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The Effect of High Frequency Trading Strategy Heterogeneity on Market Quality

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Abstract. This paper focuses on the strategic heterogeneity of high-frequency trading, and compares the differential impact of market making and strategic high-frequency trading on market quality. It is found that the heterogeneity of the two strategies is reflected in the dynamic transformation of strategies and the ability of information processing, and the two types of strategies can be transformed into each other, and the same trader can switch Market roles. This paper points out that future research needs to break through the simple dichotomy and build an innovative methodological framework that takes into account multi-dimensional identification, cross-market tracking, and dynamic evolution monitoring, to achieve the purpose of balancing the supply of market liquidity and curbing market bad operations, and ensuring the long-term stable development of the market. This paper not only systematically compares the heterogeneity of strategies in the four dimensions of micro behavior, information processing, cross platform transmission and dynamic evolution, but also embeds innovative identification methods such as transaction network topology, order book entropy quantification, causal breakpoint design and counterfactual simulation in each dimension, providing a methodological framework from static classification to dynamic structure analysis for future research.

Keywords: High Frequency Trading, Strategy Heterogeneity, Market Making High-frequency Trading, Predatory High-frequency Trading, Market Quality

1. Introduction

Over the past two decades, technological innovation has reshaped the global financial market, and the rise of high-frequency trading has become one of the core symbols. Such institutions complete transactions in microseconds with the help of complex algorithms, which have profoundly changed the market liquidity and price discovery mechanism. For example, high-frequency trading used to account for more than half of the trading volume of the US stock market [1,2], but it also triggered disputes about fairness and stability, such as the "flash crash" in 2010 and other events [3,4], making its complexity a core issue in the market.

High-frequency trading is not a homogeneous group. There are mainly four types of strategies, two of which are particularly extensive. First, the "market making type" earns bid-ask spread by continuously placing orders and plays the role of liquidity provider, which usually helps to reduce transaction costs and promote price discovery [1,5]. Second, the "predatory type" uses the speed

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advantage to "trade first" or uses the "deception" technique - a large number of orders are quickly withdrawn to manipulate the price, which has been clearly characterized as market manipulation and damages the quality of the market [6,7]. However, few existing studies have systematically compared the differences between the two under a unified framework.

This paper breaks through the homogenization perspective and provides a more refined analysis dimension through system comparison. In view of the limitations of the existing literature on strategy identification, this paper puts forward a series of innovative research methods, aiming to solve the core methodological problem of "how to effectively distinguish between market making and predatory strategies in a dynamic market". This paper is no longer limited to static behavior description, but advocates the introduction of interdisciplinary tools such as network science, information theory and causal inference to provide an operable technical path for future empirical research.

2. Micro basis of strategy classification: from behavior characteristics to role differentiation

2.1. Behavioral characteristics: identification and classification of high-frequency traders

The starting point of understanding the impact of high-frequency trading on the market is to accurately identify and distinguish its internal heterogeneity. In the analysis of the e-mini futures market during the "flash crash", some researchers provided a set of classic model forms of data-driven classification, and found that the accounts classified as high-frequency traders did not significantly change their trading mode during the crash, and the coordination relationship between inventory and price was consistent with the normal period, while the trading behavior of traditional market makers changed significantly [3]. This comparison reveals that market-making high-frequency trading lacks the obligation constraint of the traditional market maker, and its liquidity supply is based on the strategic choice under the consideration of profit, rather than unconditional market service [8]. The market-making behavior of high-frequency traders is essentially a profit strategy, and its sustainability depends on whether the market conditions are favorable. Just because high-frequency traders provide liquidity, it is equivalent to the behavior of traditional market makers, which will mislead understanding of market risk.

2.2. Role differentiation: multiple differentiation within high-frequency traders

Policy classification is complicated at the same time. Some researchers use the counterparty identification data provided by Nasdaq to distinguish each transaction of high-frequency traders into liquidity demand and liquidity supply, and find that the same high-frequency trader plays a different role in different directions. As a demander, its transaction is positively correlated with permanent price changes, which promotes price discovery and presents a "predatory" feature. As a supplier, its transaction is faced with the risk of adverse selection, which shows a "market making" behavior [1]. This shows that statically classifying an institution as a "market maker" or "Predator" may seriously not conform to the real market situation - the same institution may play two roles at the same time. Thus, the classification of strategies should not be based on the identity of traders, but on specific trading behavior. In order to capture the essence of strategy, especially when high-frequency traders deliberately disguise their behavior, future research methods should shift from "individual behavior statistics" to "group interaction structure" and "order quantitative analysis".

