variables and their sources. The fitted value ($\widehat{NASDAQ}_i$) for firm i is used to match each NASDAQ firm to a corresponding NYSE firm. Panel A reports probit regression results for pre-match and post-match samples. Matching is conducted separately for each upgrade event. Post-match samples are obtained by restricting matched pairs to have propensity score differences less than 0.01. Panel B reports the distribution of propensity scores for matched firms. In Panel A, standard errors are double-clustered by firm and quarter, with t-statistics reported in parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.

Panel A

	Co-location hosting service		Latency upgrade	
	Pre-match	Post-match	Pre-match	Post-match
$SIZE_{it}$	-0.543***	-0.019	-0.465***	-0.007
	(-26.950)	(-0.656)	(-24.615)	(-0.238)
IK_{it}	0.605**	-0.276	0.625**	-0.043
	(2.341)	(-0.782)	(2.013)	(-0.099)
ROA_{it}	-10.895***	-0.668	-6.100***	0.015
	(-9.951)	(-0.480)	(-5.739)	(0.011)
ROE_{it}	2.634**	0.359	0.187	-0.291
	(2.176)	(0.245)	(0.400)	(-0.484)
BM_{it}	-0.272***	0.054	0.237***	0.009
	(-3.576)	(0.553)	(6.122)	(0.186)
$Lever_{it}$	-0.349**	-0.165	-0.666***	-0.060
	(-2.314)	(-0.852)	(-4.725)	(-0.331)
$Cash_{it}$	0.510***	0.115	0.431**	0.077
	(2.675)	(0.445)	(2.082)	(0.274)
GP_{it}	0.029*	-0.017	0.023	-0.002
	(1.727)	(-0.704)	(1.296)	(-0.060)
PPE_{it}	0.013	-0.013	0.011	0.007
	(1.155)	(-0.738)	(1.335)	(0.631)
Constant	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Stock observations	3789	1376	3495	1320

Panel B

	Co-location hosting service				Latency upgrade			
	N	Mean	Min	Max	N	Mean	Min	Max
Treatment	688	0.556	0.031	1.000	660	0.566	0.040	0.990
Control	688	0.556	0.030	0.995	660	0.565	0.040	0.985
Difference		0.000	0.001	0.005		0.001	0.000	0.005

criterion yields a sample of 1378 matched firms (689 for each exchange) for the 2005 co-location hosting services event, and 1320 firms (660 for each exchange) for the 2010 latency upgrade. To test matching quality, we re-estimate Equation (7) using the matched pairs.

Panel A of Table 2 presents both pre-match and post-match coefficient estimates. The pre-match estimates for both technological shocks demonstrate statistically significant differences in firm characteristics between NASDAQ and NYSE firms, underscoring the necessity of matching to mitigate bias. In contrast, the post-match probit regression results show that none of the characteristics between NASDAQ and NYSE firms in our matched sample is statistically significant. Panel B presents the distribution of propensity scores from the matching process. The differences between the mean, minimum, and maximum scores for treatment and control groups are trivial, with identical mean estimates for both shocks. Thus, we have sufficient evidence that there are no fundamental differences between the treatment and control groups in our matched sample, which is necessary for the DiD analysis we conduct in the next section.

4.3.HFT and the cost of capital

We begin by examining the overall effect of HFT on firms' cost of capital using the following DiD specification:

$$CoC_{i,t} = \alpha + \beta_1 NASDAQ_{i,t} + \beta_2 NASDAQ_{i,t} \times Post_t + \gamma X_{it} + \delta_n + \rho_t + \varepsilon_{it} \quad (8),$$

where $NASDAQ_{i,t}$ is a dummy variable equal to 1 (0) for NASDAQ- (NYSE-) listed firms. $Post_t$ is a dummy variable that equals one for the quarter when either shock to HFT event is observed (2005Q2 for co-location and 2010Q2 for the latency reduction) and the subsequent four quarters, and zero for the preceding four quarters. Thus, we employ a nine-quarter event window around each technological upgrade.[4] δ_n and ρ_t correspond to industry and time fixed effects, respectively. We cannot include a separate $Post_t$ variable in the model because it is perfectly collinear with the time fixed effects. The dependent variable, $CoC_{i,t}$, denotes the firm's cost of capital, measured using two approaches: $r_{i,t}^{CAPM}$, calculated using the CAPM, and

[4] Using alternative event windows of 7 or 11 quarters around the event yield qualitatively similar results.

Table 3. HFT and the cost of capital

This table reports estimated coefficients and t-statistics (in parentheses) for the following firm-quarter difference-in-differences model using a propensity score matched sample, as outlined in Table 2:

$$CoC_{it} = \alpha + \beta_1 NASDAQ_{i,t} + \beta_2 NASDAQ_{i,t} \times Post_t + \boldsymbol{\gamma X_{it}} + \delta_n + \rho_t + \varepsilon_{it},$$

where δ_n and ρ_t correspond to industry and quarter fixed effects, respectively. Subscripts i and t indicate firm and quarter, respectively. CoC_{it} corresponds to one of $r_{i,t}^{CAPM}$ and $r_{i,t}^{FF-3}$. $NASDAQ_{i,t}$ is a dummy variable equaling one if firm i is listed on NASDAQ and zero if listed on NYSE. $Post_t$ is a dummy variable that equals one from the quarter when implementation of either technological upgrade on NASDAQ is completed and subsequently. The upgrades are the implementation of co-location hosting service on NASDAQ in Q2 2005 (Columns 1 and 2) and latency upgrade in Q2 2010 (Columns 3 and 4). X_{it} is a vector of firm controls relevant to firm i's cost of capital, including $SIZE_{it}$ (the natural logarithm of total assets), $IK_{i,t}$ (ratio of investment expenditure), ROA_i and ROE_i (returns on average total assets and common equity, respectively), $Lever_i$ (ratio of current liabilities and long-term debt to total assets), $Cash_i$ (ratio of cash and short-term equivalents to total assets), GP_i (gross profit margin), and PPE_i (ratio of gross value of property and equipment to total revenue). Appendix A defines all variables and their sources. All variables are winsorized at the 1% level. The model is estimated for each upgrade event independently using a [-4, +4]-quarter estimation window. Columns (1) and (3) report estimations using $r_{i,t}^{CAPM}$, while Columns (2) and (4) report results for $r_{i,t}^{FF-3}$. Standard errors are double-clustered by firm and quarter. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.

	Co-location hosting service		Latency upgrade	
	(1) $r_{i,t}^{CAPM}$	(2) $r_{i,t}^{FF-3}$	(3) $r_{i,t}^{CAPM}$	(4) $r_{i,t}^{FF-3}$
$NASDAQ_{i,t}$	0.096***	-0.076	-0.404***	-0.454***
	(2.906)	(-1.338)	(-14.746)	(-13.468)
$NASDAQ_{i,t} \times Post_t$	**0.031**	**0.296*** **	**0.141*** **	**0.266*** **
	(0.615)	**(3.419)**	**(3.347)**	**(5.143)**
$SIZE_{it}$	0.137***	0.028	0.041***	0.029***
	(12.917)	(1.534)	(5.047)	(2.902)
IK_{it}	0.068	0.213	-0.463***	-0.862***
	(0.591)	(1.084)	(-4.414)	(-6.675)
ROA_{it}	0.040	1.767**	-4.103***	-7.130***
	(0.076)	(1.974)	(-9.647)	(-13.608)
ROE_{it}	-0.149	0.052	-0.447*	-0.942***
	(-0.274)	(0.055)	(-1.727)	(-2.957)
BM_{it}	-0.382***	0.019	0.067***	0.143***
	(-9.562)	(0.270)	(3.309)	(5.767)
$Lever_{it}$	-0.175**	0.082	0.466***	0.523***
	(-2.321)	(0.633)	(8.195)	(7.468)
$Cash_{it}$	0.758***	-0.667***	0.088	-0.239**
	(7.704)	(-3.948)	(1.095)	(-2.400)
GP_{it}	-0.056***	-0.037*	0.006	0.033
	(-4.647)	(-1.763)	(0.327)	(1.445)
PPE_{it}	-0.005	0.004	-0.000	-0.010**
	(-0.760)	(0.419)	(-0.129)	(-2.348)
Industry fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Stock observations	11033	11033	11075	11075
$\overline{R^2}$	0.080	0.120	0.150	0.153

$r_{i,t}^{FF-3}$, based on the Fama and French (1993) three-factor model. All other variables remain as defined in Equation (7).

