# Do Exogenous Uninformed Order Flows Move Stock Prices?

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**ABSTRACT**

The literature suggests that stock prices can be influenced by exogenous order flows, even when they do not convey any information about future cash flows. Empirical studies employ various identification strategies to test this hypothesis, though identifying a truly exogenous, large-scale order flow that is uncorrelated with cash flow news remains challenging. In this paper, we analyze a large, exogenous, unprecedented asset purchase program around the boundaries of the CSI 500 and CSI 1000 indices. These boundaries are determined by market capitalization rankings well in advance of the asset purchase program. Stocks in the CSI 500 index receive a significant exogenous purchase equivalent to 4.49% of their market capitalization, while stocks in the CSI 1000 index receive only 0.51%. We find the CSI 500 stocks result in a 6.4% higher Fama-French 5-factor alpha.

***Keywords***: Demand-based Asset Pricing, Price Multipliers, Regression Discontinuity

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If stock prices are dictated by discounted future cash flows, then an exogenous order flow uncorrelated with future stock fundamentals should not be able to move prices. However, a long-standing body of literature suggests that the demand curve for stocks is downward sloping, even in the absence of fundamental information.[1] Financial economists have attempted to use various identification methods to test this hypothesis and to calibrate this demand elasticity or "price multiplier" (M)—that is, "investing $1 in the stock increases its market value by $M." Table I summarizes their estimations.

**Table I**

**Price Multiplier Summary**

Table I presents multiplier estimates from existing literature, organized by four methods: index reconstitution (Panel A), mutual/hedge fund flows and rebalances (Panel B), price impact of order execution (Panel C), and dividend, stock repurchase, IPOs, and SEOs (Panel D). The multiplier is defined as the percentage change in prices resulting from a percentage change in shares outstanding, corresponding to the amount purchased or sold by an investor. This table provides a straightforward report of the "prima facie" estimates from these studies. The table is adjusted based on Gabaix and Koijen (2022).

Panel A: Index reconstitution

| | Multiplier |
|---|---|
| Chang, Hong and Liskovich (2014) | 0.7 to 2.5 |
| Pavlova and Sikorskaya (2023) | 0.3 to 0.5 |
| Ben-David, Li, Rossi and Song (2020a) | 5.3 |
| Panel B: Mutual fund/hedge fund flows and rebalances | |
| Lou (2012) | 1.2 |
| Peng and Wang (2021) | 4.8 |
| Li (2022) | 5.7 |
| Da, Larrain, Sialm and Tessada (2018) | 2.2 |

[1] See, for example, Schleifer (1986), Koijen and Yogo (2019), Gabaix and Koijen (2022).

| Panel C: Price impact of order execution | |
|---|---|
| Frazzini et al. (2018), Bouchaud et al. (2018) | 15 |
| **Panel D: Dividend, Stock repurchase, IPO, and SEO** | |
| Li, Pearson and Zhang (2021) | 2.6-6.5 |
| Schmickler (2020) | 0.8 |
| Hartzmark and Solomon (2022) | 1.5-2.3 |

Economists still struggle to identify an order flow that is free from endogeneity issues. For example, stock repurchase programs, IPOs, and SEOs are related to private information about the firm itself, which contaminates the estimation of price elasticity (Li, Pearson, and Zhang [2021]). Additionally, index inclusions, dividend payouts, mutual fund flows, and pension fund rebalances are largely predictable. As a result, their price impacts are largely absorbed by the market or "front-run" (Brunnermeier and Pedersen [2005]). Finally, institutional order executions (e.g., from Ancerno data) may also contain private information about cash flows, making them less than "pure" estimations of the price multiplier. To estimate M accurately, we need a large enough exogenous order flow that is largely unpredicted, unprecedented, and uncorrelated with the firm's future cash flow information.

In this paper, we examine one such order flow. In July 2015, the Chinese government launched an emergency asset purchase program valued at $150 billion (approximately 5% of the market capitalization of the mainland Chinese stock market) to bolster stock prices. A stock purchase program of this size was unprecedented in Chinese history and, as of July 2024, remains

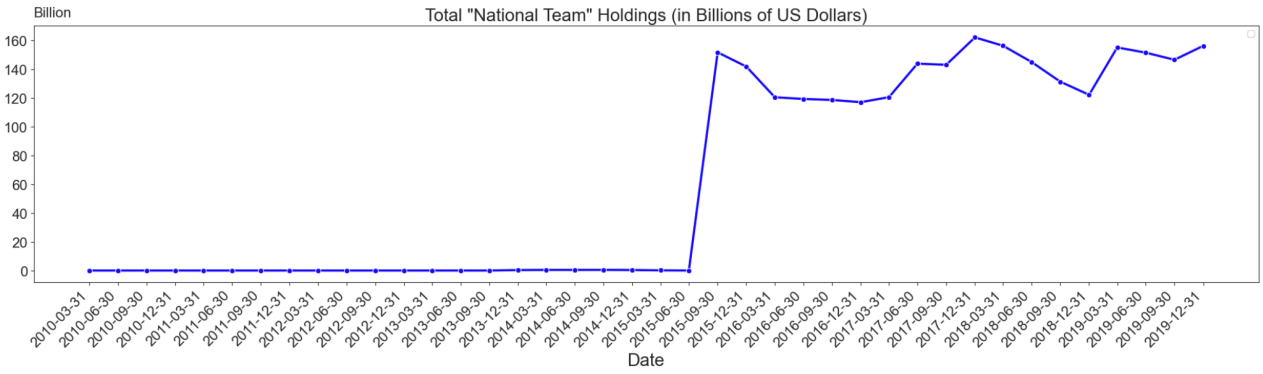
the second largest stock purchase program in the world.[2] Panel A of Figure 1 shows the total dollar holdings of the "National Team" over time. The "National Team" abruptly acquired a sizable fraction of the stock market in Q3 2015,[3] and their holdings have remained largely flat since.

We find that the "National Team" swept the market based on stock index membership, which was pre-determined by the market cap rankings one year before the ranking day (April 30, 2015). Therefore, the order flows are not correlated with any private information or firm fundamentals, [4]except for historical market caps. Specifically, the CSI 300 index consists of stocks ranked 1st–300th by market cap, the CSI 500 index consists of stocks ranked 301st–800th, and the CSI 1000 index consists of stocks ranked 801st–1800th. As shown in Panel B of Figure 1, we find that the National Team purchased 4.18% of the market cap of CSI 300, 4.49% of CSI 500, and only 0.51% of CSI 1000 constituents. Stocks ranked just above 800th (referred to as the "treated group") received significantly more purchases than those ranked just below 801st (the "control group") for exogenous reasons. This creates an ideal setting for testing the price elasticity of stock markets.

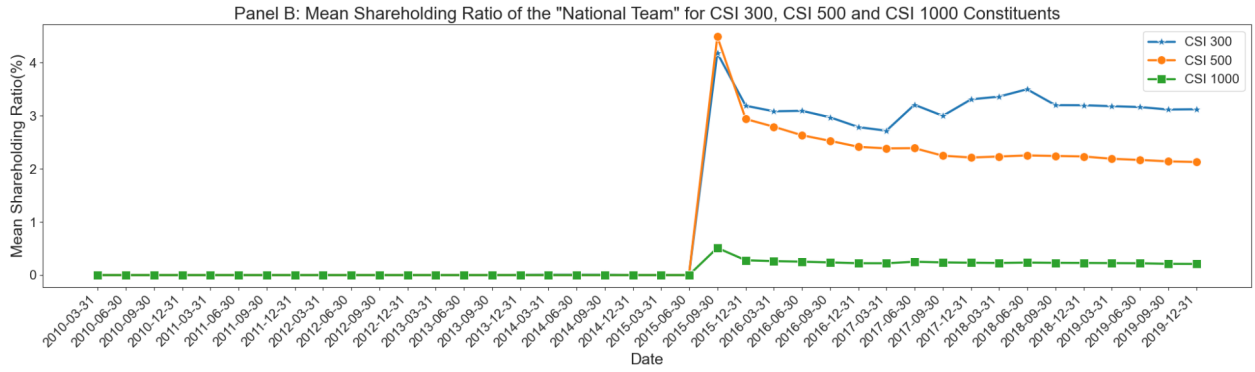
[2] The largest is the stock purchase program by the Bank of Japan, sized around $300bn, in purchasing Japanese stock ETFs (Katagiri and Takahashi [2022]). The BOJ pre-announce their purchases, and it spans over a long period of 10 years.