About the classification of strategies, some researchers have constructed a Stackelberg model from the perspective of game theory, pushing the strategy analysis from individual behavior to group

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interaction. The study found that the quotation strategy of representative market makers depends not only on their own inventory, but also on their prediction of the inventory behavior of other market makers [9]. At present, there are two equilibrium states in the market: when the competition between market players is fierce, there is a competitive state of low inventory sensitivity and narrow price difference; However, when they form implicit cooperation, they are in a cooperative state of high inventory sensitivity and wide price difference. "Market making" and "predatory" are not the inherent attributes of the two types of traders, but the expression of the same set of technologies in different market conditions.

To solve the problems caused by this phenomenon, the transaction network topology analysis method provides a new perspective; using this method is no longer to look at a single account in isolation, but to build a binary network of "traders" and "counterparties". From the above research, the market-making strategy is usually the more stable party in the network, with uniform node degree distribution and high clustering coefficient. On the other hand, the predatory strategy shows the side with attack characteristics, with high betweenness centrality and short-term variability of connections. Therefore, by calculating the dynamic evolution index of the network, people will have the opportunity to more accurately identify those predatory nodes that are hidden in individual statistics but abnormal in the network structure in the future.

In addition, for the identification of the order book level, the order book microstructure entropy analysis is helpful to quantify the market order. Unlike the simple cancellation rate statistics, this method can use Shannon entropy in information theory to measure the degree of chaos in the trading order. Market-making transactions tend to reduce entropy, making the price discovery process more orderly. Predatory trading will artificially create violent fluctuations in local entropy, such as deception. Future research can establish a strategy classification model based on the "order" and "chaos" dimensions by tracking the time series changes of entropy, so as to achieve a more essential distinction at the micro behavior level.

3. Asymmetric distribution of information processing capacity: "secondary utilization of information" and speed advantage

Some researchers found a two-stage model in the trading analysis of NASDAQ-listed companies before and after the financial report announcement, that is, the model of first obtaining information from providing liquidity for the market, and then realizing the information into the profits of active trading [10]. Therefore, this discovery reveals that the core advantage of high-frequency traders over non-high-frequency traders is that they have the full chain ability of information processing, and can switch freely between passive and active roles, so as to realize the intertemporal arbitrage of information. It is precisely this asymmetric distribution of capabilities that constitutes the fundamental source of predatory strategy profits.

The other side of the advantage of information processing is the advantage of execution speed. The researchers' research on the Istanbul stock exchange used the simulated market method to compare the arbitrage earnings of high-frequency traders and non-high-frequency traders, and found that high-frequency traders were faster than non-high-frequency traders to identify and use arbitrage opportunities, and the profits of the two were very different; the former was more profitable than the latter [11]. The quantitative results in the study attribute the profit advantage of the predatory strategy to the advantage of information processing and the advantage of execution speed, which are interdependent and mutually supportive. But speed itself is only a representation, and the real core is the integrity of the information processing chain.

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The root of speed advantage is equally important. From the perspective of market design, the researchers found that the continuous trading mechanism itself will generate arbitrage rent by analyzing the cross-market arbitrage opportunities of ES and spy [7]. Because the transaction is processed in series, the first arriving trader can monopolize the arbitrage opportunity, which leads to an endless race on "reserve resources". The core is that predatory strategy is not the product of pure technological progress, but the result of an endogenous equilibrium under specific market design.

To sum up, the information advantage of high-frequency traders is not an exogenous given technological endowment, but an endogenous strategic ability of market structure and trading mechanism. The market-making strategy obtains information through passive listing, and the predatory strategy realizes information through active trading. The two are mutually reinforcing. Therefore, attempts to curb predatory trading by restricting certain types of behavior may have limited benefits. As long as access to information, advantages and cash channels still exist, market forces will push traders to find new ways to express their strategies.

However, in order to deeply analyze the information-driven mechanism behind the strategy, future research methods must break through the boundary of single transaction data and turn to "multimodal data fusion analysis". That is to integrate high-frequency trading data and unstructured external data, extract the precise time and emotional direction of information impact by using natural language processing technology, and align it with the trading instruction flow in microseconds. This cross-validation of multi-source information will provide more accurate empirical evidence for distinguishing predatory strategies from market-making strategies.