Table 3 presents the estimation results for both technological shocks. Columns (1) and (2) report the results for the 2005Q2 co-location introduction, while Columns (3) and (4) correspond to the 2010Q2 latency reduction event. For each event, we present results for both cost of capital measures: $r_{i,t}^{CAPM}$ in Columns (1) and (3), and $r_{i,t}^{FF-3}$ in Columns (2) and (4). The interaction term $\widehat{\beta_2}$ is consistently positive and statistically significant for both cost of capital measures following the 2010 latency upgrade, and for $r_{i,t}^{FF-3}$ following the 2005 co-location upgrade. These results indicate that increased HFT activity, induced by the technological enhancements, is associated with a higher cost of capital. The magnitudes of these effects are also economically meaningful. For the 2010 latency reduction, the estimated coefficients for $r_{i,t}^{CAPM}$ and $r_{i,t}^{FF-3}$ are 0.141 and 0.266, respectively. Relative to the pre-shock average values of these measures for the control group (NYSE-listed firms), this corresponds to increases of approximately 4.1% and 7.5%. For the 2005 co-location upgrade, the increase in $r_{i,t}^{FF-3}$ is about 7.3%, also reflecting substantial economic significance.

We also estimate Equation (8) as a dynamic DiD specification and plot the time-varying estimates of $\widehat{\beta_2}$, along with their 90% confidence intervals. Panel A (B) presents the results for the co-location (latency) upgrade. As shown in Figure 1, there are no statistically significant differences in the cost of capital between NASDAQ and NYSE firms prior to both technological shocks, supporting the parallel trends assumption. This confirms the reliability of our sample matching process and hence, DiD framework. Following the upgrades, however, we observe a significant divergence.

Specifically, for the co-location upgrade, the cost of capital for NASDAQ-listed firms increases relative to their NYSE counterparts. The increase is statistically significant for $r_{i,t}^{FF-3}$ in the quarter immediately following the upgrade at the 0.05 level and remains significant in

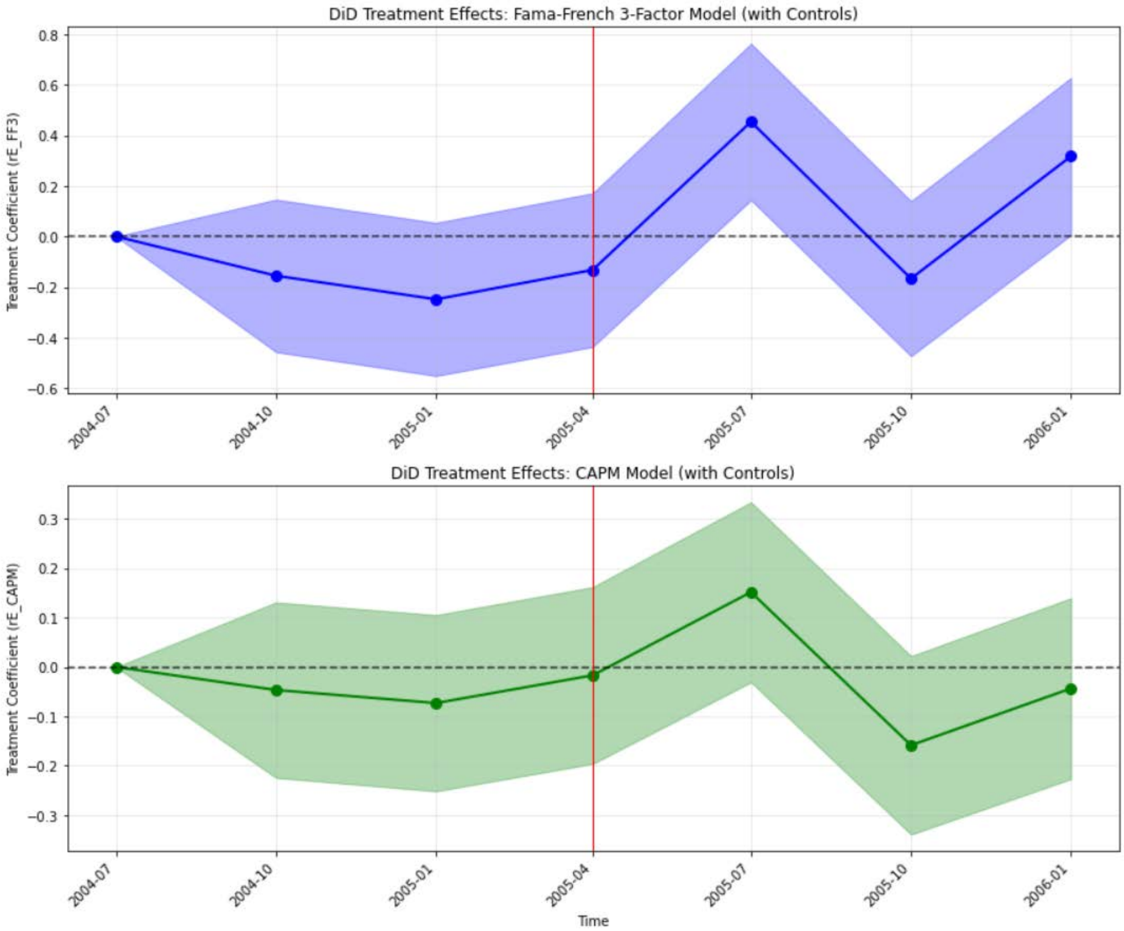
Figure 1. The dynamics of HFT and cost of capital surrounding the technological upgrades

This figure plots the coefficients β_t from the following dynamic DiD model estimated using a 6-quarter window [-3 quarters, +3 quarters] surrounding two technological upgrades:

$$CoC_{it} = \alpha + \sum_{t=-3}^{t=3} \beta_t NASDAQ_{i,t} \times Post_t + \beta_1 NASDAQ_{i,t} + +\delta_n + \varepsilon_{it},$$

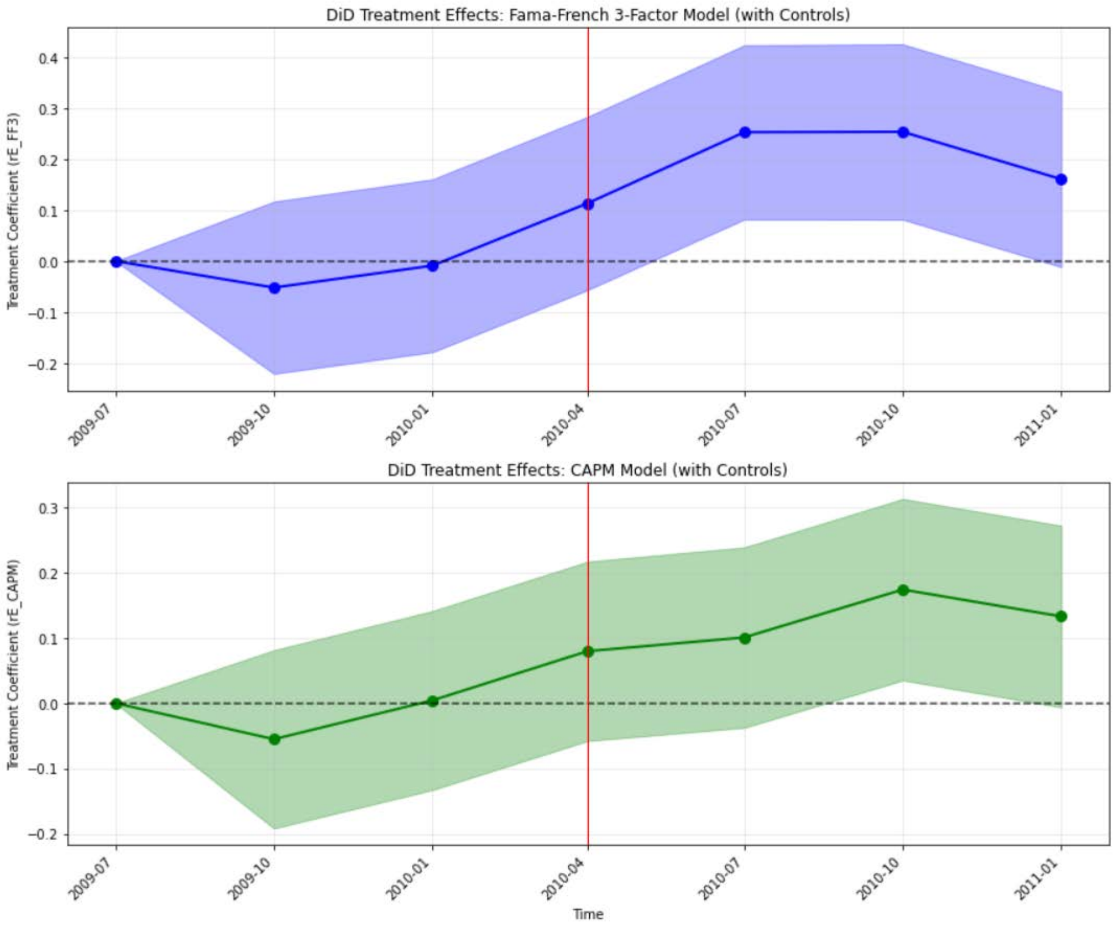
where δ_n corresponds to industry fixed effects. Subscripts i and t indicate firm and quarter, respectively. CoC_{it} corresponds to one of $r_{i,t}^{CAPM}$ and $r_{i,t}^{FF-3}$. $NASDAQ_{i,t}$ is a dummy variable equaling one if firm i is listed on NASDAQ and zero if listed on NYSE. $Post_t$ is a time indicator that takes the value of one for the t^{th} time period following the completion of either technological upgrade on NASDAQ. The upgrades are the implementation of co-location hosting service on NASDAQ in Q2 2005 (Panels A and B) and latency upgrade in Q2 2010 (Panels C and D). The dots represent the coefficients β_t while the shaded areas denote their corresponding 90% confidence intervals. Standard errors are double-clustered by firm and quarter.