[3] We manually process the Chinese version of 13-F holdings in identifying holders and “National Teams”, which is a quarterly data. Anecdotal evidences indicate that most of the purchases happened between July 4th and July 21st, the first few weeks of 2015Q3. Indeed, the abnormal alphas also appear in July, while there’s no reversal in August and September.

[4] As a robustness check, Section III.D checks the profitability of the stocks after the national team purchases. We do not observe significant differences in the profitability, which reassures the validity of our identification assumption that the national team’s order flow does not contain future cash flow information.




**Panel A. The aggregated dollar holdings of the National Team**




**Panel B. National Team purchases for CSI 300, CSI 500, and CSI 1000 constituents**

**Figure 1. Profile of the "national team" purchases.** Panel A illustrates the change in the dollar value of the National Team's shareholdings from March 31, 2010, to December 31, 2019. Panel B illustrates the National Team's shareholding ratio as a fraction of market cap. The orange line represents CSI 500 stocks, and the blue line represents CSI 300 stocks. The green line represents CSI 1000 stocks. Each quarter, we first sort the shareholding ratio of the national team holders and then calculate the average shareholding ratio for the CSI 300, CSI 500 stocks and CSI 1000 stocks respectively. The data span from the first quarter of 2010 to the last quarter of 2019 and are collected from CSMAR.

We consider 100 pairs of stocks as the treated and control groups. The treated group receives an exogenous order flow worth 5.77% of their market cap, while the control group receives only 0.76%. As a result, we find that the treated stocks' FF5 alpha in Q3 2015 is 6.4% higher than that of the control stocks. This difference allows us to estimate the price multiplier as $M =$

$\frac{6.4\%}{5.77\%-0.76\%} = 1.28$. Our result is robust when considering 50 or 150 stocks around the CSI 500/CSI 1000 boundary. In a placebo test, we find that the National Team's order flows on CSI 300 and CSI 500 stocks are similar, and there is no significant return difference between the bottom stocks of CSI 300 and the top stocks of CSI 500. Additionally, we do not observe significant reversals in the return gaps between the treated and control groups.

Our data also allows us to address the question: "Who are the marginal investors that would sell in response to an exogenous purchase flow?" The National Team purchased stock equivalent to 5.77% of the market cap of the treated group. We find that small investors' holdings sharply declined by 5.0% of the market cap, roughly matching the purchase size of the National Team in the treated group. In the control group, the National Team purchased only 0.7%, and small investors sold just 0.4%. The holding structures of other types of investors, as well as in the control stocks, remain largely unchanged. Thus, we identify small investors as the main sellers in response to exogenous purchase flows. The National Team's holdings have been long-lasting for years, leading to a structural change in the investor base of these firms. We do not observe any reversal or rebalancing between small and large investors.

To our knowledge, we are the first to identify the sharp cliff in the National Team's purchases around the CSI 500/CSI 1000 breakpoint. The National Team was ambiguous about which stocks they were going to buy, and market participants largely learned this information through the firms'

2015 Q3 quarterly reports, which were disclosed months later (Huang, Miao, and Wang [2019]).[5] Therefore, the stocks around the CSI 500/CSI 1000 breakpoint arguably received a clean exogenous shock in non-fundamental order flows. The appendix lists the 100 stocks that barely made it into CSI 500 and the 100 stocks that barely missed. We encourage future research to apply this identification strategy to more topics, such as corporate governance, liquidity, and long-term impacts.

The paper proceeds as follows. Section I introduces the data and methodology. Section II discusses the national team's holding change and its price impact. Section III discusses robustness checks. Section IV concludes.

## I. Data and Methodology

### *A. Data*

The stock characteristics and return data are collected from the China Stock Market and Accounting Research (CSMAR) database. For this study, we utilize transaction data from CSMAR's China Stock Market Trading Database, which provides comprehensive information such as stock and market returns with reinvested cash dividends, top shareholders and their shareholding ratios, closing prices, and other relevant data described in the following table.

[5] There are a few exceptions that the market learned about the purchase sooner, mostly because the firm was required to disclose the change in its largest shareholder. Those announcements are scarce and late. For example, the first such announcement was made on August 3, 2015 by Meiyan Jixiang Hydropower Co., Ltd., which is later than the CSI 500 stocks' FF5 alpha showed up in July.

Importantly, firms disclose their top shareholders on a quarterly basis, and our analysis focuses on the shareholding ratios of the Top 10 shareholders.

**Table II**

**Variable descriptions**

| *Variable of interest* | Description |
|---|---|
| *PB* | Price-to-book ratio: (today's closing price * total share capital) / total ending value of owners' equity in the previous year |
| *Momentum* | 12 months – 1 month return before portfolio formation |
| *Ln(Mktcap)* | The logarithm of the daily average total market value (the product of the total number of shares and the closing price) from May 1, 2014 to April 30, 2015 |
| *National Team Shareholding Ratio* | Share holdings by the "National Team" divided by the total shares outstanding |
| *Quarterly Return* | Daily stock returns considering cash dividend reinvestment |
| *ROE* | Net profit/shareholders' equity balance |
| *ROA* | Net profit/total assets balance |
| *Asset to Debt Ratio* | Total Liabilities/Total Assets |
| *Age* | Company age until 2015 |
| *Ownership* | 1-State-owned enterprises, 2-private enterprises, 3-foreign-owned enterprises, 4-others |

*B. China Securities Index (CSI) membership and Sample Selection*

According to the announcement by the China Securities Index Company, CSI membership is ranked by market capitalization and is updated biannually. Specifically, adjustments to the sample stocks are implemented on the next trading day following the second Friday of June and December each year. In 2015, the membership change occurred on Monday, June 15. Therefore, the membership remained unchanged between June 15 and December, and we use the membership data from this period. The CSI Company sorts the average market capitalization of stocks between May 1, 2014, and April 30, 2015, and we replicate their approach to calculate the market cap breakpoints. For the June 15, 2015 reconstitution, we find that the CSI 300/CSI 500 market cap breakpoint is 17.37 billion CNY (2.48 billion USD), and the CSI 500/CSI 1000 market cap breakpoint is 5.13 billion CNY (0.73 billion USD).

To form two comparable groups of stocks from the two indexes, we focus on the stocks near the CSI 500/CSI 1000 market cap breakpoints. In addition to market capitalization, we match stocks based on two additional characteristics: price-to-book value (P/B) and momentum, to further control for stock characteristic heterogeneities.[6] We apply the propensity score method (Rosenbaum and Rubin, 1983). For market cap and P/B, we use data as of June 30, 2015, and for momentum, we calculate the average daily returns from July 1, 2014, to May 31, 2015. After propensity score matching, we obtain 162 pairs of similar stocks in total and select the 100 pairs

[6] Previous literature often excludes the bottom 20% market cap of Chinese A shares because they are illiquid and their pricing are driven by M&A values (see, e.g., Massimo and Xu, 2013). We confirm that all CSI 500 and CSI 1000 stocks are in the top 80% market cap.

with the highest propensity scores as our sample stocks. This selection results in 100 stocks that barely made it into the CSI 500 and 100 stocks that are in relatively advanced positions within the CSI 1000—essentially, stocks that barely missed inclusion in the CSI 500.

