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 it is difficult to find an exogenous, unexpected large order flow uncorrelated with cash flow news. 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 predetermined 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 (Lucas, 1978). 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).

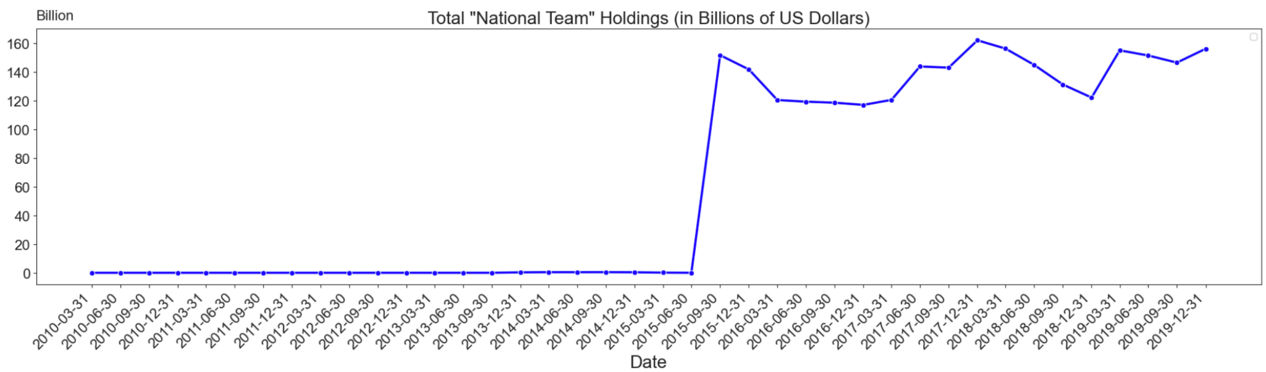
Panel C: Price impact of order execution	
Frazzini et al. (2018), Bouchaud et al. (2018)	15
Panel D: Dividend, Stock repurchase, IPO, and SEO	
Li, Pearson and Zhang (2021)	2.6-6.5
Schmickler (2020)	0.8
Hartzmark and Solomon (2022)	1.5-2.3

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. 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). Thirdly, 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. Finally, asset prices not only react to the current purchase flow but also react to the rational change in anticipation of future purchase flows. To estimate M accurately, we need a large enough exogenous order flow that is largely unpredicted, unprecedented, uncorrelated with future cash flow information, and unforeseeable to be repeated.

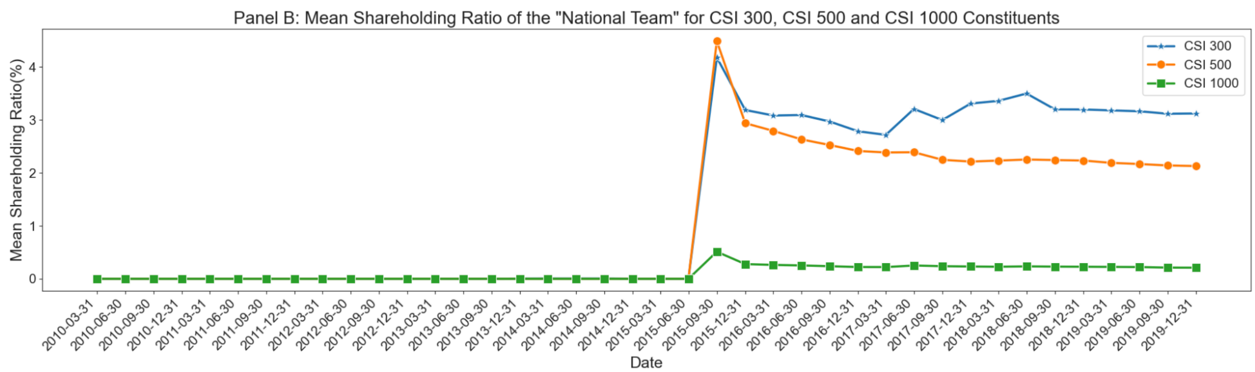
In this paper, we examine one such order flow. In July 2015, the Chinese government launched an emergency asset purchase program valued at $150 billion (approximately 5% of the market capitalization of the mainland Chinese stock market) to bolster stock prices. A stock purchase program of this size was 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, 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, [3]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] 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. [4]

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 non-National Team large investors.

[4] Note that the price elasticity we estimate here are commonly referred as "micro" elasticity in the literature (see, e.g., Appexdix G.4 of Gabaix and Koijen (2021)). Although the National Team purchased a wide range of stocks, we focus on our identification strategy that extracts the return differences around the index breakpoints. Thus, the elasticity is in line with the "micro" elasticity in the literature. The National Team's purchase indeed created a marketwise price impact, as they purchase the top 1^{st} – 800^{th} stocks but barely any 801^{st} – 2800^{th} stocks. Indeed, the Fama-French SMB factor is -5.22% for July 2015, one of the most negative monthly readings in the Chinese A-shares history. We control for the Fama-French factors in our regressions to extract the pure micro elasticity estimation.