Panel A: Co-location



the third quarter following the upgrade at the 0.10 level. For $r_{i,t}^{CAPM}$, we do not observe significant changes, consistent with the baseline DiD results. For the latency upgrade, the increase in both cost of capital measures is statistically significant. Specifically, the increase is statistically significant at the 0.05 level for $r_{i,t}^{FF-3}$ in the first and second quarters following the shock. For $r_{i,t}^{CAPM}$, the increase is statistically significant at the 0.05 level in the second quarter following the shock.

(continued) Figure 1. Panel B: Latency upgrade



5. TESTING THE MECHANISMS

Our baseline results show that HFT – on average – leads to higher cost of capital. In this section, we explore the economic mechanisms underpinning this relationship. In Section 2, we highlight that HFT impacts the cost of capital either via the *systematic risk* or the *liquidity premium* channel. In this section we, therefore, investigate these channels in detail. We formally test the systematic risk channel by re-estimating Equation (8), however using firm-level beta as the dependent variable. Thus, by testing whether the HFT shock events are associated with increases to the beta of stocks in our sample, we can observe any change to systematic risk levels arising from a positive shock to HFT. To capture heterogeneity in how stocks respond to market-wide shocks, we estimate this model for the full sample, and separately for low-beta ($\beta < 1$) and high-beta ($\beta \geq 1$) stocks. This distinction is motivated by

Table 4. Systematic risk channel: beta as dependent variable

This table reports estimated coefficients and t-statistics (in parentheses) for the following firm-quarter difference-in-differences model using a propensity score matched sample, as outlined in Table 2:

$$\beta_{it} = \alpha + \beta_1 NASDAQ_{i,t} + \beta_2 NASDAQ_{i,t} \times Post_t + \boldsymbol{\gamma X_{it}} + \delta_n + \rho_t + \varepsilon_{it},$$

where δ_n and ρ_t correspond to industry and quarter fixed effects, respectively. Subscripts i and t indicate firm and quarter, respectively. β_{it} is the systematic risk measure estimated by regressing the stock returns on market returns. $NASDAQ_{i,t}$ is a dummy variable equaling one if firm i is listed on NASDAQ and zero if listed on NYSE. $Post_t$ is a dummy variable that equals one from the quarter when implementation of either technological upgrade on NASDAQ is completed and subsequently. The upgrades are the implementation of co-location hosting service on NASDAQ in Q2 2005 (Columns 1 to 3) and latency upgrade in Q2 2010 (Columns 4 to 6). X_{it} is a vector of firm controls relevant to firm i's cost of capital, including $SIZE_{it}$ (the natural logarithm of total assets), $IK_{i,t}$ (ratio of investment expenditure), ROA_i and ROE_i (returns on average total assets and common equity, respectively), $Lever_i$ (ratio of current liabilities and long-term debt to total assets), $Cash_i$ (ratio of cash and short-term equivalents to total assets), GP_i (gross profit margin), and PPE_i (ratio of gross value of property and equipment to total revenue). Appendix A defines all variables and their sources. All variables are winsorized at the 1% level. The model is estimated for each upgrade event independently using a [-4, +4]-quarter estimation window. Columns (1) and (4) report estimations using the whole sample, while Columns (2) and (5) report results for low beta stocks ($\beta < 1$) and Columns (3) and (6) report results for high beta stocks ($\beta \geq 1$). Standard errors are double-clustered by firm and quarter. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.

	Co-location hosting service			Latency upgrade		
	(1) Whole	(2) $\beta < 1$	(3) $\beta \geq 1$	(4) Whole	(5) $\beta < 1$	(6) $\beta \geq 1$
$NASDAQ_{i,t}$	0.028*	-	0.236***	-0.202***	-	0.058**
	(1.775)	(-16.078)	(11.467)	(-14.697)	(-30.188)	(3.664)
$NASDAQ_{i,t} \times Post_t$	**-0.012**	**0.217*** **	**-**	**0.071*** **	**0.151*** **	**-0.030**
	(-0.479)	**(5.235)**	**(-2.792)**	**(3.395)**	**(6.146)**	**(-1.271)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Stock-quarter	11033	2664	5040	11075	6354	7542
$\overline{R}^2$	0.075	0.186	0.104	0.159	0.228	0.153

prior literature: Black (1972) and Frazzini and Pedersen (2014) show that low- and high-beta stocks behave asymmetrically and respond differently to funding conditions and investor constraints. Similarly, Hong and Sraer (2016) argue that these two groups vary in their sensitivity to investors' disagreements regarding market prospects, i.e., differences in beliefs about future stock market earnings and returns.

Table 4 presents the estimation results. In the full sample, HFT activity is not significantly associated with changes in systematic risk following the co-location upgrade. For the order transmission latency upgrade, HFT is positively and statistically significantly associated with stock beta. For the whole sample, the results suggest that the 2010Q2 order submission latency upgrade increased NASDAQ stock betas by approximately 7% relative to

NYSE stocks. Nevertheless, given that this impact is statistically significant only for the latency upgrade, this finding should be interpreted with caution.

The split-sample analysis reveals a notable asymmetry. Among low-beta stocks, HFT activity is positively and statistically significantly related to increases in beta. Following the introduction of NASDAQ's co-location and latency-reducing technologies, the betas of low-beta NASDAQ stocks rose by approximately 24% (0.217 estimated coefficient relative to a pre-shock average of 0.888) and 17%, respectively, compared to matched NYSE counterparts. These effects are statistically significant at the 1% level across all specifications and economically meaningful. In contrast, for high-beta stocks, HFT activity is associated with a modest ~6%, nevertheless, statistically significant decline (at the 0.01 level) in beta around the co-location upgrade; no statistically significant change in beta is observed following the latency reduction.

The fact that the positive association between HFT and the systematic risk measure, beta, holds for only low-beta stocks emphasizes the importance of estimating our baseline DiD framework separately for low and high-beta stocks when investigating the association between HFT and the cost of capital. The logic is straightforward: if HFT increases systematic risk primarily for low-beta stocks, and if investors price systematic risk accordingly, then the effect of HFT on the cost of capital should be concentrated among this group. Consistent with this hypothesis, the results in Table 5 confirm that the positive association between HFT activity and the cost of capital is driven entirely by low-beta stocks. In the baseline results, HFT is not significantly related to the$r_{i,t}^{CAPM}$ for the co-location upgrade. However, for low-beta stocks, HFT is statistically significantly and positively associated with the cost of capital in all four specifications (2 technology upgrades × 2 cost of capital measures). Additionally, examining the magnitudes of the coefficients, they increase by at least 50% when we restrict our sample