*C. National Team Member*

By the end of June 2015, the CSI 300 index had fallen 18.88% over the course of three weeks, marking the fastest decline in the index since its inception. The CSI 500 fell by 23.67%, and the CSI 1000 dropped by 23.94% during the same period. In response to the stock market crash, the Chinese government decided to create a National Team to provide strong support to the stock market (Li and Liu [2024]). On July 4th, they intervened by injecting approximately 150 billion USD into the stock market. The list of stocks to be bought was not announced, and the market only learned this information from the firms' quarterly reports.[7] Central Huijin Investment and China Securities Finance were the primary entities leading this initiative. Additionally, 50 Chinese securities firms collectively invested over 200 billion yuan (28 billion USD), coordinated by the China Securities Finance Corporation.[8]

[7] 2015Q3 quarterly reports are generally released in October and early November, which is several months after the national team's purchase concludes.

[8] We exclude 8 state-owned companies held by China Securities Finance Corp and Central Huijin Investment Company Limited on behalf of the Chinese government. These companies have been held by the national team for an extended period, and their holdings were unchanged throughout the year 2015. The central government hold more than 50% of their market cap. Thus, it is not fair to count them as the national team's rescue money. Therefore, we exclude these 8 stocks in calculating the exogenous national team rescue funds. In addition, these companies are among the largest firms in China. They are not members of CSI 500 and CSI 1000 indices, nor do they affect our estimation of the price multiplier. The 8 state-owned companies are Sinopec, Agricultural Bank of China, New China Life Insurance, Industrial and Commercial Bank of China, China Everbright Bank, PetroChina, China Construction Bank, and Bank of China.

The shareholding ratios of these National Team members are included in the firms' quarterly reports, and we match these fund names with the CSMAR data to retrieve their shareholding ratios. For each sample stock group, we calculate both the mean and the sum of the National Team members' shareholding ratios.

*D. Shareholders' Categories*

It is particularly interesting to analyze which shareholders sold stock shares to the National Team. Shareholders can be categorized into two main groups: large shareholders (disclosed by the firm) and small investors. Large shareholders are further divided into six subcategories: the National Team, natural persons, the social security fund, mutual funds/hedge funds, Shanghai-HK Stock Connect (foreign investors), and nonfinancial (industrial) investors. For each category, we manually filter the shareholding ratios based on shareholder names as follows.

The National Team is identified by searching for the members' names among the shareholders. Natural persons are filtered by limiting the length of shareholders' names to two or three Chinese characters. Names with four characters are manually checked, and we verify that no natural person with a name longer than four characters is included. The social security fund is identified using the keyword "social security." Mutual funds or hedge funds are identified by searching for the keyword "securities investment fund," which is the standard suffix required by Chinese regulation. Shanghai-HK Stock Connect is filtered by searching for "Hong Kong Securities Clearing Company Limited (HKSCC)" among the shareholders. Aside from these financial investors, other

top investors disclosed by the firm are categorized as industrial investors. Shareholders who do not appear on the list of top investors are considered small investors.

*E. Regression Discontinuity*

Regression Discontinuity (RD) is typically used as a cutoff point for assigning treatment. Since the Chinese Securities Index is sorted by market capitalization, and our sample of 200 stocks includes those just below and just above the CSI 500 threshold, RD is an effective method to study the impact of exogenous cash flow. This approach assumes that stocks near the cutoff are similar, except for the treatment. We create a binary variable, *if_500*, to denote the different groups: if a stock is from the CSI 500, then *if_500* = 1; if a stock is from the CSI 1000, then *if_500* = 0.

Upon aggregating the shareholding ratios for the National Team members, we observe a clear discrepancy in the National Team's shareholding ratios between the CSI 500 and CSI 1000 samples.

*F. Fama French Five Factors and Carhart Four Factors Regressions*

To determine the excess return generated by the exogenous flow, we conduct Fama-French five-factor and Carhart four-factor regression analyses for the period from May 2015 to December 2015. The Chinese Fama-French factors are sourced from Li et al. (2023). The five factors are market risk premium (RMRF), size (SMB), value (HML), profitability (RMW), and investment (CMA). The Carhart four factors include the Fama-French three factors along with momentum. First, we regress the past 36 months (from July 2012 to June 2015) returns of the sample stocks on

the Fama-French five factors and Carhart four factors to obtain stock-specific loadings for those factors. Next, predicted returns are calculated as the sum of the products of the five/four factors and their respective loadings. Finally, alphas are derived by subtracting the predicted returns from the realized returns for each month.

## II. Empirical Results

### *A. Matched Treated and Control Groups*

Using propensity score matching, we identify 100 stocks that barely made it into the CSI 500 and 100 stocks that are in relatively advanced positions within the CSI 1000—essentially, stocks that barely missed inclusion in the CSI 500. We match the stocks based on three characteristics: market capitalization, P/B ratio, and momentum. For the first two characteristics, we use data from June 15, 2015, and for momentum, we use the average of daily returns from July 1, 2014, to May 31, 2015. Table III presents the summary statistics of the matched stock pairs.

Table III shows that the two groups of stocks are well-matched in terms of P/B ratio and momentum. Although other control variables were not used in the matching process, the two groups are also similar across those dimensions. The only notable difference is in market capitalization, which is by design. However, this difference in market cap cannot explain the difference in returns for two reasons. First, the market capitalization of our treated group ranges from the 18.38th to 21.00th percentile of the entire market, while the control group ranges from the 21.03rd to 23.63rd percentile. The Fama-French size factor's return (smallest 30% of stocks minus largest 30% of stocks) in Q3 2015 is only -0.60%, meaning the size factor is unlikely to

have affected our treated and control groups differently. Nevertheless, we use FF5 alpha as the main metric for return differences, as raw return differences are largely the same. Second, in Section A of the robustness tests, we consider a smaller bandwidth of 50 stock pairs, and the results remain consistent. In summary, our treated and control groups are very similar ex-ante.

**Table III**

**Descriptive statistics of sample stock pairs**

Table III summarizes the descriptive statistics of the sample stock pairs. The national team shareholding ratio is the proportion of shares held by the national team in the third quarter of 2015, and we aggregate all national team members' shareholdings. We calculate the monthly return for each stock using the sum of the logarithms of daily returns. Return on equity (ROE) and return on assets (ROA) are measures of financial performance for a stock. The asset-to-debt ratio is calculated as total debt divided by total assets, and we obtain this ratio directly from the dataset. We use data from June 30, 2015, for ROE, ROA, and the asset-to-debt ratio. Company age is determined by the number of years from the listing year of the stock to 2024. Ownership is categorized as state or non-state, with state-owned companies assigned a value of 1 and non-state companies assigned a value of 0. If the ownership is a mixture of state and other types (private, foreign-invested, and others), we still assign a value of 1 to indicate state identity. The end date of the ownership status is December 31, 2015. All data are collected from CSMAR.

| | CSI500 | | | CSI1000 | | | t-value |
|---|---|---|---|---|---|---|---|
| | Median | Mean | SD | Median | Mean | SD | |
| PB | 4.015 | 4.120 | 1.547 | 4.312 | 4.428 | 1.515 | 1.420 |
| Momentum | 0.004 | 0.004 | 0.001 | 0.004 | 0.003 | 0.001 | -0.872 |
| Ln (Mktcap) | 15.788 | 15.768 | 0.143 | 15.304 | 15.264 | 0.136 | -25.570*** |
| National Team Shareholding Ratio | 4.688 | 5.765 | 3.710 | 0.461 | 0.758 | 1.354 | -12.679*** |
| ROE | 0.028 | 0.028 | 0.036 | 0.023 | 0.018 | 0.060 | -1.395 |
| ROA | 0.014 | 0.016 | 0.020 | 0.013 | 0.014 | 0.021 | -0.539 |
| Asset to Debt Ratio | 0.470 | 0.459 | 0.188 | 0.422 | 0.448 | 0.207 | -0.407 |
| Age | 15.000 | 13.590 | 5.842 | 12.000 | 11.960 | 6.452 | -1.872 |
| Ownership | 1.000 | 0.560 | 0.499 | 1.000 | 0.540 | 0.501 | -0.283 |
| Observations | | 100 | | | 100 | | |

*p<0.05, **p<0.01, ***p<0.001

The most dramatic difference, however, comes from the National Team's shareholding ratio. The mean National Team shareholding ratio for CSI 500 stocks is 5.77% of the market cap, while for CSI 1000 stocks it is only 0.76%. This indicates that the National Team invested nearly five

times more in CSI 500 stocks than in CSI 1000 stocks. This observation forms the basis of our identification strategy.