Most central bank interventions not only create an immediate demand for the asset but also lead market participants to rationally and correctly expect that the intervention may be repeated in the future (Haddad, Moreira, and Muir, 2023). Such expectations can distort the estimation of the price multiplier; however, our empirical identification is largely unaffected by this for two reasons. First, to our knowledge, we are the first to identify the sharp discontinuity in the National Team's purchases around the CSI 500/CSI 1000 breakpoint. The National Team provided no clear guidance on which stocks they intended to buy, and market participants primarily inferred this information through firms' 2015 Q3 quarterly reports, which were disclosed months later (Huang, Miao, and Wang, 2019).[5] As of December 2024, we have found no news, announcements, or academic papers discussing this breakpoint. Without knowledge of the purchase list, the anticipation of future purchase is limited. Second, even if some market participants had privately observed this breakpoint, it can't be rationally expected that the National Team would use the same breakpoint again in future interventions.[6] Therefore, the stocks around the CSI 500/CSI 1000 breakpoint arguably reacted purely to the current order flows.[7]

Finally, we find that exogenously inflating a stock's price by 6.4% does not have a significant impact on its number of shareholders, turnover, dividend rate, volatility, number of employees,

[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.
[6] The Chinese government conducted a new round of stock market rescuing in January 2024, in which CSI1000 stocks were also included in the rescuing basket. It was neither unanticipated nor unprecedented, though.
[7] The appendix B 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 explore more topics, such as corporate governance, liquidity, and long-term impacts of "the helicopter cash".

R&D expenditure, ROA, capital expenditure or delisting probability in the following years. These results should not be interpreted as evidence that inflated asset prices have no real economic effects. Instead, the lack of observed impact could stem from limited economic significance (a 6.4% price inflation may be insufficient to generate measurable effects), limited statistical power (a larger cross-section of stocks may yield more robust results), or a combination of both factors.

Our paper adds to a long literature documenting the price effects on stocks due to demand and supply shocks. On the demand side, economists find stock prices rise due to various types of purchase flows. Such flows may be induced by financial institutions such as mutual funds (Teo and Woo, 2004; Coval and Stafford, 2007; Froot and Teo, 2008; Lou, 2012; Huang, Song, and Xiang, 2019; Li, 2022), exchange-traded funds (Chang, Hong, and Liskovich, 2015; Ben-David, Franzoni, and Moussawi, 2018; Brown, Davies, and Ringgenberg, 2021), or index reconstitutions that may motivate all market participants to trade (Shleifer, 1986; Harris and Gurel, 1986; Wurgler and Zhuravskaya, 2002; Greenwood, 2005, Gabaix and Koijen, 2020). They may also be driven by corporate decisions such as repurchases (Lakonishok and Vermaelen, 1990; Ikenberry et al., 2000; Peyer and Vermaelen, 2009; Dittmar and Field, 2015) and dividends (Chen 2024; Hartzmark and Solomon, 2022). Market microstructure may also drive flows, e.g., limit and market order flows on futures markets (Deuskar and Johnson, 2011), trading costs (Hasbrouck, 2007), and interest in attention-grabbing stocks (Barber and Odean, 2007)[8]. Some literature also looks at how investor beliefs shape demand (Giglio et al., 2021), inelastic demand due to non-substitutable

[8] Order flows and transaction-level dynamics have also been shown to impact prices in shallow markets (Kyle, 1985; Madhavan, Richardson, and Roomans, 1997).

stocks (Davis, Kargar, and Li, 2023), and how concentrated flows in passive funds impact prices (Haddad, Huebner, and Loualiche, 2021). On the supply side, economists find stock prices fall after announcements of seasoned equity offerings (Masulis and Korwar, 1986; Rangan, 1998; Mola and Loughran 2004; Gao and Ritter, 2010). However, Denis and Sarin (2001) argues that the market will price-in the expected poor earnings following the offering, so it is difficult to cleanly identify the price effects non-related to the cash flow news. Finally, Gabaix and Koijen (2021) use the granular instrumental variable approach to estimate the price multiplier, demonstrating that inelastic markets can magnify the effects of demand shocks. Gabaix et al. (2003, 2006) provide additional insights by showing that institutional trading and power-law distributions in order flows contribute to price volatility[9]. Our paper adds to the literature by identifying a clean exogenous order flow that is unrelated to cash flow news, which allows us to estimate the pure price impact of order flows.

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 real impacts of inflated asset prices and conducts various robustness checks. Section IV concludes.

[9] This builds on behavioral theories, such as Lillo, Mike, and Farmer (2005), who model the persistence of supply and demand imbalances, and Torre and Ferrari (1998), who offer a practical framework for estimating market impacts. Similarly, Koijen and Yogo (2019) provide a structural framework to model investor demand and its influence on prices, while Gabaix (2012, 2014, 2019) explores behavioral and macroeconomic that amplify demand-driven effects. These insights are consistent with theories highlighting limits to arbitrage (Gromb and Vayanos, 2010) and institutional trading behaviors driving momentum and reversals (Vayanos and Woolley, 2013).