Table 5. Systematic risk channel: heterogeneous effects by beta

This table reports estimated coefficients and t-statistics (in parentheses) for the following firm-quarter difference-in-differences model using a propensity score matched sample, as outlined in Table 2:

$$CoC_{it} = \alpha + \beta_1 NASDAQ_{i,t} + \beta_2 NASDAQ_{i,t} \times Post_t + \boldsymbol{\gamma X_{it}} + \delta_n + \rho_t + \varepsilon_{it},$$

where δ_n and ρ_t correspond to industry and quarter fixed effects, respectively. Subscripts i and t indicate firm and quarter, respectively. CoC_{it} corresponds to one of $r_{i,t}^{CAPM}$ and $r_{i,t}^{FF-3}$. $NASDAQ_{i,t}$ is a dummy variable equaling one if firm i is listed on NASDAQ and zero if listed on NYSE. $Post_t$ is a dummy variable that equals one from the quarter when implementation of either technological upgrade on NASDAQ is completed and subsequently. The upgrades are the implementation of co-location hosting service on NASDAQ in Q2 2005 (Columns 1 to 4) and latency upgrade in Q2 2010 (Columns 5 to 8). X_{it} is a vector of firm controls relevant to firm i's cost of capital, including $SIZE_{it}$ (the natural logarithm of total assets), $IK_{i,t}$ (ratio of investment expenditure), ROA_i and ROE_i (returns on average total assets and common equity, respectively), $Lever_i$ (ratio of current liabilities and long-term debt to total assets), $Cash_i$ (ratio of cash and short-term equivalents to total assets), GP_i (gross profit margin), and PPE_i (ratio of gross value of property and equipment to total revenue). Appendix A defines all variables and their sources. All variables are winsorized at the 1% level. The model is estimated for each upgrade event independently using a [-4, +4]-quarter estimation window. The model is estimated for low-beta and high-beta stocks separately. Columns (1), (3), (5) and (7) report estimations for low beta stocks (β < 1), while Columns (2), (4), (6) and (8) report estimations for high beta stocks ($\beta \geq 1$). Standard errors are double-clustered by firm and quarter. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.

	Co-location hosting service				Latency upgrade			
	$rE\_CAPM_{i,t}$		$rE\_FF3_{i,t}$		$rE\_CAPM_{i,t}$		$rE\_FF3_{i,t}$	
	(1) $\beta < 1$	(2) $\beta \geq 1$	(3) $\beta < 1$	(4) $\beta \geq 1$	(5) $\beta < 1$	(6) $\beta \geq 1$	(7) $\beta < 1$	(8) $\beta \geq 1$
$NASDAQ_{i,t}$	-0.952*** (-16.127)	0.504*** (11.627)	-0.924*** (-8.692)	0.110 (1.384)	-0.986*** (-29.995)	0.108*** (3.440)	-1.073*** (-26.211)	0.079* (1.958)
$NASDAQ_{i,t} \times Post_t$	**0.466*** (5.332)**	**-0.177*** (-2.737)**	**0.393** (2.499)**	**0.031 (0.262)**	**0.288*** (5.862)**	**-0.053 (-1.124)**	**0.431*** (7.048)**	**0.036 (0.596)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-quarter observations	2664	5040	2664	5040	6354	7542	6354	7542
$\overline{R^2}$	0.195	0.106	0.227	0.196	0.218	0.138	0.199	0.150

to low-beta stocks. Conversely, for high-beta stocks, HFT is statistically significantly related to the cost of capital in only one of four specifications, and this association is negative.

Why does this effect appear only for low-beta stocks? A plausible explanation lies in the nature of HFT information transmission. HFTs enhance the speed and efficiency with which market-wide information is impounded into prices through arbitrage and market-making. For low-beta stocks, which are typically less sensitive to aggregate market movements, the introduction of HFT may substantially increase their responsiveness to market-wide information, thereby raising their co-movements with the market, which in turn increases systematic risk and the cost of capital. This occurs because HFTs, unlike traditional market makers with limited capacity and selective stock coverage, can simultaneously monitor and trade across thousands of securities (Malceniece et al., 2019). Their algorithms rapidly process market-wide signals and execute trades within microseconds, effectively transmitting systematic information to stocks that previously responded more slowly to market movements. Traditional market makers, constrained by human limitations and capital requirements, often focus on a subset of liquid stocks, leaving many securities with delayed incorporation of market information.

In contrast, high-beta stocks are already tightly linked to market movements, limiting the marginal effect of additional information transmission. Consistent with this, we do not detect a significant increase in the systematic risk of high-beta stocks, and we even note a decline in one specification. The decline in high-beta stocks' beta may reflect HFTs' role in reducing noise and pricing errors, as suggested by Brogaard et al. (2014). Specifically, if high-beta stocks exhibit high beta because they overreact to market-wide information, HFTs can reduce their beta by mitigating the overreaction of these stocks to systematic information.[5]

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[5] One can also draw parallels to the "beta compression" mechanism discussed by Frazzini and Pedersen (2014). They show that in the presence of funding liquidity risk, betas tend to compress toward one across the cross-section of assets. In such environments, low-beta stocks experience upward pressure on their betas, while high-beta stocks see a downward adjustment. The intuition is that during funding liquidity shocks, all assets begin to

If this explanation is valid, among low-beta stocks, the effect of HFT would be stronger for firms whose stocks are relatively illiquid – those with more pronounced informational frictions that are often overlooked by traditional market makers due to limited profitability (Lyle and Naughton, 2015). In these stocks, a positive shock to HFT can facilitate the diffusion of market-wide information and increase co-movement with the broader market. In contrast, for more liquid stocks, where market-wide information is already incorporated efficiently due to high trading volume and analyst coverage, the marginal impact of HFT on price responsiveness and return co-movement is likely to be minimal even within the low-beta group. This prediction is consistent with Glosten et al. (2021), who show that ETF-induced co-movement is strongest among small firms, and with Malceniece et al. (2019), who find that HFT-driven co-movement is concentrated in less liquid stocks. To test this, we estimate the following extended DiD model:

$$CoC_{i,t} = \alpha + \beta_1 NASDAQ_{i,t} + \beta_2 NASDAQ_{i,t} \times Post_t + \beta_3 IlliqD_{i,t} + \beta_4 NASDAQ_{i,t} \times IlliqD_{i,t} + \beta_5 Post_t \times IlliqD_{i,t} + \beta_6 NASDAQ_{i,t} \times IlliqD_{i,t} \times Post_t + \gamma X_{it} + \delta_n + \rho_i + \varepsilon_{it} \quad (9),$$

where $IlliqD_{i,t}$ is an indicator variable that equals one if firm i's inverse measure of liquidity exceeds the cross-sectional median in the three quarters prior to the event. We use both $ILLIQ_{i,t}$ and $Relative\ Qspread_{i,t}$ as inverse proxies of liquidity. Standard errors are clustered by stock and quarter, and we estimate Equation (9) separately for low- and high-beta stocks.

The results, presented in Table 6, support our prediction. Among low-beta firms, the double interaction term is positive and statistically significant across all 8 specifications (2

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co-move more closely with the market, regardless of their usual levels volatility, resulting in convergence of betas toward unity. While Frazzini and Pedersen (2014) focus on funding liquidity constraints, which may not be directly affected by HFT, Brunnermeier and Pedersen (2009) establish a link between funding liquidity and market liquidity. Given that HFTs significantly influence market liquidity, they may indirectly affect funding conditions and thus contribute to beta compression. Through this channel, HFT could raise the systematic risk of low-beta stocks by amplifying liquidity-related constraints in financial markets.

Table 6. Systematic risk channel: illiquidity interaction effects

This table reports estimated coefficients and t-statistics (in parentheses) for the following firm-quarter difference-in-differences model using a propensity score matched sample, as outlined in Table 2:

$$CoC_{i,t} = \alpha + \beta_1 NASDAQ_{i,t} + \beta_2 NASDAQ_{i,t} \times Post_t + \beta_3 IlliqD_{i,t} + \beta_4 NASDAQ_{i,t} \times IlliqD_{i,t} + \beta_5 Post_t \times IlliqD_{i,t} + \beta_6 NASDAQ_{i,t} \times IlliqD_{i,t} \times Post_t + \boldsymbol{\gamma X_{it}} + \delta_n + \rho_i + \varepsilon_{it}$$

where δ_n and ρ_t correspond to industry and quarter fixed effects, respectively. Subscripts i and t indicate firm and quarter, respectively. CoC_{it} corresponds to one of $r_{i,t}^{CAPM}$ and $r_{i,t}^{FF-3}$. $NASDAQ_{i,t}$ is a dummy variable equaling one if firm i is listed on NASDAQ and zero if listed on NYSE. $Post_t$ is a dummy variable that equals one from the quarter when implementation of either technological upgrade on NASDAQ is completed and subsequently. The upgrades are the implementation of co-location hosting service on NASDAQ in Q2 2005 (Columns 1 to 4) and latency upgrade in Q2 2010 (Columns 5 to 8). $IlliqD_{i,t}$ is an indicator equal to one if firm i's illiquidity measure exceeds the cross-sectional median in the three quarters prior to the event. We use both Amihud's illiquidity measure ($ILLIQ_{i,t}$) in Panel A and relative quoted spread ($Relative\ Qspread_{i,t}$) in Panel B as our liquidity proxy. X_{it} is a vector of firm controls relevant to firm i's cost of capital, including $SIZE_{it}$ (the natural logarithm of total assets), $IK_{i,t}$ (ratio of investment expenditure), ROA_i and ROE_i (returns on average total assets and common equity, respectively), $Lever_i$ (ratio of current liabilities and long-term debt to total assets), $Cash_i$ (ratio of cash and short-term equivalents to total assets), GP_i (gross profit margin), and PPE_i (ratio of gross value of property and equipment to total revenue). Appendix A defines all variables and their sources. All variables are winsorized at the 1% level. The model is estimated for each upgrade event independently using a [-4, +4]-quarter estimation window. The model is estimated for low-beta and high-beta stocks separately. Columns (1), (3), (5) and (7) report estimations for low beta stocks (β < 1), while Columns (2), (4), (6) and (8) report estimations for high beta stocks (β > 1). Standard errors are double-clustered by firm and quarter. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.