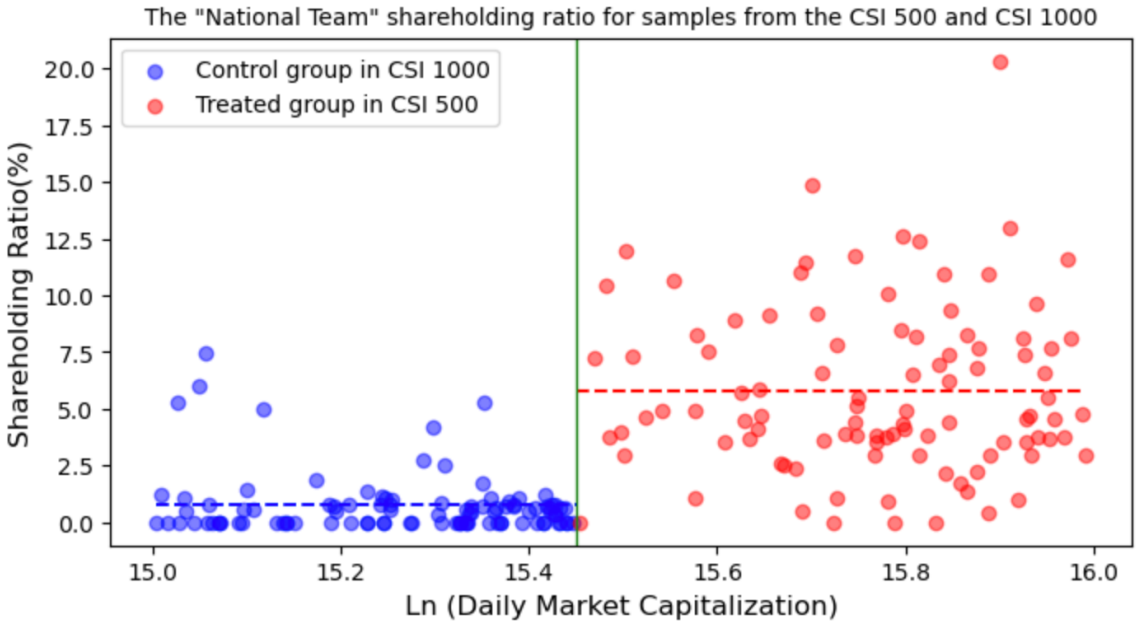



**Figure 2. The national team shareholding ratio for sample stocks.** This graph illustrates the national team shareholding ratio for a sample of 100 stock pairs. Blue dots represent stocks in the CSI 1000, while red dots represent stocks in the CSI 500 with higher market capitalization. Dashed lines indicate different levels of national team shareholding ratio. The blue dashed line corresponds to the CSI 1000 group, and the red dashed line corresponds to the CSI 500 group. The horizontal axis represents the natural logarithm of the sum of daily market capitalizations from May 1, 2014, to April 30, 2015. The vertical axis shows the national team shareholding ratio as a percentage. Data for this graph are sourced from CSMAR.

Figure 2 illustrates a distinct discontinuity in the national team shareholding ratio between the two index groups. The national team acquired 5.76% of the market capitalization of stocks that narrowly made it into the CSI 500, whereas they made minimal purchases of CSI 1000 stocks.

*B. Return differences between treated and control groups*

**Table IV**

**Fama-French Five Factors Regression Results**

This table presents the excess returns derived from Fama-French five-factor regressions. The Chinese Fama-French factors are sourced from Li et al. (2023) and include market risk premium (RMRF), size (SMB), value (HML), profitability (RMW) and investment (CMA). Missing values in monthly stock returns are substituted with 0. T-statistics obtained from paired t-tests are reported in parentheses. The dataset comprises 200 observations for all months. Data are collected from CSMAR and Li et al. (2023).

| | May | June | July | August | September | October | November | December |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Constant | -0.045 | 0.030 | 0.172 | 0.022 | -0.020 | 0.029 | -0.008 | 0.015 |
| | (-5.693)*** | (1.977)* | (12.311)*** | (1.470) | (-1.462) | (1.876) | (-0.339) | (1.195) |
| If_500 | 0.007 | -0.015 | 0.064 | -0.026 | 0.008 | -0.028 | 0.003 | -0.013 |
| | (0.617) | (-0.814) | (3.941)*** | (-1.265) | (0.468) | (-1.361) | (0.118) | (-0.791) |
| Observations | 200 | 200 | 200 | 200 | 200 | 200 | 200 | 200 |
| Adjusted-$R^2$ | -0.003 | -0.002 | 0.045 | 0.003 | -0.004 | 0.005 | -0.005 | -0.002 |

*p<0.05, **p<0.01, ***p<0.001. t-statistics are reported in parentheses.

The table IV illustrates that compared to stocks that narrowly missed inclusion in the CSI 500, stocks impacted by the exogenous cash flow achieved a significantly higher FF5 alpha of 6.4%, which is significant at the 1% level. In other months, FF5 alphas are not statistically significant and are relatively small in absolute value. Given that stocks in the CSI 500 group received approximately 5% cash flow from the national team, the demand elasticity is estimated at 1.28 (6.4% / 5.0% = 1.28).

We reach a similar conclusion using the Carhart four-factor regression presented in Table V. The coefficient of *'if_500'* is statistically significant for July, indicating that stocks in the CSI 500 generated a 6.7% excess return compared to those in the control group. The estimated demand elasticity is 1.34 (6.7% / 5.0% = 1.34).

## Table V

## Carhart Four Factors Regression Results

This table presents the excess returns derived from Carhart four-factor regressions. The Chinese Fama-French factors are sourced from Li et al. (2023) and include market risk premium (RMRF), size (SMB), value (HML) and momentum. Missing values in monthly stock returns are substituted with 0. T-statistics obtained from paired t-tests are reported in parentheses. The dataset comprises 200 observations for all months. Data are collected from CSMAR and Li et al. (2023).

| | May | June | July | August | September | October | November | December |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Constant | -0.031 | 0.021 | 0.160 | -0.017 | -0.029 | 0.032 | -0.014 | 0.013 |
| | (-3.960)*** | (1.498) | (11.513)*** | (-1.082) | (-2.432)* | (2.015)* | (-0.598) | (1.114) |
| If_500 | -0.001 | -0.013 | 0.067 | -0.020 | 0.001 | -0.031 | -0.009 | -0.022 |
| | (-0.062) | (-0.795) | (4.030)*** | (-0.960) | (0.079) | (-1.504) | (-0.308) | (-1.548) |
| Observations | 200 | 200 | 200 | 200 | 200 | 200 | 200 | 200 |
| Adjusted-$R^2$ | -0.005 | -0.002 | 0.051 | -0.000 | -0.005 | 0.008 | -0.005 | 0.007 |

*p<0.05, **p<0.01, ***p<0.001. t-statistics are reported in parentheses.

*C. Who sold to the exogenous purchase flow?*

In this subsection, we examine the sources of the shares purchased by the exogenous order flow. Figure 3 illustrates a notable increase in the mean shareholding ratio for the national team during the third quarter of 2015. Concurrently, there is a distinct decline in the shareholding ratio of small investors. In contrast, the ratio for other investors shows no significant decrease or fluctuations. This suggests that small investors were the primary sellers of shares.

The table VI presents specific data for seven types of investors. It is evident that the national team entered the market in the third quarter of 2015, with the rescue fund's ratio on the CSI 500 group to CSI 1000 group approximately 5:1. During this quarter, natural persons among the top 10 shareholders of CSI 500 sold their shares to the national team, whereas this proportion did not

experience a significant decline for the CSI 1000 group. Similarly, the social security fund sold shares in the CSI 500 group but purchased shares in the CSI 1000 group. Mutual funds or hedge funds sold their shares in both groups. Foreign investors via the Shanghai-Hong Kong Stock Connect sold shares in the CSI 500 group but saw no significant change in the CSI 1000 group. Industrial investors' shareholding ratios changed negligibly in both groups.