I. Data and Methodology

A. National Team and Institutional Details

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.[10] 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.[11]

The motivation of the purchase, stated by the Chinese SEC, is simply "to maintain the stability of stock market",[12] and the fell in stock market did not result in economic crisis, massive layoffs,

[10] 2015Q3 quarterly reports are generally released in October and early November, which is several months after the national team's purchase concludes.

[11] 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.

[12] https://www.sse.com.cn/lawandrules/regulations/csrcannoun/c/c_20150906_3976319.shtml

or bank runs.[13] Following the intervention, the market indeed stabilized and gradually recovered, let to an unrealized gain for the National Team, though the market never recovered to its May 2015 level.

B. 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[14], closing prices, and other relevant data described in the following table. Importantly, firms disclose their top shareholders on a quarterly basis, and our analysis focuses on the shareholding ratios of the Top 10 shareholders. The shareholding ratios of 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. We consider only on-shore A-shares, as the B-shares and H-shares are traded in foreign currency and issued to offshore investors. We find that B-shares and H-shares are not included in the National Team's purchase program.

[13] The Chinese GDP growth was 7.4%, 7%, and 6.8% for 2014 – 2016, and unemployment rate was 4.1%, 4.1%, 4% respectively. Of course, we could not observe what would happen if the intervention did not occur.
[14] In 2005, China's capital market implemented an equity split reform, allowing non-tradable shares to be redeemed and converted into tradable shares. By 2007, most companies had completed this reform. Since our study uses shareholding ratio data from 2015, it is not impacted by the earlier equity split reform.

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
Turnover	Daily trading volume/the stock's outstanding shares
Number of Shareholders	Total number of shareholders
Number of Employees	Total number of employees of listed companies
Volatility	Standard deviation of daily stock returns
Dividend Rate	(Dividend per share/Market price per share) × 100%
R&D Spending	R&D investment amount
Capital Expenditure	Cash paid for the purchase and construction of fixed assets, intangible assets and other long-term assets
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

C. 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.[15] We apply the propensity score method

[15] 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.

(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 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.

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 A-shares 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.

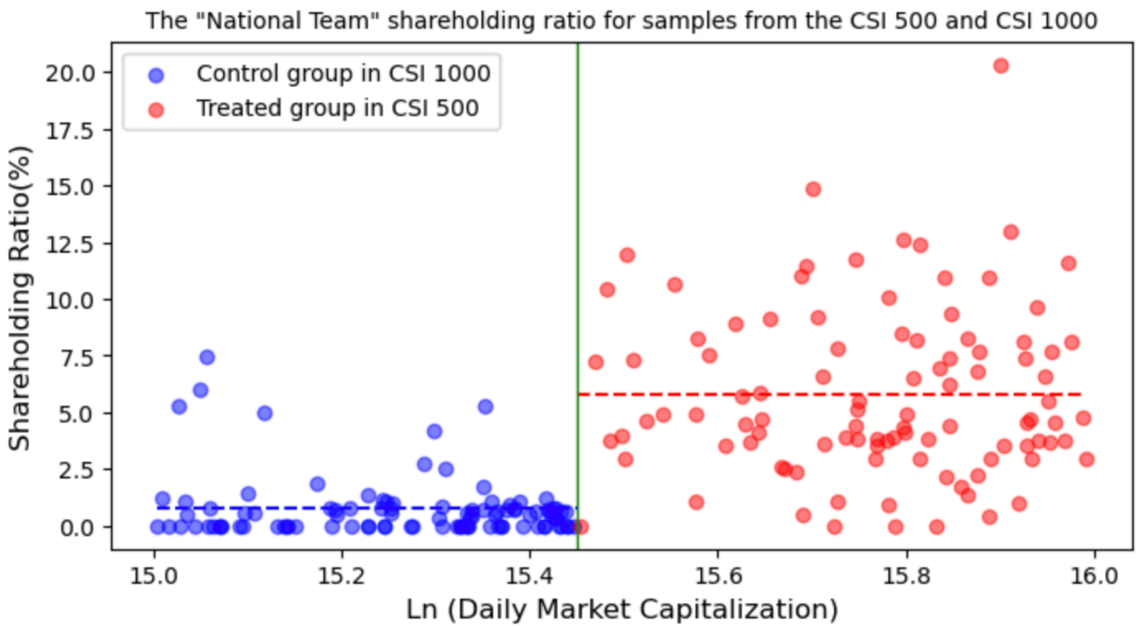


Figure 2. The national team shareholding ratio for sample stocks. This graph illustrates the national team shareholding ratio for a sample of 100 stock pairs. Blue dots represent stocks in the CSI 1000, while red dots represent stocks in the CSI 500 with higher market capitalization. Dashed lines indicate 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.