Panel A: $ILLIQ_{i,t}$ is used as an illiquidity proxy

	Co-location hosting service				Latency upgrade			
	$rE\_CAPM_{i,t}$		$rE\_FF3_{i,t}$		$rE\_CAPM_{i,t}$		$rE\_FF3_{i,t}$	
	(1) $\beta < 1$	(2) $\beta \geq 1$	(3) $\beta < 1$	(4) $\beta \geq 1$	(5) $\beta < 1$	(6) $\beta \geq 1$	(7) $\beta < 1$	(8) $\beta \geq 1$
$NASDAQ_{i,t}$	-0.544***	0.660***	-0.494***	0.275**	-0.515***	0.262***	-0.557***	0.276***
	(-6.358)	(10.962)	(-3.181)	(2.476)	(-11.379)	(5.938)	(-9.887)	(4.907)
$NASDAQ_{i,t} \times Post_t$	0.049	-0.303***	-0.190	-0.167	0.193***	-0.106	0.311***	-0.050
	(0.385)	(-3.384)	(-0.824)	(-1.015)	(2.864)	(-1.612)	(3.710)	(-0.596)
$IlliqD_{i,t}$	0.070	0.370***	0.113	0.368***	0.723***	0.393***	0.718***	0.388***
	(0.790)	(5.705)	(0.708)	(3.081)	(14.547)	(8.019)	(11.599)	(6.210)
$NASDAQ_{i,t} \times IlliqD_{i,t}$	-0.726***	-0.312***	-0.851***	-0.334**	-0.923***	-0.305***	-1.004***	-0.391***
	(-5.960)	(-3.661)	(-3.850)	(-2.124)	(-14.279)	(-4.902)	(-12.458)	(-4.937)

$Post_t \times IlliqD_{i,t}$	-0.147	0.125	-0.261	0.282*	-0.033	0.078	0.306***	0.434***
	(-1.163)	(1.402)	(-1.140)	(1.714)	(-0.494)	(1.179)	(3.649)	(5.183)
$NASDAQ_{i,t} \times IlliqD_{i,t} \times Post_t$	**0.735*** **	**0.272** **	**1.139*** **	**0.447* **	**0.192** **	**0.108**	**0.243** **	**0.174**
	(4.118)	**(2.155)**	**(3.514)**	**(1.920)**	**(2.015)**	**(1.164)**	**(2.049)**	**(1.468)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-quarter observations	2610	5022	2610	5022	6354	7542	6354	7542
$\overline{R^2}$	0.207	0.113	0.273	0.207	0.265	0.152	0.246	0.174

Panel B: $Relative\ Qspread_{i,t}$ is used as an illiquidity proxy

	Co-location hosting service				Latency upgrade			
	$rE\_CAPM_{i,t}$		$rE\_FF3_{i,t}$		$rE\_CAPM_{i,t}$		$rE\_FF3_{i,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\beta < 1$	$\beta \geq 1$	$\beta < 1$	$\beta \geq 1$	$\beta < 1$	$\beta \geq 1$	$\beta < 1$	$\beta \geq 1$
$NASDAQ_{i,t}$	-0.467***	0.557***	-0.318**	0.273**	-0.463***	0.307***	-0.482***	0.324***
	(-5.467)	(9.238)	(-2.049)	(2.462)	(-10.264)	(6.977)	(-8.556)	(5.757)
$NASDAQ_{i,t} \times Post_t$	0.157	-0.234***	-0.071	-0.226	0.125*	-0.111*	0.198**	-0.085
	(1.248)	(-2.618)	(-0.308)	(-1.374)	(1.860)	(-1.689)	(2.361)	(-1.020)
$IlliqD_{i,t}$	0.278***	0.316***	0.544***	0.449***	0.799***	0.553***	0.820***	0.577***
	(3.089)	(4.868)	(3.323)	(3.766)	(16.374)	(11.643)	(13.462)	(9.522)
$NASDAQ_{i,t} \times IlliqD_{i,t}$	-0.878***	-0.113	-1.202***	-0.336**	-1.026***	-0.391***	-1.154***	-0.482***
	(-7.186)	(-1.328)	(-5.410)	(-2.144)	(-15.940)	(-6.313)	(-14.354)	(-6.095)
$Post_t \times IlliqD_{i,t}$	0.073	0.139	-0.021	0.195	-0.170**	-0.078	0.066	0.201**
	(0.577)	(1.559)	(-0.091)	(1.184)	(-2.529)	(-1.193)	(0.791)	(2.401)
$NASDAQ_{i,t} \times IlliqD_{i,t} \times Post_t$	**0.521*** **	**0.135**	**0.907*** **	**0.564** **	**0.327*** **	**0.118**	**0.468*** **	**0.245** **
	(2.931)	**(1.069)**	**(2.807)**	**(2.424)**	**(3.446)**	**(1.270)**	**(3.946)**	**(2.071)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-quarter observations	2610	5022	2610	5022	6354	7542	6354	7542
$\overline{R^2}$	0.213	0.112	0.278	0.209	0.270	0.160	0.247	0.176

technology upgrades × 2 cost of capital measures × 2 liquidity measures), indicating that the effect of HFT on the cost of capital is amplified for illiquid stocks. Notably, in the case of the co-location shock, statistical significance shifts entirely from the interaction term ($NASDAQ_{i,t} \times Post_t$) to the double interaction term ($NASDAQ_{i,t} \times Illiq_{i,t} \times Post_t$), suggesting that the observed effect of HFT on the cost of capital for low-beta stocks is concentrated exclusively among the least liquid stocks, where HFTs are more likely to increase co-movement with the market.

Conversely, for high-beta firms, the double interaction term is either statistically insignificant at the conventional 0.05 level (insignificant in 5 out of 8 specifications) or economically small across specifications, with no consistent pattern. The magnitude of the coefficient for the double interaction term $NASDAQ_{i,t} \times Illiq_{i,t} \times Post_t$ is approximately 2 to 3 times lower for high-beta stocks compared to low-beta stocks. Given that high-beta stocks mostly have a higher cost of capital, the economic magnitude is even smaller. Taken together, these findings provide strong support for the systematic risk channel as a key mechanism through which HFT activity increases the cost of capital – specifically, by increasing systematic risk for low-beta stocks.