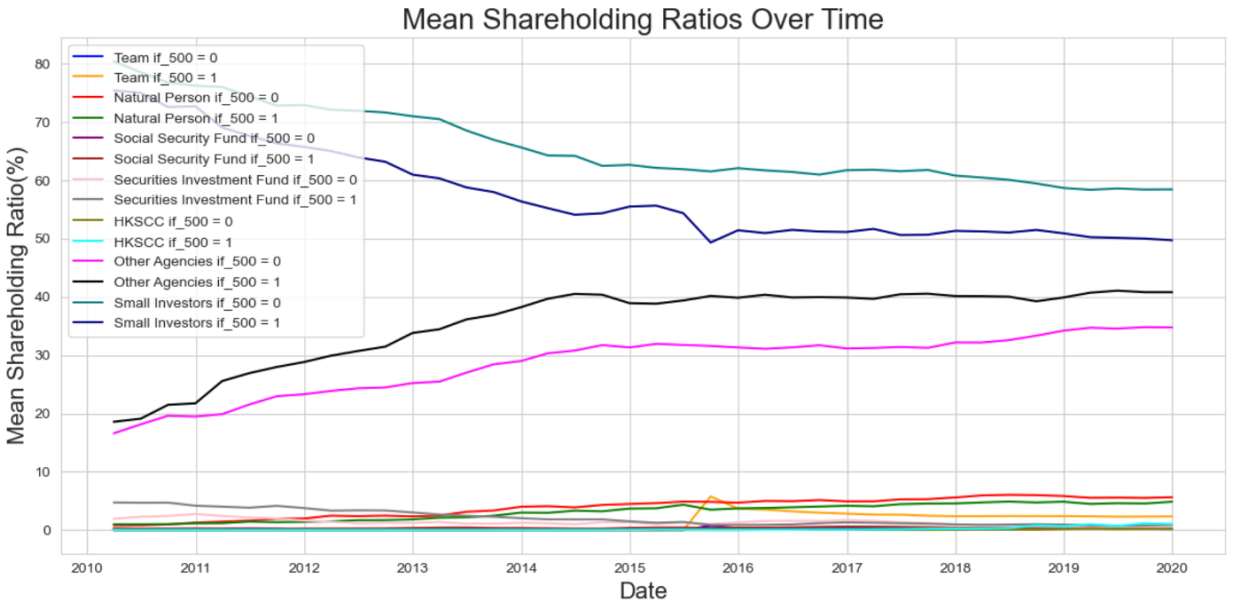



**Figure 3. Mean shareholding ratio of different categories of investors.** Shareholders can be classified into two primary groups: large shareholders (Top 10) and small investors. Among large shareholders, there are six distinct subcategories: the national team, natural persons, the social security fund, mutual funds/hedge funds, Shanghai-HK Stock Connect, and nonfinancial investors. Each category's shareholding ratio is filtered based on specific criteria. The national team is identified by searching for its members' names among the shareholders. Natural persons are filtered by restricting shareholder names to two or three characters. After excluding natural persons, we manually verify remaining shareholders to ensure no names longer than three characters are included. The social security fund is identified using the keyword "social security fund." Shareholders containing this keyword are categorized under the social security fund for shareholding ratio purposes. Mutual funds or hedge funds are identified by searching for the keyword "securities investment fund." Shanghai-HK Stock Connect participants are filtered by identifying "Hong Kong Securities Clearing Company Limited (HKSCC)" among shareholders. Apart from these financial investors, other Top 10 investors are categorized as nonfinancial investors. Data for this graph are sourced from CSMAR.

## Table VI

## Shareholding ratio changes in the last three quarters of 2015

This table presents detailed shareholding ratios (%) for various categories of shareholders in two stock groups from the second quarter of 2015 to the fourth quarter of 2015. These categories are defined according to the rules outlined in the methodology.

| Shareholders | | If_500 = 1 | | | If_500 = 0 | | |
|---|---|---|---|---|---|---|---|
| | | 2015-06-30 | 2015-09-30 | 2015-12-31 | 2015-06-30 | 2015-09-30 | 2015-12-31 |
| Large Shareholders (TOP 10) | National Team | 0.000 | 5.765 | 3.667 | 0.000 | 0.758 | 0.332 |
| | Natural Persons | 4.342 | 3.486 | 3.718 | 4.873 | 4.825 | 4.691 |
| | Social Security Fund | 0.435 | 0.352 | 0.418 | 0.158 | 0.216 | 0.229 |
| | Mutual Fund / Hedge Fund | 1.378 | 0.856 | 0.876 | 1.277 | 1.057 | 1.305 |
| | HKSCC (Shanghai-HK Foreign Investors) | 0.078 | 0.026 | 0.025 | 0.011 | 0.013 | 0.018 |
| | Industrial Investors | 39.395 | 40.171 | 39.861 | 31.759 | 31.593 | 31.326 |
| Small Shareholders | Small Investors | 54.372 | 49.344 | 51.436 | 61.923 | 61.538 | 62.097 |

Considering these large investors, it appears that small investors are the primary source selling shares to the national team rescue fund. Specifically, for CSI 500 stocks, the mean shareholding ratio of small investors notably declined, whereas there was no significant change for CSI 1000 stocks.

## III. Robustness Tests

In this section, we perform various robustness checks to our results. Section A considers alternative bandwidths around the CSI 500/CSI 1000 breakpoint. Section B excludes potential

concurrent exogenous order flows (e.g., foreign investor flows) that may distort the estimation. Section C presents a placebo test indicating that there was no significant return difference between the bottom stocks of the CSI 300 and the top stocks of the CSI 500 in July 2015. Section D demonstrates that their probabilities remain consistently comparable over time.

*A. Alternative bandwidths around the CSI 500/CSI 1000 breakpoint*

In this subsection, we consider alternative bandwidths around the CSI 500/CSI 1000 market cap breakpoint. Table VII presents the Fama-French and Carhart regressions with sample sizes of 50 stocks and 150 stocks. In the 50 vs. 50 group, the coefficient of *if_500* in July is 0.074 in the FF5 regression and 0.077 in the Carhart 4 regression, both of which are statistically significant at the 1% significance level. In the 150 vs. 150 group, the coefficient of *if_500* is 0.053 for FF5 and 0.052 for Carhart 4 regression, and both are significant. Therefore, our findings are robust to the bandwidth selection.

**Table VII**

**Fama-French Five Factors Regression and Carhart Four Factors Regression Results of 50 vs. 50 group and 150 vs. 150 group**

This table presents the excess returns derived from Fama-French five-factor regressions and Carhart four-factor regressions from May 2015 to December 2015. The Chinese Fama-French factors are sourced from Li et al. (2023) and include market risk premium (RMRF), size (SMB), value (HML), profitability (RMW) and investment (CMA). Missing values in monthly stock returns are substituted with 0. T-statistics obtained from paired t-tests are reported in parentheses. The dataset comprises 200 observations for all months. Data are collected from CSMAR and Li et al. (2023).