4. Conduction effect of cross-platform behavior: spatial segmentation of liquidity supply and risk management

With the increasingly complex market structure, high-frequency traders are not limited to a single platform, so the distinction between market making and predatory strategies needs to be discussed again in the context of multi-platform interaction. Some researchers' research on the Swedish stock market provides empirical evidence for understanding this cross-platform behavior. The research found that when high-frequency traders trade with customers as market makers on proprietary platforms, they will reduce liquidity supply and increase liquidity intake on public exchanges in order to manage the resulting inventory imbalance. This behavior led to the decline of liquidity, the expansion of price spread and the reduction of depth of public exchanges, but the price efficiency was improved [12]. Therefore, it can be seen that the market-making behavior of high-frequency traders on the proprietary platform is at the expense of the liquidity of the public market, in exchange for the improvement of the overall market information efficiency. This research finding makes it possible to judge the market impact of high-frequency trading in the observation limited to a single place. This cross-platform strategic arbitrage is precisely one of the core characteristics that distinguish high-frequency traders from traditional market makers.

The complexity of cross-platform behavior is also reflected in the gradual change of the types of trading places. In the study of dark pool trading in the U.S. stock market, the researchers compared the evolution of dark pool trading in 2009 and 2020. The study found that the composition and impact of dark pool trading are significantly changing with the change of investor structure. In 2009, dark pool trading was mainly used by institutional investors to avoid large transaction costs, showing market-making characteristics. In 2020, with the influx of high-frequency traders and retail orders, dark pool trading will become more and more predatory [13]. It can be seen that the same trading platform may serve different types of strategies in different periods. The nature of the

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strategy depends more on the composition of the participants than on the system of the platform itself.

Cross-platform behavior patterns are becoming more and more complex, and the traditional classification criteria based on behavior characteristics are gradually showing defects. From the perspective of virtue ethics, researchers provide an analytical framework to distinguish between "natural" and "unnatural" market-making behavior. "Natural" market-making behavior serves the real economy and provides continuous liquidity supply; The purpose of "unnatural" market-making behavior is to obtain wealth and stop providing liquidity during the period of market pressure. This standard no longer judges which strategy is based on behavior characteristics, but also takes behavior intention and market impact into consideration [8]. Therefore, the strategy choice of high-frequency traders is the result of maximizing returns under the influence of multiple platforms in order to pursue risks. This behavior segmentation in space means that the regulatory measures of a single platform may have unexpected effects across platforms; that is, the policy of encouraging market-making behavior in one market may succeed at the expense of the liquidity of another market in the space.

However, the complexity of cross-platform behavior makes it difficult to establish a causal relationship by simple correlation analysis: is it cross-platform arbitrage that leads to market volatility, or does market volatility attract cross-platform transactions? To solve this endogenous problem, future research should introduce the "causal inference breakpoint regression design (RDD)". Researchers can use the technical threshold in the trading rules as the starting point, such as cross-market reporting threshold, high-frequency trading speed recognition standard, specific order size limit, etc. as the breakpoint to build the experimental framework. By comparing the structural mutations in the cross-platform behavior of accounts slightly above and slightly below these thresholds, people can effectively identify the critical point. If significant cross-market predatory characteristics are observed on one side of the breakpoint, and normal liquidity replenishment is observed on the other side, such as canceling orders in one market while trading in another market. Then this breakpoint effect can effectively prove that the cross-platform behavior belongs to a predatory strategy rather than normal market-making arbitrage. This method can promote the cross-platform research from simple phenomenon description to causal identification.

5. Dynamic evolution of strategy and market structure

The boundary between market-making strategy and predatory strategy is vague, and there is no clear boundary. The strategy of the same trader may change with market conditions, its own inventory and technical environment. In order to reveal this dynamic evolution, a research tool that can identify strategies in a controllable environment is needed. Some researchers have adopted the deep reinforcement learning method for the Hawkes process-driven limit order book market, and found a hybrid strategy: carry out aggressive trading with predatory characteristics to establish inventory in the early stage, and make profits through passive listing with market-making characteristics in the later stage [14]. This shows that the same algorithm plays different roles in different stages. Therefore, it is difficult to know the real and exact impact of static strategy classification. It can be seen that the classification of features should consider not only space, but also time. That is, those classifications based on short-term behavior are likely to produce bias. The existing research has a huge blind spot in this area, and it also needs recognition methods to monitor the dynamic evolution.