We have established that HFT activity is associated with an increase in the cost of capital, and that this increase is concentrated in low-beta stocks that become more responsive to market-wide information in the presence of HFT. However, as discussed in Section 2, HFT may also impact the cost of capital by changing the liquidity premium. To test this channel, we re-estimate Equation (9) with a sole focus on highly liquid stocks. This is because, as discussed in Section 2, most of the HFT activity is concentrated in liquid stocks. The estimated stock-quarter panel regression is as follows:

$$CoC_{i,t} = \alpha + \beta_1 NASDAQ_{i,t} + \beta_2 NASDAQ_{i,t} \times Post_t + \beta_3 LiqD_{i,t} + \beta_4 NASDAQ_{i,t} \times LiqD_{i,t} + \beta_5 Post_t \times LiqD_{i,t} + \beta_6 NASDAQ_{i,t} \times LiqD_{i,t} \times Post_t + \gamma X_{it} + \delta_n + \rho_i + \varepsilon_{it} \quad (10).$$

Table 7. HFT and the cost of capital: liquidity channel

This table reports estimated coefficients and t-statistics (in parentheses) for the following firm-quarter difference-in-differences model using a propensity score matched sample, as outlined in Table 2:

$$CoC_{i,t} = \alpha + \beta_1 NASDAQ_{i,t} + \beta_2 NASDAQ_{i,t} \times Post_t + \beta_3 LiqD_{i,t} + \beta_4 NASDAQ_{i,t} \times LiqD_{i,t} + \beta_5 Post_t \times LiqD_{i,t} + \beta_6 NASDAQ_{i,t} \times LiqD_{i,t} \times Post_t + \boldsymbol{\gamma X_{it}} + \delta_n + \rho_i + \varepsilon_{it}$$

where δ_n and ρ_t correspond to industry and quarter fixed effects, respectively. Subscripts i and t indicate firm and quarter, respectively. CoC_{it} corresponds to one of $r_{i,t}^{CAPM}$ and $r_{i,t}^{FF-3}$. $NASDAQ_{i,t}$ is a dummy variable equaling one if firm i is listed on NASDAQ and zero if listed on NYSE. $Post_t$ is a dummy variable that equals one from the quarter when implementation of either technological upgrade on NASDAQ is completed and subsequently. The upgrades are the implementation of co-location hosting service on NASDAQ in Q2 2005 (Columns 1 and 2) and latency upgrade in Q2 2010 (Columns 3 and 4). $LiqD_{i,t}$ is an indicator equal to one if firm i's illiquidity measure is lower than the 30th percentile in the three quarters prior to the event. We use both Amihud's illiquidity measure ($ILLIQ_{i,t}$) and relative quoted spread ($Relative\ Qspread_{i,t}$) as proxies. X_{it} is a vector of firm controls relevant to firm i's cost of capital, including $SIZE_{it}$ (the natural logarithm of total assets), $IK_{i,t}$ (ratio of investment expenditure), ROA_i and ROE_i (returns on average total assets and common equity, respectively), $Lever_i$ (ratio of current liabilities and long-term debt to total assets), $Cash_i$ (ratio of cash and short-term equivalents to total assets), GP_i (gross profit margin), and PPE_i (ratio of gross value of property and equipment to total revenue). Appendix A defines all variables and their sources. All variables are winsorized at the 1% level. The model is estimated for each upgrade event independently using a [-4, +4]-quarter estimation window. The model is estimated for low-beta and high-beta stocks separately. Columns (1) and (3) report estimations using $r_{i,t}^{CAPM}$, while Columns (2) and (4) report results for $r_{i,t}^{FF-3}$. Standard errors are double-clustered by firm and quarter. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.

Panel A: $ILLIQ_{i,t}$ is used as an illiquidity proxy

	Co-location hosting service		Latency upgrade	
	(1) $r_{i,t}^{CAPM}$	(2) $r_{i,t}^{FF-3}$	(3) $r_{i,t}^{CAPM}$	(4) $r_{i,t}^{FF-3}$
$NASDAQ_{i,t}$	-0.087**	-0.379***	-0.510***	-0.592***
	(-2.040)	(-5.036)	(-17.831)	(-16.729)
$NASDAQ_{i,t} \times Post_t$	0.089	0.316***	0.162***	0.359***
	(1.394)	(2.814)	(3.790)	(6.815)
$LiqD_{i,t}$	-0.685***	-0.679***	-0.556***	-0.564***
	(-10.521)	(-5.918)	(-13.365)	(-10.954)
$NASDAQ_{i,t} \times LiqD_{i,t}$	0.475***	0.598***	0.438***	0.546***
	(5.819)	(4.155)	(8.193)	(8.251)
$Post_t \times LiqD_{i,t}$	-0.337***	-0.475***	-0.058	-0.328***
	(-3.824)	(-3.056)	(-1.024)	(-4.643)
$NASDAQ_{i,t} \times LiqD_{i,t} \times Post_t$	**-0.134**	**-0.427****	**-0.173****	**-0.426*****
	(-1.105)	**(-1.996)**	**(-2.173)**	**(-4.325)**
Controls	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Stock observations	7632	7632	13896	13896
$\overline{R^2}$	0.103	0.218	0.157	0.165

Panel B: $Relative\ Qspread_{i,t}$ is used as an illiquidity proxy

	Co-location hosting service		Latency upgrade	
	(1) $r_{i,t}^{CAPM}$	(2) $r_{i,t}^{FF-3}$	(3) $r_{i,t}^{CAPM}$	(4) $r_{i,t}^{FF-3}$
$NASDAQ_{i,t}$	-0.112***	-0.378***	-0.530***	-0.611***

	(-2.605)	(-5.018)	(-18.712)	(-17.389)
$NASDAQ_{i,t} \times Post_t$	0.126**	0.340***	0.173***	0.378***
	(1.973)	(3.033)	(4.095)	(7.215)
$LiqD_{i,t}$	-0.703***	-0.752***	-0.801***	-0.838***
	(-11.060)	(-6.732)	(-19.629)	(-16.565)
$NASDAQ_{i,t} \times LiqD_{i,t}$	0.539***	0.593***	0.542***	0.651***
	(6.608)	(4.137)	(10.216)	(9.889)
$Post_t \times LiqD_{i,t}$	-0.227**	-0.450***	0.088	-0.129*
	(-2.579)	(-2.916)	(1.545)	(-1.833)
$NASDAQ_{i,t} \times LiqD_{i,t} \times Post_t$	**-0.280****	**-0.517****	**-0.221*****	**-0.499*****
	(-2.306)	**(-2.424)**	**(-2.793)**	**(-5.095)**
Controls	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Stock observations	7632	7632	13896	13896
$\overline{R^2}$	0.102	0.222	0.172	0.175

This specification is identical to Equation (9), except that we now define the liquidity indicator $Liq_{i,t}$ to equal one if firm i's $ILLIQ_{i,t}$ or $Relative\ Qspread_{i,t}$ value places it in the bottom tercile (i.e., more liquid than the 30th percentile) based on the three quarters preceding the technological upgrade events. This threshold allows us to isolate the top tier of liquid stocks, also avoiding perfect negative correlation with the illiquidity dummy used in earlier tests in Equation (9) (which was based on the median).

The results, reported in Table 7, show that HFT activity significantly reduces the cost of capital among the most liquid stocks. In 7 out of 8 specifications, the coefficient on the double interaction term ($NASDAQ_{i,t} \times Liq_{i,t} \times Post_t$) is negative and statistically significant at the 0.05 level or lower. Additionally, the coefficient on the interaction term $NASDAQ_{i,t} \times Post_t$ remains positive and statistically significant in most specifications – and, notably, its magnitude increases by more than 50%. This suggests that the overall increase in the cost of capital identified in the baseline results is even larger once the most liquid stocks in the sample are controlled for.

Taken together, the findings in this section indicate that HFT affects the cost of capital through two channels. First, HFT increases the cost of capital by amplifying systematic risk, particularly among low-beta firms. This occurs because HFT activity increases these firms' responsiveness to market-wide information, thereby raising their co-movement with the overall market. Second, HFT reduces the cost of capital by improving liquidity – but only for the most liquid stocks, where HFTs are actively engaged as liquidity providers. These offsetting effects underscore the importance of accounting for firm-level heterogeneity when assessing the broader implications of HFT for the cost of capital.

6. EXTERNAL VALIDITY: EVIDENCE FROM THE STOCK EXCHANGE OF HONG KONG

As discussed in the Introduction, HFT and market fragmentation exhibit a symbiotic relationship. Generally, increases in HFT activity are associated with greater market fragmentation. For instance, Menkveld (2013) shows that the entry of new HFT firms not only affects market quality but also increases fragmentation. The study suggests that HFT may be a channel through which fragmentation influences market quality. Moreover, Menkveld (2013) argues that one of the key reasons behind the high degree of fragmentation in U.S. stock markets is the intense activity of HFTs. While fragmentation itself is not the focus of our study, the possibility that HFTs affect the cost of capital through their influence on market fragmentation raises an interesting question: do HFTs impact the cost of capital in markets that are less fragmented? To explore this, we replicate our main analysis using exogenous HFT shocks in a large, essentially unfragmented market – the Stock Exchange of Hong Kong (SEHK).