| | | 50 vs. 50 | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | May | June | July | August | September | October | November | December |
| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| FF5 | Constant | -0.040 | 0.025 | 0.106 | 0.043 | -0.024 | 0.027 | 0.028 | 0.032 |
| | | (-4.679)*** | (2.268)* | (7.386)*** | (2.570)* | (-1.728) | (1.280) | (0.648) | (1.686) |
| | If_500 | -0.003 | -0.002 | 0.074 | -0.039 | 0.011 | -0.009 | -0.044 | -0.043 |
| | | (-0.218) | (-0.152) | (3.138)** | (-1.592) | (0.585) | (-0.407) | (-0.924) | (-1.915) |
| | Adjusted-$R^2$ | -0.010 | -0.010 | 0.108 | 0.018 | -0.007 | -0.009 | -0.001 | 0.024 |
| Carhart 4 | Constant | -0.025 | 0.011 | 0.099 | -0.002 | -0.030 | 0.025 | 0.021 | 0.029 |
| | | (-3.082)** | (1.011) | (6.795)*** | (-0.150) | (-2.352)* | (1.209) | (0.475) | (1.803) |
| | If_500 | -0.004 | -0.006 | 0.077 | -0.042 | 0.008 | -0.011 | -0.049 | -0.047 |
| | | (-0.397) | (-0.394) | (3.316)** | (-2.109)* | (0.550) | (-0.511) | (-1.001) | (-2.499)* |
| | Adjusted-$R^2$ | -0.009 | -0.009 | 0.120 | 0.035 | -0.007 | -0.008 | 0.001 | 0.047 |
| | Observations | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| | | 150 vs. 150 | | | | | | | |
| FF5 | Constant | -0.033 | 0.027 | 0.205 | 0.010 | -0.016 | 0.024 | -0.020 | 0.014 |
| | | (-4.589)*** | (2.027)* | (14.743)*** | (0.717) | (-1.441) | (1.983)* | (-1.118) | (1.172) |
| | If_500 | 0.014 | -0.006 | 0.053 | -0.017 | 0.002 | -0.022 | 0.012 | -0.022 |
| | | (1.389) | (-0.373) | (3.104)** | (-0.885) | (0.097) | (-1.420) | (0.546) | (-1.441) |
| | Adjusted-$R^2$ | 0.003 | -0.003 | 0.024 | 0.000 | -0.003 | 0.004 | -0.002 | 0.004 |
| Carhart 4 | Constant | -0.023 | 0.024 | 0.193 | -0.013 | -0.026 | 0.024 | -0.030 | 0.011 |
| | | (-3.231)** | (1.989)* | (13.365)*** | (-1.025) | (-2.674)** | (2.012)* | (-1.636) | (1.045) |
| | If_500 | 0.008 | -0.005 | 0.052 | -0.007 | -0.004 | -0.020 | 0.006 | -0.030 |
| | | (0.792) | (-0.339) | (2.949)** | (-0.426) | (-0.383) | (-1.308) | (0.269) | (-2.042)* |
| | Adjusted-$R^2$ | -0.001 | -0.003 | 0.022 | -0.003 | -0.003 | 0.003 | -0.003 | 0.012 |
| | Observations | 200 | 200 | 200 | 200 | 200 | 200 | 200 | 200 |

$*p<0.05$, $**p<0.01$, $***p<0.001$. t-statistics are reported in parentheses.

*B. Robustness check: concurrent order flows from other traders*

In this subsection, we exclude two concurrent order flows from other traders. We show that both ETFs and the foreign investors (through the Shanghai-Hong Kong Stock Connect) are very

small compared to the national team's order sizes. Thus, their order flows' impact on our estimates are largely negligible.

### *B.1. CSI 500 ETF and CSI 1000 ETF*

**Table VIII**

**Size of CSI 500 ETF and CSI 1000 ETF**

This table provides a summary of statistics for the CSI 500 ETF and CSI 1000 ETF. Panel A presents the assets under management (AUM) in yuan for the CSI500 exchange-traded fund (ETF) and the CSI 1000 exchange-traded fund (ETF) from 2013 to 2019. Panel B documents the asset management ratio for the same period. The management ratio is calculated by dividing the AUM by the corresponding market capitalization of the CSI 500 and CSI 1000.

Panel A: AUM (billion)

| | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|
| CSI500ETF | 8.669 | 7.471 | 26.115 | 21.128 | 22.699 | 44.146 | 68.022 |
| CSI1000ETF | | | | 0.159 | 0.101 | 0.121 | 0.199 |

Panel B: Management Ratio

| | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|
| CSI500ETF | 0.237% | 0.136% | 0.303% | 0.272% | 0.272% | 0.710% | 0.778% |
| CSI1000ETF | | | | 0.002% | 0.001% | 0.002% | 0.002% |

Table VIII shows the total assets under management (AUM) of CSI 500 and CSI 1000 ETFs. Since 2013, the AUM of the CSI 500 ETF have shown a steady increase, yet in 2015, the ETF managed 26.12 billion CNY, constituting only 0.3% of the market cap of CSI 500. We confirm that the AUM change of CSI 500 ETFs is minuscule compare to the national team's trades. The CSI 1000 ETF was launched in 2016, and it managed an even smaller amount of assets, which constituted a negligible proportion of the CSI 1000.

### *B.2. The Shanghai-Hong Kong Stock Connect*

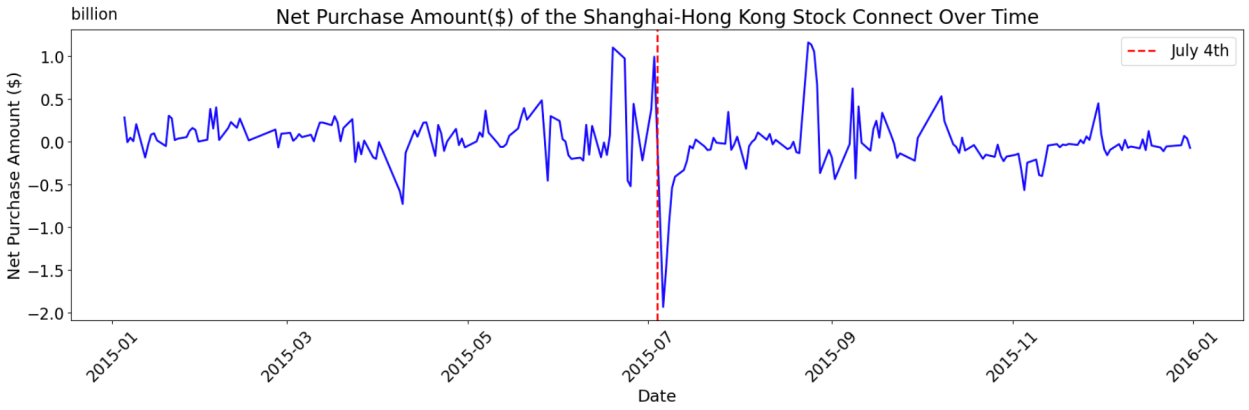



**Figure 4. Net Purchase Amount of the Shanghai-HK Stock Connect.** This graph illustrates the inflow of foreign investors via the Shanghai-HK Stock Connect from January 2015 to December 2015. Data on the index of net purchase amount of Northbound Funds ($) are collected to depict the incoming flow from Hong Kong. The red dashed line marks July 4th, the day the rescue fund entered the market.

Figure 4 shows that the foreign net purchase slumped after the "national team" entered the market, hitting a low of -1.93 billion USD on July 6th, 2015. Subsequently, the net purchase amounts increased but remained negative, indicating that foreign investors continued to sell shares rather than inject foreign cash into the market. The net purchase turned positive for the first time on July 17th, 2015, with a modest value of approximately 0.03 billion USD, which is negligible compared to the contributions from the "national team." By the end of the third quarter, the net purchase peaked at about 1.16 billion USD on August 24th, 2015. Given these figures, when considering the Shanghai-HK Stock Connect, the foreign cash flow is too minimal to significantly impact the efficacy of the rescue fund. In summary, the foreign investors net sold to the national team, and they are too small to affect our estimation.