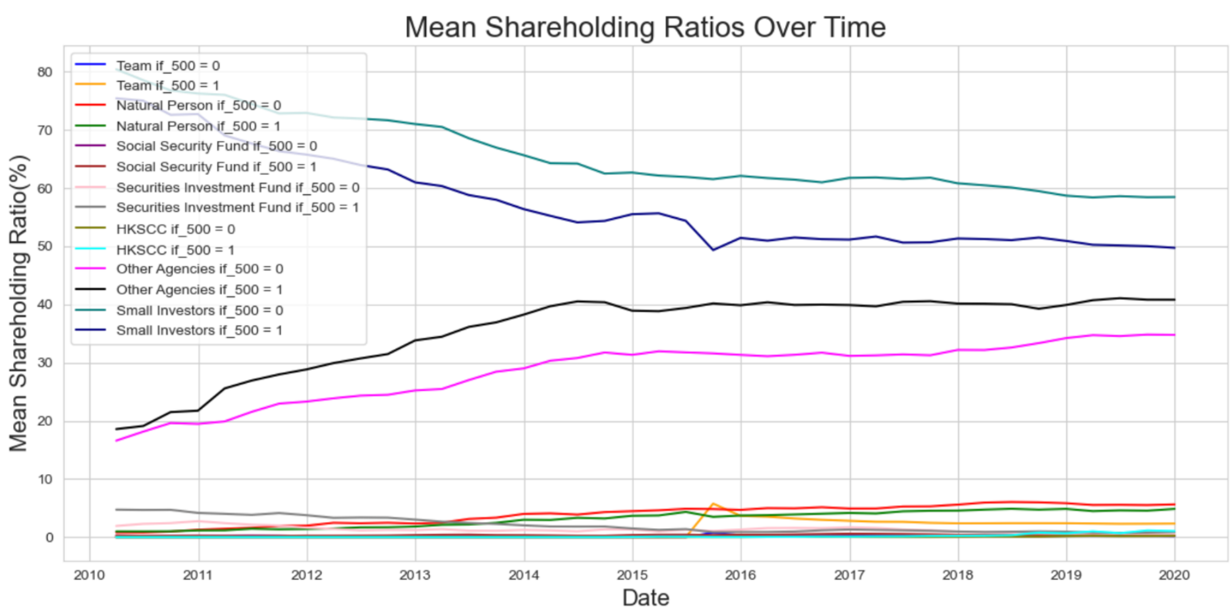


Figure 3. Mean shareholding ratio of different categories of investors. Shareholders can be classified into two primary groups: large shareholders (Top 10) and small investors. Among large shareholders, there are six distinct subcategories: the national team, natural persons, the social security fund, 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.

One potential concern is that order flow crowding-out and spillovers could influence our estimates. For instance, if an investor intends to buy a treated stock but finds its price too high, they might shift to a similar alternative in the control group, potentially affecting our estimation of return gaps. However, we note that such spillovers would bias our estimates toward zero, which actually reduces concerns about false discoveries. Second, Davis, Kargar, and Li (2022) demonstrate that stocks generally serve as poor substitutes for one another, thereby limiting the potential for spillover effects. Third, we perform a robustness check on stock "substitutability" by varying the matching criteria. Under narrower bandwidths, the matched stock pairs are more “substitutable.” If spillover effects were significant, we would expect them to be most pronounced with narrower bandwidths, resulting in smaller price multiplier estimates. However, as shown in Table VII, the results do not support the presence of spillover effects; in fact, the price multiplier is slightly larger with narrower matching bandwidths.

B. 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 compared 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

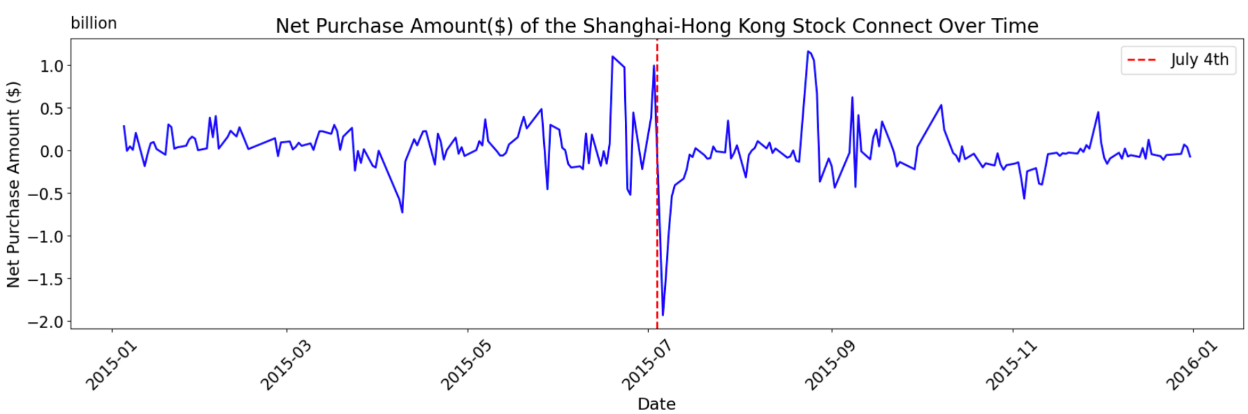


Figure 4. Net Purchase Amount of the Shanghai-HK Stock Connect. This graph illustrates the inflow of foreign investors via the Shanghai-HK Stock Connect from January 2015 to December 2015. Data on