The SEHK is the seventh-largest stock exchange in the world by market capitalization, with a total listing value of $4.2 trillion as of August 2024.[6] It comprises two distinct equity

[6] https://statistics.world-exchanges.org.

listing platforms: the Main Board, which hosts large and blue-chip firms, and the Growth Enterprise Market, which is tailored to small and mid-sized firms. As of December 2023, the Main Board accounts for 99.83% of SEHK's total market capitalization; accordingly, our analysis focuses on firms listed on the Main Board. Starting with the launch of AMS 3.8 in December 2011, over the past fifteen years, the Hong Kong Exchanges and Clearing Limited has undertaken major upgrades to the SEHK's trading infrastructure to maintain its status as a leading global exchange. One of the most important technological advancements affecting trading latency was the introduction of the Orion Central Gateway (OCG) in Q2 2014. The OCG serves as a secure gateway between the Broker Supplied Systems of Exchange Participants and HKEX's securities market trading platform. Its primary benefits, as promoted by HKEX, are significant reductions in trading latency and improvements in system resilience.

The Main Board of the SEHK serves as the exclusive platform for trading blue-chip and large-cap stocks in Hong Kong, and as such, the market lacks the kind of trading fragmentation commonly observed in U.S. and European markets. Nevertheless, an important structural feature of the SEHK is its link to Mainland China's financial markets via the Stock Connect program, which facilitates cross-border trading of eligible securities, including Hong Kong-listed, China-headquartered firms designated as H shares. The Connect was launched in November 2014; however, trading activity through this channel only gained momentum in 2017 – about three years after the technological shock we analyze. More importantly, the structure of the Connect programme does not fragment execution across venues. Although orders are routed through the participating exchanges, each operates its own order-receiving system and ultimately forwards trades to the listing exchange for execution. Thus, all trades in SEHK-listed stocks are executed on SEHK itself, preserving a unified trading venue. Given this institutional structure, SEHK provides a clean and non-fragmented environment, offering a neat quasi-natural experimental setting to assess whether HFT also affects the cost of capital in the absence of market fragmentation. In addition, trading in Hong Kong provides an out-of-sample setting that allows us to assess whether our main results hold in a markedly different market context.

To investigate the impact of HFT on the cost of capital in SEHK, we employ a DiD framework similar to our baseline specification in Equation (8). As noted earlier, we use the introduction of the OCG, a new order input gateway, in Q2 2014 as the exogenous shock. For the control group, we use firms listed on the Shanghai Stock Exchange (SSE). Specifically, we apply the same matching procedure described in Section 3.2 to construct a matched sample of SSE firms, thereby controlling for macroeconomic factors that may simultaneously affect trading activity in both markets. We use SSE stocks as the control group because the SSE is the largest stock exchange in the region, subject to similar macroeconomic and regional factors as the SEHK, while remaining unaffected by the OCG implementation in Hong Kong.

Our matching procedure yields a total of 756 firms: 378 treated firms from the SEHK and 378 matched control firms from the SSE. As in the baseline DiD model for the U.S. markets, we employ an estimation window of [-4, +4] quarters around the shock. For this test, we obtain the cost of equity ($r_{i,t}^{CAPM}$) and market beta (β_{it}) from Bloomberg. Daily data used to compute liquidity measures, including ask price, bid price, trading volume, and return, are sourced from Refinitiv Eikon. Quarterly firm characteristics used as control variables are also obtained from Refinitiv Eikon. This analysis uses the same set of control variables, fixed effects, and clustering approach as in our baseline specification.

The results are reported in Table 8. Overall, our findings are consistent with the baseline estimates based on the U.S. market. First, we find that HFT activity is positively associated with the cost of capital. Second, this positive effect is entirely driven by low-beta firms, with a marginally stronger impact observed among the less liquid stocks within this group (the double interaction term with the illiquidity dummy is statistically significant at the 0.1 level of

Table 8. HFT and Cost of capital: evidence from the Stock Exchange of Hong Kong

This table reports estimated coefficients and t-statistics (in parentheses) for three series of firm-quarter difference-in-differences model using a propensity score matched sample, constructed by firms listed on Stock Exchange of Hong Kong (SEHK, treatment group) with those listed on on Shanghai Stock Exchange (SSE, control group). The pre-match probit regression is estimated using cross-sectional observations at quarter t-4, four quarters prior to the implementation of technological upgrades: Orion Central Gateway (OCG) on SEHK in Q2 2014. Columns (1) reports estimations using the whole sample, while Columns (4) and (5) reports the results for low beta stocks ($\beta < 1$) and high beta stocks ($\beta \geq 1$), for the following difference-in-differences (DiD) model:

$$CoC_{it} = \alpha + \beta_1 HK_{i,t} + \beta_2 HK_{i,t} \times Post_t + \boldsymbol{\gamma X_{i,t}} + \delta_n + \rho_t + \varepsilon_{it},$$

where δ_n and ρ_t correspond to industry and quarter fixed effects, respectively. Subscripts i and t indicate firm and quarter, respectively. CoC_{it} corresponds to the cost of capital measure, $r_{i,t}^{CAPM}$. $HK_{i,t}$ is a dummy variable equaling one if firm i is listed on SEHK and zero if listed on SSE. $Post_t$ is a dummy variable that equals one from the quarter when implementation of OCG on SEHK is completed and subsequently. $\boldsymbol{X_{i,t}}$ is a vector of firm controls relevant to firm i's cost of capital, including $SIZE_{i,t}$ (the natural logarithm of total assets), $IK_{i,t}$ (ratio of investment expenditure), $ROA_{i,t}$ and $ROE_{i,t}$ (returns on average total assets and common equity, respectively), $BM_{i,t}$ (ratio of book and market value of equity), $Lever_{i,t}$ (ratio of current liabilities and long-term debt to total assets), $Cash_{i,t}$ (ratio of cash and short-term equivalents to total assets), $GP_{i,t}$ (gross profit margin), and $PPE_{i,t}$ (ratio of gross value of property and equipment to total revenue). Columns (2) and (3) report the results for low beta stocks ($\beta < 1$) and high beta stocks ($\beta \geq 1$), for the following DiD model:

$$\beta_{it} = \alpha + \beta_1 HK_{i,t} + \beta_2 HK_{i,t} \times Post_t + \boldsymbol{\gamma X_{i,t}} + \delta_n + \rho_t + \varepsilon_{it},$$

where β_{it} is the systematic risk measure estimated by regressing the stock returns on market returns, and other variables are defined same with the above estimation. Columns (6) and (7) report the results for low beta stocks ($\beta < 1$), for the following DiD model:

$$CoC_{i,t} = \alpha + \beta_1 HK_{i,t} + \beta_2 HK_{i,t} \times Post_t + \beta_3 IlliqD_{i,t} + \beta_4 HK_{i,t} \times IlliqD_{i,t} + \beta_5 Post_t \times IlliqD_{i,t} + \beta_6 HK_{i,t} \times IlliqD_{i,t} \times Post_t + \boldsymbol{\gamma X_{i,t}} + \delta_n + \rho_i + \varepsilon_{it},$$

where $IlliqD_{i,t}$ is an indicator equal to one if firm i's illiquidity measure exceeds the cross-sectional median in the three quarters prior to the event, other variables are defined same with the above estimation. Columns (8) and (9) report the results for the following DiD model:

$$CoC_{i,t} = \alpha + \beta_1 HK_{i,t} + \beta_2 HK_{i,t} \times Post_t + \beta_3 LiqD_{i,t} + \beta_4 HK_{i,t} \times LiqD_{i,t} + \beta_5 Post_t \times LiqD_{i,t} + \beta_6 HK_{i,t} \times LiqD_{i,t} \times Post_t + \boldsymbol{\gamma X_{i,t}} + \delta_n + \rho_i + \varepsilon_{it},$$

where $LiqD_{i,t}$ is an indicator equal to one if firm i's illiquidity measure is lower than the 30th percentile in the three quarters prior to the event, other variables are defined same with the above estimation. We use both Amihud's illiquidity measure ($ILLIQ_{i,t}$) (Columns (6) and (8)) and relative quoted spread ($Relative\ Qspread_{i,t}$) (Columns (7) and (9)) to define $IlliqD_{i,t}$ and $LiqD_{i,t}$. The model is estimated for each upgrade event independently using a [-4, +4]-quarter estimation window. The cost of equity ($r_{i,t}^{CAPM}$) and market beta (β_{it}) are obtained from Bloomberg; daily data used to compute liquidity measures, including ask price, bid price, trading volume, and return are obtained from Refinitiv Eikon; quarterly firm characteristics used as control variables are obtained from Refinitiv Eikon. All variables are winsorized at the 1% level. The whole sample estimation includes 378 pairs of firms, and the low (high) beta group estimation includes 232 (193) pairs of firms. Standard errors are double-clustered by firm and quarter. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.