*C. The placebo test on CSI 300 and CSI 500 stocks*

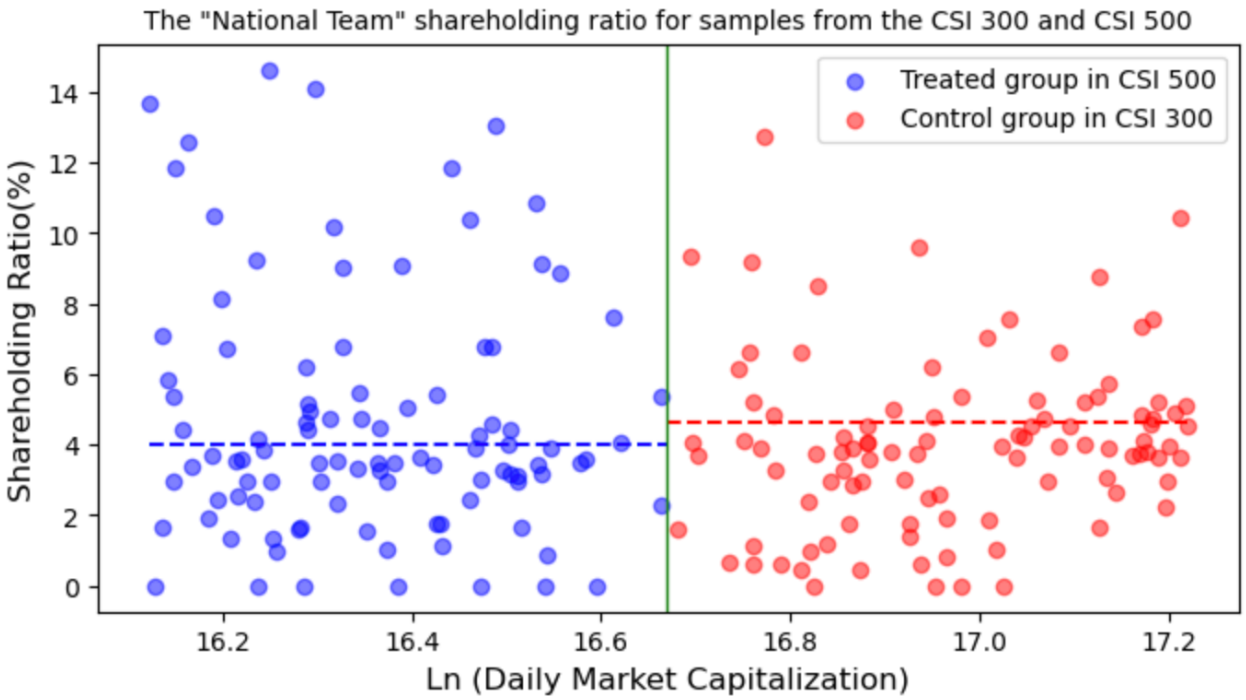



**Figure 5. The national team shareholding ratio for sample stocks in CSI 300 and CSI 500.** This graph illustrates the national team shareholding ratio for a sample of 100 stock pairs. Blue dots represent stocks in the CSI 500, while red dots represent stocks in the CSI 300 with higher market capitalization. Dashed lines indicate different levels of national team shareholding ratio. The blue dashed line corresponds to the CSI 500 group, and the red dashed line corresponds to the CSI 300 group. The horizontal axis represents the natural logarithm of the sum of daily market capitalizations from May 1, 2014, to April 30, 2015. The vertical axis shows the national team shareholding ratio as a percentage. Data for this graph are sourced from CSMAR.

Figure 5 illustrates the national team's shareholding ratio for sample stocks in CSI 300 and CSI 500. There is no significant difference in the "national team" shareholding ratio between the groups. Stocks in the top CSI 500 received slightly more extra order flow compared to stocks in the bottom CSI 300, yet the national team is largely purchasing the same portion of them.

## Table IX

## Fama-French Five Factors Regression Results for CSI 300 and CSI 500 groups

This table presents the excess returns derived from Fama-French five-factor regressions. The Chinese Fama-French factors are sourced from Li et al. (2023) and include market risk premium (RMRF), size (SMB), value (HML), profitability (RMW) and investment (CMA). Missing values in monthly stock returns are substituted with 0. T-statistics obtained from paired t-tests are reported in parentheses. The dataset comprises 200 observations for all months. Here, *if_300* = 1 represents the CSI 300 group, while *if_300* = 0 represents the CSI 500 group. Data are collected from CSMAR and Li et al. (2023).

| | May | June | July | August | September | October | November | December |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Constant | -0.029 | 0.007 | 0.228 | -0.008 | -0.051 | 0.030 | -0.023 | -0.006 |
| | (-3.592)*** | (0.734) | (17.944)*** | (-0.474) | (-4.070)*** | (2.765)** | (-1.141) | (-0.511) |
| If_300 | 0.022 | -0.031 | -0.007 | 0.019 | 0.026 | -0.028 | -0.023 | 0.002 |
| | (1.608) | (-1.861) | (-0.356) | (0.747) | (1.257) | (-1.765) | (-0.930) | (0.105) |
| Observations | 200 | 200 | 200 | 200 | 200 | 200 | 200 | 200 |
| Adjusted-$R^2$ | 0.009 | 0.015 | -0.004 | -0.002 | 0.004 | 0.009 | -0.000 | -0.005 |

∗p<0.05, ∗∗p<0.01, ∗∗∗p<0.001. t-statistics are reported in parentheses.

## Table X

## Carhart Four Factors Regression Results for CSI 300 and CSI 500 groups

This table presents the excess returns derived from Carhart four-factor regressions. The Chinese Fama-French factors are sourced from Li et al. (2023) and include market risk premium (RMRF), size (SMB), value (HML) and momentum. Missing values in monthly stock returns are substituted with 0. T-statistics obtained from paired t-tests are reported in parentheses. The dataset comprises 200 observations for all months. Here, *if_300* = 1 still represents the CSI 300 group, while *if_300* = 0 represents the CSI 500 group. Data are collected from CSMAR and Li et al. (2023).

| | May | June | July | August | September | October | November | December |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Constant | -0.024 | 0.009 | 0.223 | -0.030 | -0.050 | 0.032 | -0.024 | -0.009 |
| | (-2.892) | (0.970) | (18.374)*** | (-1.861) | (-4.895)*** | (3.011) | (-1.259) | (-0.741) |
| If_300 | 0.008 | -0.012 | -0.003 | 0.060 | 0.031 | -0.027 | -0.018 | 0.006 |
| | (0.576) | (-0.790) | (-0.144) | (2.801)** | (1.876)* | (-1.711) | (-0.767) | (0.323) |
| Observations | 200 | 200 | 200 | 200 | 200 | 200 | 200 | 200 |
| Adjusted-$R^2$ | -0.003 | -0.001 | -0.005 | 0.034 | 0.014 | 0.009 | -0.002 | -0.005 |

∗p<0.05, ∗∗p<0.01, ∗∗∗p<0.001. t-statistics are reported in parentheses.

Table IX shows that compared to bottom stocks in CSI 300, top stocks in CSI 500 exhibited 0.7% lower FF5 alpha in July 2015, which is not statistically significant. Similarly, FF5 alphas in other months also did not achieve statistical significance. The Carhart four-factor regression shown

in Table X is similar. The coefficient of *'if_300'* for July is not statistically significant, indicating no significant return difference between the stock samples.

*D. Profitability comparison on sample stocks*

This subsection is a robustness check on whether the national team possesses advance information about the future profitability of the stocks they choose to buy (and not buy). Below, we compare the ROA change since 2015Q2 of the treated group in CSI 500 and control group stocks in CSI 1000.