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

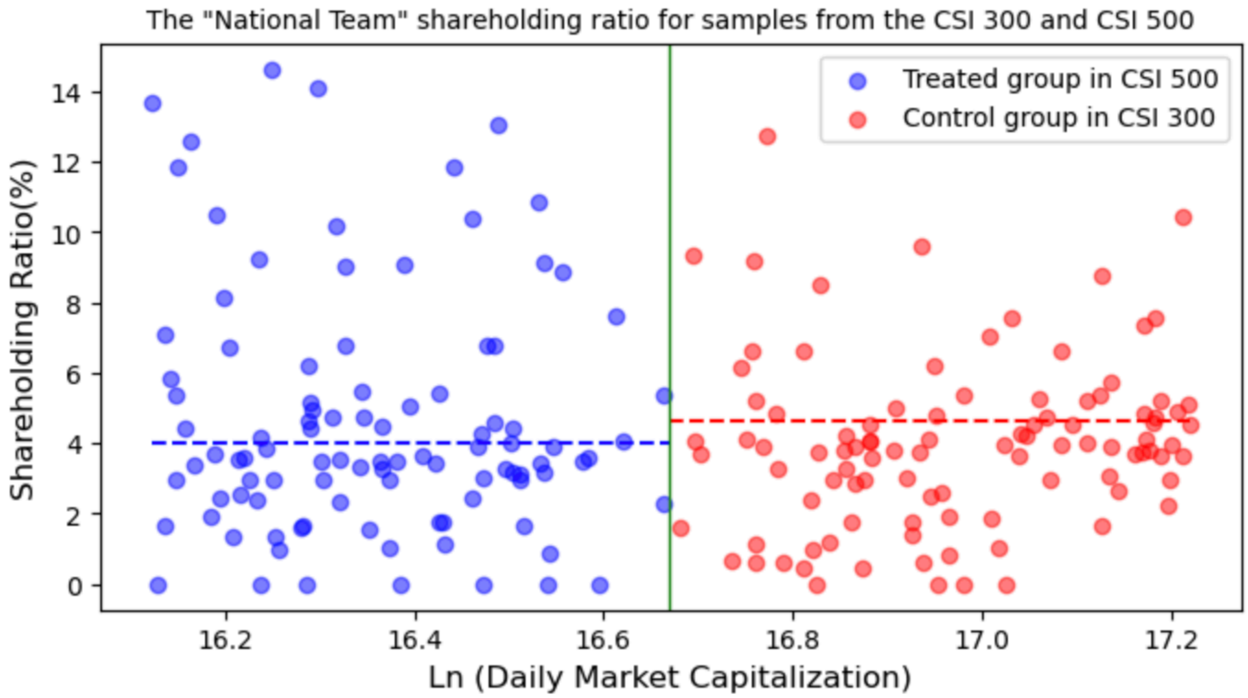


Figure 5. The national team shareholding ratio for sample stocks in CSI 300 and CSI 500. This graph illustrates the national team shareholding ratio for a sample of 100 stock pairs. Blue dots represent stocks in the CSI 500, while red dots represent stocks in the CSI 300 with higher market capitalization. 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).

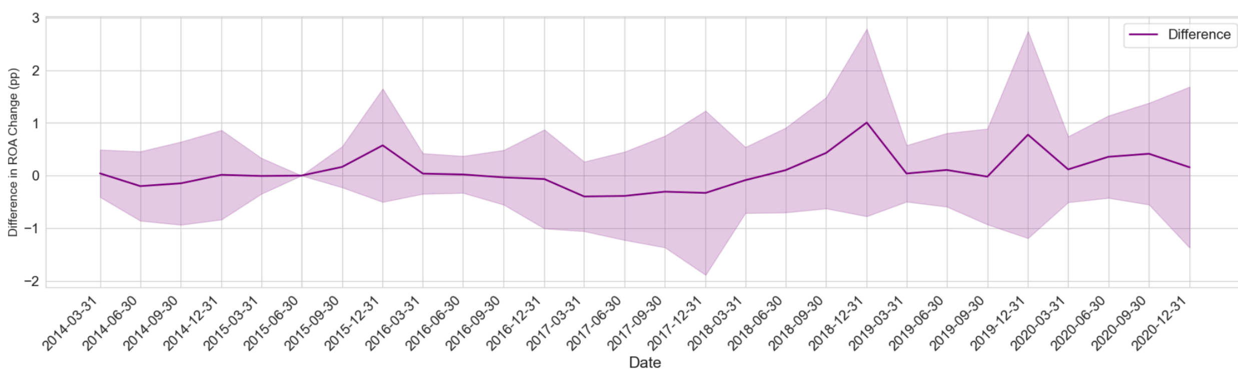
	May	June	July	August	September	October	November	December
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-0.024	0.009	0.223	-0.030	-0.050	0.032	-0.024	-0.009
	(-2.892)	(0.970)	(18.374)***	(-1.861)	(-4.895)***	(3.011)	(-1.259)	(-0.741)
If_300	0.008	-0.012	-0.003	0.060	0.031	-0.027	-0.018	0.006
	(0.576)	(-0.790)	(-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.