	(1) $rE\_CAPM_{i,t}$ Whole sample	(2) β $\beta < 1$	(3) β $\beta \geq 1$	(4) $rE\_CAPM_{i,t}$ $\beta < 1$	(5) $rE\_CAPM_{i,t}$ $\beta \geq 1$	(6) $rE\_CAPM_{i,t}$ $\beta < 1$	(7) $rE\_CAPM_{i,t}$ $\beta < 1$	(8) $rE\_CAPM_{i,t}$ Whole sample	(9) $rE\_CAPM_{i,t}$ Whole sample
$HK_{i,t}$	-4.245***	-0.879***	-0.064**	-5.421***	-2.475***	-4.824***	-4.872***	-4.460***	-4.378***
	(-53.175)	(-36.706)	(-2.443)	(-60.991)	(-22.318)	(-39.007)	(-38.746)	(-44.637)	(-43.672)
$HK_{i,t} \times Post_t$	0.786***	0.551***	0.061	1.733***	-0.422**	1.197***	1.264***	1.023***	0.943***
	(6.000)	(17.070)	(1.421)	(11.917)	(-2.320)	(6.096)	(6.470)	(6.297)	(5.785)
$IlliqD_{i,t}$						-0.102	-0.502***		
						(-0.805)	(-4.094)		
$HK_{i,t} \times IlliqD_{i,t}$						-0.899***	-0.793***		
						(-5.041)	(-4.328)		
$Post_t \times IlliqD_{i,t}$						-0.029	0.098		
						(-0.149)	(0.507)		
$HK_{i,t} \times Post_t \times IlliqD_{i,t}$						0.468*	0.343		
						(1.697)	(1.251)		
$LiqD_{i,t}$								0.099	0.472***
								(0.741)	(3.618)
$HK_{i,t} \times LiqD_{i,t}$								0.881***	0.610***
								(4.697)	(3.201)
$Post_t \times LiqD_{i,t}$								0.296	-0.101
								(1.428)	(-0.487)
$HK_{i,t} \times Post_t \times LiqD_{i,t}$								-0.862***	-0.541*
								(-2.939)	(-1.838)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-quarter observations	6024	3712	3088	3712	3088	3440	3440	5372	5380
$\overline{R}^2$	0.534	0.318	0.156	0.638	0.494	0.671	0.676	0.542	0.540

statistical significance, suggesting a weaker effect in this setting). Third, while HFT increases the cost of capital on average, we find that it reduces the cost of capital for the most liquid stocks, where HFTs are likely the primary liquidity providers.

The consistency of these findings with our U.S.-based results is noteworthy. It suggests, first, that our baseline conclusions regarding the causal impact of HFT on the cost of capital are robust and generalizable across countries. Second, it indicates that HFT affects the cost of capital in both highly fragmented and non-fragmented trading environments.

7. CONCLUSION

Investigating the market quality implications of HFT has been the focus of a thriving research stream in the market microstructure literature, with most studies focusing on the effects of HFT on traders and market participants. However, market quality is only valuable to the extent it serves its core economic purpose – facilitating asset allocation, hedging, diversification, and other vital activities that underpin the real economy. Hence, understanding HFT's effects on real economic factors is crucial, particularly from policymaking and regulatory perspectives. In contrast to the existing literature that focuses on the role of HFTs in market quality and, hence, on traders, we focus on the role of HFT for issuers – the corporations that rely on well-functioning capital markets to raise funds for their investment activities. While existing research offers insights into potential effects on market participants, deducing clear implications for firms' financing costs from extant studies is challenging because the overall effects of HFT are often ambiguous. Specifically, while it enhances certain market quality characteristics, it impedes others; therefore, it is not clear whether changes in market quality at the ultra-high frequency level can have an impact on low frequency corporate decisions.

We address the gap at the nexus of the real economy and HFT by directly investigating HFT's effects on one of the most fundamental real economy signals: the firm-level cost of capital. We mitigate potential endogeneity concerns and establish causality by exploiting speed-inducing technological upgrades on NASDAQ (co-location upgrade and order dissemination, submission, and data latency improvements) as exogenous shocks to HFT activity. We show that HFT, on average, increases the cost of capital. This aggregate effect is driven primarily by HFT's tendency to significantly increase systematic risk, particularly for low-beta stocks that previously co-moved less with the market. However, we also find evidence of heterogeneous effects: while HFT increases the cost of capital for the overall sample (driven by low-beta stocks), it reduces the cost of capital for the most liquid stocks, consistent with enhanced liquidity provision in these securities. To further test the generalizability of our results, we replicate the analysis using data from the Hong Kong Stock Exchange, a market that is essentially unfragmented. Our results remain consistent, suggesting that the impact of HFT on the cost of capital persists across different countries and market structures.

Our findings hold broad implications for practice, policymaking, and regulation. HFT has been the subject of intense debate among investors, brokers, exchanges, policymakers, regulators, and academic researchers. Detractors argue that HFTs unfairly harm traditional investors, while advocates claim that faster trading improves market quality and aids real economic activities such as asset allocation. This paper contributes to this debate by providing evidence on how HFT impacts the cost of capital. Specifically, our results suggest that the benefits and costs of HFT are not uniformly distributed across stocks, providing potential justification for exploring stock characteristics-dependent access to fast trading infrastructure from a risk-based regulatory perspective. As HFT appears to reduce the cost of capital for the most liquid stocks while increasing it for low-beta stocks, a more nuanced approach to HFT regulation, one that considers stock characteristics, may be warranted.

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Appendix A. Variable definition and data source

Variable	Definition (Compustat/CRSP item in parentheses)	Source
Calculation of Cost of Equity Measures		
$r_{i,d}$	Return (*ret*)	CRSP
$r_{f,d}$	Ten-year Treasury yield	FRED
$r_{m,d} - r_{f,d}$	Excess market return	
SMB_d	Difference between return on portfolios of small and big market capitalization stocks.	Ken French's website
HML_d	Difference between return on portfolios of high and low book-to-market stocks.	
$\beta_{i,t}$	Firm i's market beta in quarter t, estimated using daily return data via the Capital Asset Pricing Model (CAPM), by regressing the firm's excess return on the market excess return. See Eq. (1) in the main text.	
$r_{E,CAPM}$	Firm i's cost of equity in quarter t, computed using the estimated quarterly market beta $\hat{\beta}_{i,t}$ from CAPM, multiplied by the expected market excess return (i.e., the historical average), and added to the risk-free rate. See Eq. (2) in the main text.	
$r_{E,FF3}$	Firm's cost of equity in quarter t, calculated as the sum of the products of estimated Fama-French three-factor betas and the expected returns of the corresponding factor portfolios. See Eq. (3) and Eq. (4) in the main text.	
Calculation of Illiquidity Measure		
$Ask_{i,d}$	Ask price (*ask*)	CRSP
$Bid_{i,d}$	Bid price (*bid*)	

$V_{i,d}$	Number of shares traded (*vol*) times price (*prc*)	
$r_{i,d}$	Return (*ret*)	
$Relative\ Qspread_{i,t}$	Quarterly average of the daily relative bid-ask spread, calculated as the difference between the daily ask $Ask_{i,d}$ and bid prices $Bid_{i,d}$, divided by their average. See Eq. (5) in the main text.	
$ILLIQ_{i,t}$	Quarterly average of daily absolute return $\left\|r_{i,d}\right\|$ scaled by the dollar trading volume $V_{i,d}$. See Eq. (6) in the main text.	
Calculation of Firm Characteristics		
$SIZE_{it}$	Logarithm of total assets (*atq*).	
IK_{it}	Ratio of Investment expenditure (*capxy*) to total net property lant and equipment (*ppentq*).	
ROA_{it}	Return on average total assets, the ratio of operating income before depreciation (*oibdpq*) to the most recent two-year's total assets.	
ROE_{it}	Return on average common Equity, the ratio of income before extraordinary items (*ibq*) to the most recent two years' equity market value (*cshoq* * *prccq*).	
BM_{it}	Book value of equity (*seqq*) divided by the market value of equity (*cshoq* * *prccq*).	Compustat
$Lever_{it}$	Current liabilities (*dlcq*) plus long-term debt (*dlttq*) divided by total assets	
$Cash_{it}$	Ratio of cash and short equivalents (*cheq*) to total assets	
GP_{it}	Gross profit margin, the ratio of the difference between sales (*saleq*) and cost of good sold (*cogsq*) and sales.	
PPE_{it}	Ratio of the net property lant and equipment (*ppentq*) and total sales.	

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