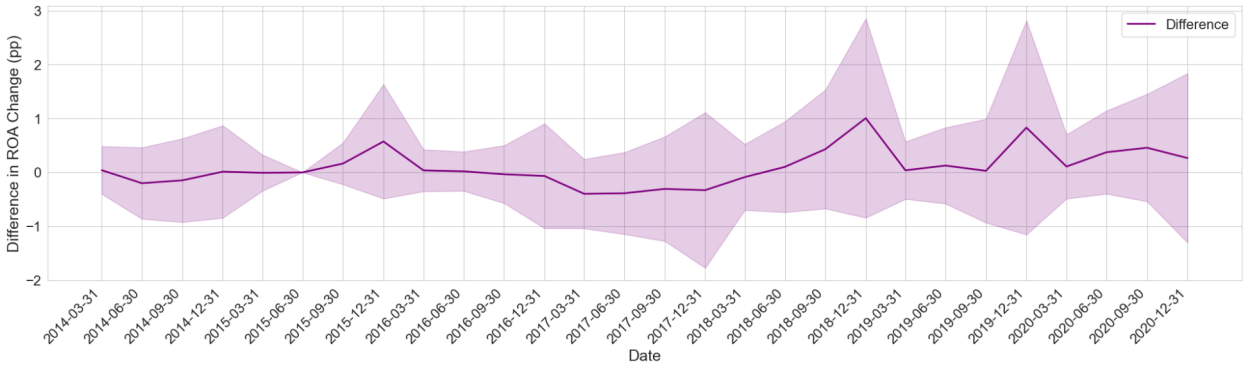



**Figure 6. Difference in ROA change (percentage points) between CSI 500 and CSI 1000 sample stocks.** This graph illustrates the changes in ROA, measured in percentage points, for sample stocks from the CSI 500 and CSI 1000 indices. Using June 30, 2015, as the baseline date, we calculate the quarterly change in ROA percentage points for each stock. We then average these changes within the CSI 500 and CSI 1000 groups and compute the difference in ROA change between the two groups from 2014 to 2020. The shaded area represents the 95% confidence interval. The quarterly ROA data for this graph are sourced from CSMAR.

The Figure 6 shows the two group of stocks show no significant difference in the ROA change from 2014 to 2020. Furthermore, the confidence interval shadow encompasses 0, indicating that

the difference in ROA change between the groups is not statistically significant. This suggests that our sample stocks remain comparable even after the intervention of the rescue fund in the market. This finding reassures our identification assumption that the national team's order flow is not driven by future cash flow news of the underlying firms.

## IV. Conclusion

If stock prices are dictated solely by future cash flows, an exogenous, non-informative order flow would not affect stock prices. However, financial economists have long conjectured that the demand curve for stocks is downward sloping—meaning that stock prices are influenced not only by cash flow news but also by supply and demand dynamics. Finding an empirical test for this conjecture is challenging, as order flows that are truly unrelated to future cash flows are rare.

We identify and utilize a clean, exogenous, uninformed order flow to calibrate the price elasticity of the equity market. In July 2015, the Chinese government established a "National Team" as a rescue fund to stabilize the market. This team injected $150 billion into the market, representing approximately 5% of the total market capitalization of the mainland Chinese stock market. This substantial and unexpected cash influx offers an excellent opportunity to test the market's elasticity.

We use the market cap threshold between the CSI 500 and CSI 1000 indices as our identification strategy. We find that the National Team bought about 5% of the CSI 500 stocks but

barely bought any CSI 1000 stocks. Due to the exogenous purchase flow, the treated group (stocks barely above the CSI 500/CSI 1000 market cap threshold) achieved a 6.4% FF5 excess return relative to the control group (stocks that missed the threshold).

## APPENDIX

***The "National Team" members***

Central Huijin Asset Management Co., Ltd., Central Huijin Investment Ltd., China Securities Finance Co., Ltd., Dacheng Fund - Agricultural Bank of China - Dacheng CSI Financial Asset Management Plan, China Asset Management - Agricultural Bank of China - ChinaAMC CSI Financial Asset Management Plan, Harvest Fund - Agricultural Bank of China - Harvest CSI Financial Asset Management Plan, GF Fund - Agricultural Bank of China - GF CSI Financial Asset Management Plan, Southern Fund - Agricultural Bank of China - Southern CSI Financial Asset Management Plan, E Fund - Agricultural Bank of China - E Fund CSI Financial Asset Management Plan, Yinhua Fund - Agricultural Bank of China - Yinhua CSI Financial Asset Management Plan, ICBC Credit Suisse Fund - Agricultural Bank of China - ICBC Credit Suisse CSI Financial Asset Management Plan, Bosera Fund - Agricultural Bank of China - Bosera CSI Financial Asset Management Plan, China Europe Fund - Agricultural Bank of China - China Europe CSI Financial Asset Management Plan, Bank of China Ltd. - China Merchants Fund Fengqing Flexible Allocation Hybrid Initiated Securities Investment Fund, Agricultural Bank of China Ltd. - E Fund Ruihui Flexible Allocation Hybrid Initiated Securities Investment Fund, Industrial and Commercial Bank of China Ltd. - Southern Consumer Vitality Flexible Allocation Hybrid Initiated Securities Investment Fund, Harvest New Opportunities Flexible Allocation Hybrid Initiated Securities Investment Fund, Industrial and Commercial Bank of China Ltd. -

Harvest New Opportunities Flexible Allocation Hybrid Initiated Securities Investment Fund, and China AMC New Economy Flexible Allocation Hybrid Initiated Securities Investment Fund

## REFERENCES


Ben-David, I., Li, J., Rossi, A., & Song, Y. (2020). *Advice-driven demand and systematic price. fluctuations*. National Bureau of Economic Research.

Bouchaud, J. P., Bonart, J., Donier, J., & Gould, M. (2018). *Trades, quotes and prices: financial. markets under the microscope*. Cambridge University Press.

Brunnermeier, M. K., & Pedersen, L. H. (2005). Predatory trading. *The Journal of Finance*, *60*(4), 1825-1863.

Chang, Y. C., Hong, H., & Liskovich, I. (2015). Regression discontinuity and the price effects of. stock market indexing. *The Review of Financial Studies*, *28*(1), 212-246.

Da, Z., Larrain, B., Sialm, C., & Tessada, J. (2018). Destabilizing financial advice: Evidence from. pension fund reallocations. *The Review of Financial Studies*, *31*(10), 3720-3755.

Frazzini, A., Israel, R., & Moskowitz, T. J. (2018). Trading costs. *Available at SSRN 3229719*.

Gabaix, X., & Koijen, R. S. (2021). *In search of the origins of financial fluctuations: The inelastic. markets hypothesis* (No. w28967). National Bureau of Economic Research.

Hartzmark, S. M., & Solomon, D. H. (2022). *Predictable price pressure* (No. w30688). National. Bureau of Economic Research.

Huang, Y., Miao, J., & Wang, P. (2019). Saving China's stock market?. *IMF Economic Review*, *67*, 349-394.

Katagiri, M., Shino, J., & Takahashi, K. (2022). The announcement effects of a change in the Bank of Japan's ETF purchase program: An event study. *Finance Research Letters*, *50*, 103230.

Koijen, R. S., & Yogo, M. (2019). A demand system approach to asset pricing. Journal of Political. Economy, 127(4), 1475-1515.

Li, H., & Liu, K. (2024). China's National Team: A Game Changer in Stock Market Stabilization?. *Finance Research Letters*, *61*, 104984.

Li, J. J., Pearson, N. D., & Zhang, Q. (2021). Impact of demand shocks on the stock market: Evidence from chinese ipos. *Neil D. and Zhang, Qi, Impact of Demand Shocks on the Stock Market: Evidence from Chinese IPOs (December 16, 2021)*.

Li, J. (2022). What drives the size and value factors?. *Review of Asset Pricing Studies*, *12*(4), 845-885.

Li, Z., Liu, L. X., Liu, X., & John Wei, K. C. (2023). Replicating and digesting anomalies in the Chinese A-share market. *Management Science*.

Lou, D. (2012). A flow-based explanation for return predictability. *The Review of Financial Studies*, *25*(12), 3457-3489.

Massa, M., & Xu, M. (2013). The value of (stock) liquidity in the M&A market. *Journal of Financial and Quantitative Analysis*, *48*(5), 1463-1497.

Pavlova, A., & Sikorskaya, T. (2023). Benchmarking intensity. *The Review of Financial Studies*, *36*(3), 859-903.

Peng, C., & Wang, C. (2023). Factor demand and factor returns. *Available at SSRN 3327849*.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41-55.

Shleifer, A. (1986). Do demand curves for stocks slope down?. The Journal of Finance, 41(3), 579-590.

Schmickler, S. (2020). Identifying the price impact of fire sales using high-frequency surprise mutual fund flows. *Available at SSRN 3488791*.