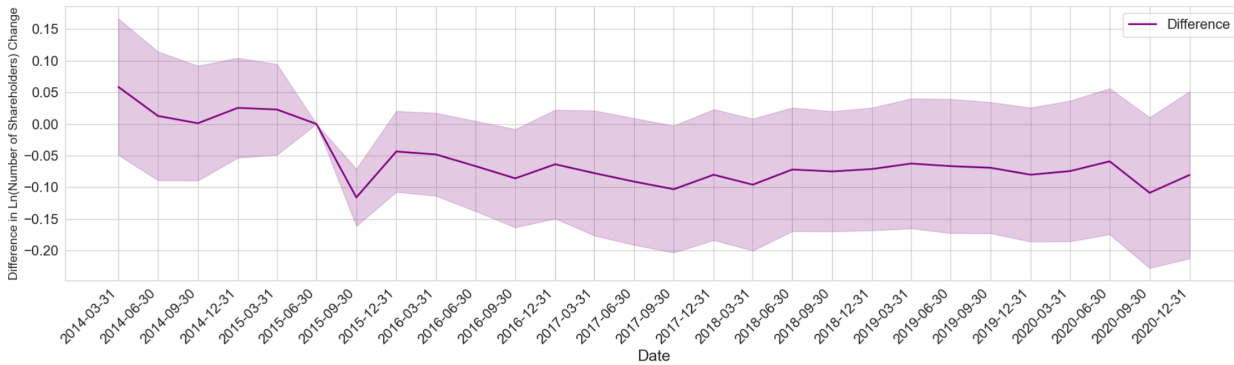
Table IX shows that compared to bottom stocks in CSI 300, top stocks in CSI 500 exhibited 0.7% lower FF5 alpha in July 2015, which is not statistically significant. Similarly, FF5 alphas in other months also did not achieve statistical significance. The Carhart four-factor regression shown in Table X is similar. The coefficient of *'if_300'* for July is not statistically significant, indicating no significant return difference between the stock samples.

D. Characteristics comparison on sample stocks

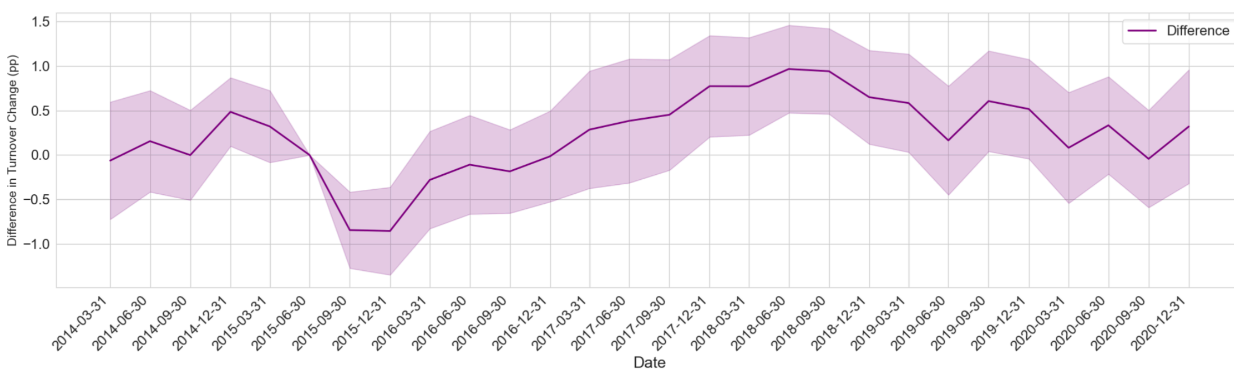
This subsection is robustness checks on whether the national team possesses advance information about the future profitability of the stocks they choose to buy (and not buy) and firm characteristics comparison after the shock.



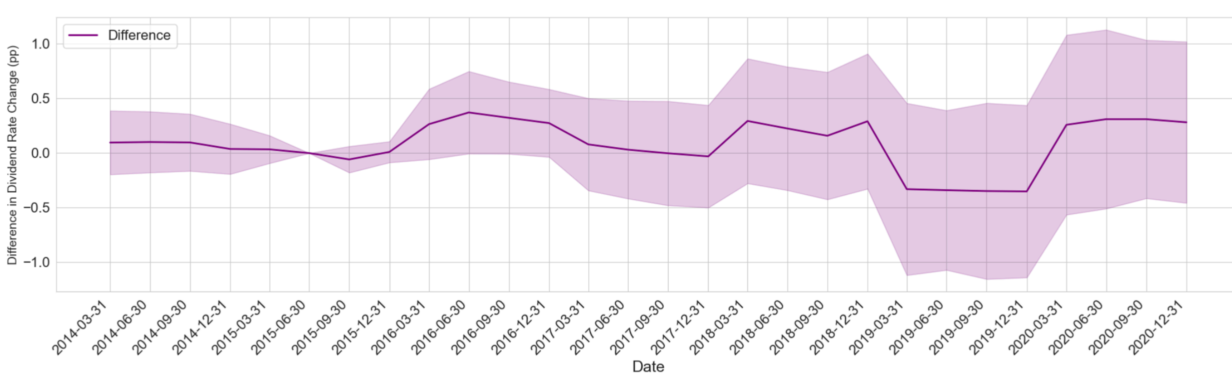
Panel A. Difference in ROA cumulative change (percentage points) between CSI 500 and CSI 1000 sample stocks.