The key window period to observe the evolution of strategy is when the market is under pressure. In the "flash crash" study, researchers found that the behavior pattern of high-frequency traders during the crash was basically the same as that in the normal period, while the trading behavior of

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traditional market makers changed significantly [3]. Therefore, not only will market making high-frequency trading be forced to provide liquidity for the market due to the lack of obligation constraints, but its stability may be better than that of traditional market makers; And when the market needs liquidity most, high-frequency traders are likely to make choices according to the principle of profit maximization, rather than helping to stabilize the market.

Moreover, the dynamic evolution of strategy also depends on the market structure. The researchers simulated the dynamic impact of transaction tax in different market structures and found that moderate provision of tax rate in non-high-frequency trading dominated markets can help curb excessive trading and improve market quality, while in high-frequency trading active markets, the adjustment of tax rate will not have too much impact [15]. It can be seen that the same strategy may have different effects in different trading environments. For example, market-making strategies are sensitive to liquidity, while predatory strategies are more sensitive to the transparency of information.

This dynamic transformation brings great challenges to strategy evaluation, that is, it is difficult to determine the true net effect of a certain type of strategy under extreme market conditions. The traditional historical back test can not remove the interference of other factors, so the future research methods should vigorously promote counterfactual simulation and removal experiments. Researchers can reconstruct historical extreme markets (such as the "flash crash") and conduct systematic removal experiments. That is, in the simulation, the transaction records of suspected market making or predatory accounts are removed, respectively, and then the counterfactual path of market quality indicators (such as price difference, depth, volatility, etc.) is observed.

If, after removing a certain type of account, the simulation market shows that the bid spread has expanded significantly and the liquidity has dried up, it proves that this group mainly plays a market-making function in reality. On the contrary, if the market volatility decreases significantly and the price recovery speed accelerates after removing some accounts, it proves that these accounts have predatory characteristics. This method of controlling variables can dynamically and quantitatively peel off the real contributions of different strategies in the process of market evolution, and provide rigorous methodological support for understanding the dynamic heterogeneity of strategies.

6. Conclusion

The strategy heterogeneity of high-frequency trading is the key to understanding the microstructure of modern financial markets. Through the previous analysis of micro behavior identification, information processing mechanism, cross-platform transmission effect and dynamic evolution of strategies, this civilization has confirmed that market making and predatory strategies are not two distinct types of subjects, but the dynamic equilibrium results of interweaving and transforming each other in a complex market environment. Most of the existing studies rely on a single behavior index for classification, which has a large deviation. Research limited to single market data is also difficult to capture the spatial segmentation characteristics of high-frequency traders' strategies. At the same time, the previous research conclusions of mature markets in Europe and the United States may not apply to emerging markets, and the instantaneous transformation of strategy with the market environment poses a fundamental challenge to the traditional static classification method. Therefore, the core challenge of high-frequency trading research is not to simply label behaviors as "good" or "bad" but to understand how these behaviors evolve in a complex market ecology.

Based on this, future academic research should be deepened in the following directions. First, build a multi-dimensional strategy identification framework, integrate multi-dimensional indicators

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such as transaction frequency, order cancellation rate, transaction network topology and order book entropy, and shift from "individual research" to "structural order" analysis. Second, develop cross-platform data integration and causal identification methods, develop technologies that can monitor the complete behavior trajectory of the same trader in different exchanges, dark pools and proprietary platforms, and use the technical threshold in the trading rules to build breakpoint regression design, to evaluate the real impact of the strategy from the perspective of causal inference. Third, deepen the empirical test and multimodal data fusion of local market microstructure, deeply analyze the unique trading mechanism of emerging markets such as China, integrate diversified data such as news texts and social media sentiment trends, and establish an empirical test framework in line with specific market situations. Fourth, establish an early warning model and counterfactual simulation mechanism for the dynamic evolution of strategy, use time series analysis and deep reinforcement learning methods to identify the early signals of strategy transformation, and accurately quantify its impact on market quality through counterfactual removal experiments. Future research should shift from static classification to dynamic structure analysis, from single data source to multi-source information fusion, and from correlation description to causal identification, providing a more solid support for understanding the strategic heterogeneity of high-frequency trading.

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