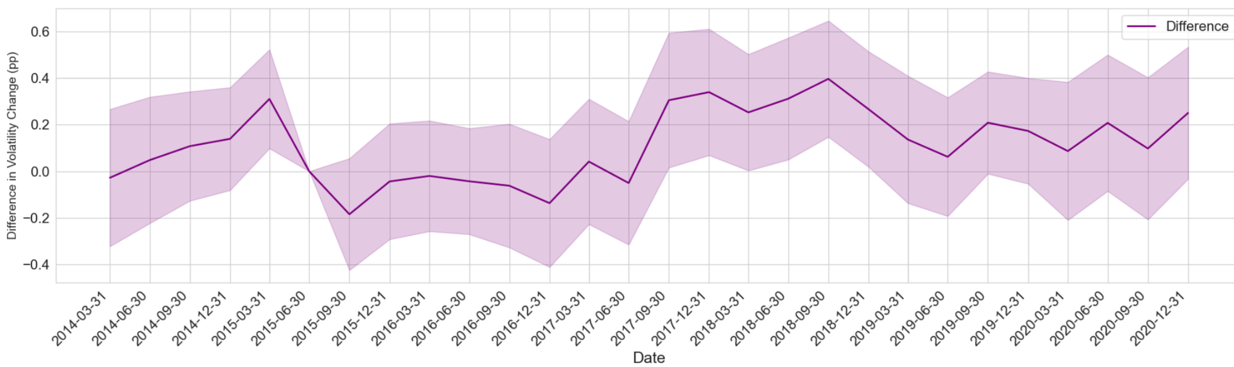
Panel B. Difference in Ln(number of shareholders) cumulative change between CSI 500 and CSI 1000 sample stocks.



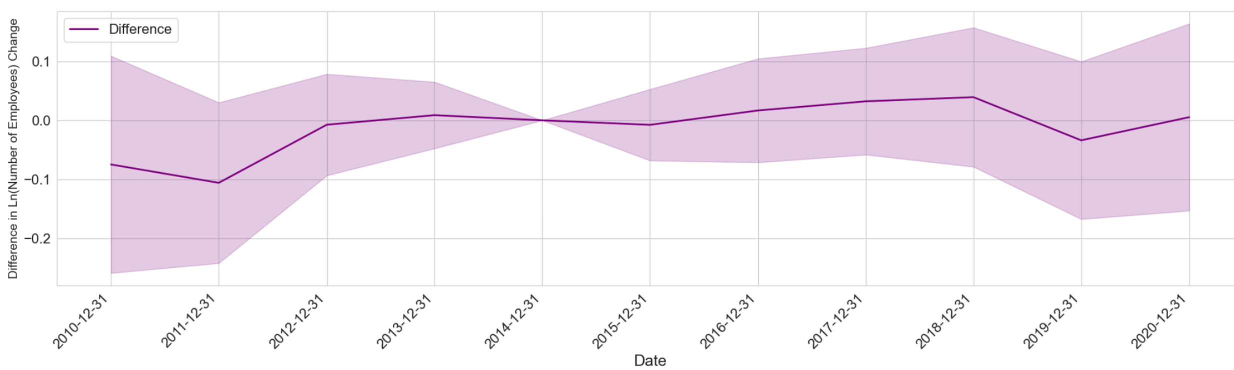
Panel C. Difference in turnover cumulative change (percentage points) between CSI 500 and CSI 1000 sample stocks.



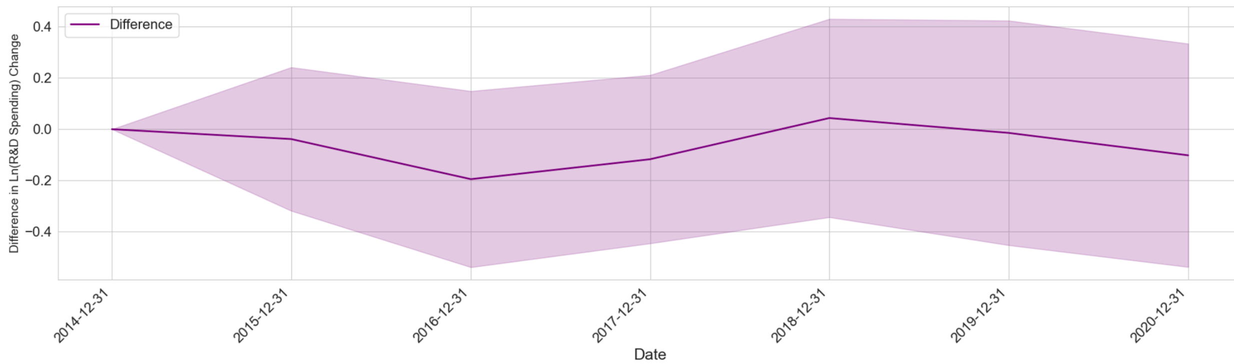
Panel D. Difference in dividend rate cumulative change (percentage points) between CSI 500 and CSI 1000 sample stocks.



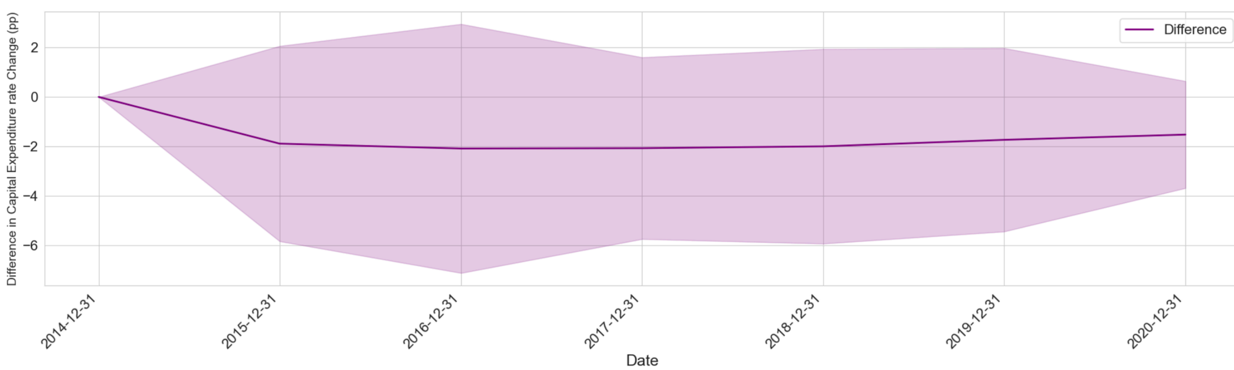
Panel E. Difference in volatility cumulative change (percentage points) between CSI 500 and CSI 1000 sample stocks.



Panel F. Difference in Ln(number of employees) cumulative change between CSI 500 and CSI 1000 sample stocks.



Panel G. Difference in Ln(R&D spending) cumulative change between CSI 500 and CSI 1000 sample stocks.



Panel H. Difference in capital expenditure rate cumulative change between CSI 500 and CSI 1000 sample stocks.

Figure 6. Profile of firm characteristics comparisons of sample stocks. Panel A illustrates the changes in ROA, measured in percentage points. 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 cumulative change between the two groups from 2014 to 2020. Panel B illustrates the cumulative changes in the logarithm of the number of shareholders. Using June 30, 2015, as the baseline date, we calculate the quarterly change in Ln(number of shareholders) for each stock. We then average these changes within each group and compute the quarterly differences between the CSI 500 and CSI 1000 groups from 2014 to 2020. Panel C illustrates the cumulative changes in the turnover rate. We collect daily turnover data and calculate quarterly averages. Using June 30, 2015, as the baseline date, we generate cumulative turnover changes for each stock. Within the CSI groups, we compute the average turnover changes. Finally, we calculate the difference in cumulative turnover changes

from 2014 to 2020. Panel D illustrates the dividend rate cumulative changes in sample stocks. We collect daily dividend rate data and calculate quarterly averages. Using June 30, 2015, as the baseline date, we generate cumulative dividend rate changes for each stock. Within each group, we compute the average dividend rate changes. Finally, we calculate the difference in cumulative changes from 2014 to 2020. Panel E illustrates the volatility changes between CSI 500 and CSI 1000 sample stocks. We gather daily stock return data and calculate the standard deviation each quarter for each stock to measure volatility. Using June 30, 2015, as the baseline date, we compute cumulative changes in volatility for each stock. For each CSI group, we then calculate the average volatility changes. Lastly, we assess the difference in cumulative volatility changes between the CSI 500 and CSI 1000 groups from 2014 to 2020. The shaded area indicates the 95% confidence interval. Panel F illustrates the Ln(number of employees) cumulative changes between CSI 500 and CSI 1000 sample stocks. Using December 31, 2014, as the baseline date, we calculate the changes in Ln(number of employees) for each sample stock, average these changes within each CSI group, and then compute the difference in cumulative changes between the CSI 500 and CSI 1000 groups. Panel G illustrates the Ln(R&D spending) cumulative changes in sample stocks. We collect yearly R&D spending data, using December 31, 2014, as the baseline date. We calculate the changes in Ln(R&D spending) for each sample stock, average these changes within each CSI group, and then compute the difference in cumulative changes between the CSI 500 and CSI 1000 groups. Panel H illustrates the capital expenditure rate cumulative changes in sample stocks. We collect yearly capital expenditure data, using December 31, 2014, as the baseline date. The capital expenditure rate is calculated by the capital expenditure amount/ the market capitalization. We calculate the capital expenditure rate changes for each sample stock, average these changes within each CSI group, and then compute the difference in cumulative changes between the treated and control groups. All the shaded area represents the 95% confidence interval. All data are sourced from CSMAR.

The Panel A shows the two group of stocks show no significant difference in the ROA cumulative change from 2014 to the second quarter of 2018. Furthermore, the confidence interval shadow encompasses 0 in this period, 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.

Panel B, Panel C and Panel D provide additional information on future trading characteristics. We compare the changes in Ln(number of shareholders) between the treated group in the CSI 500 and the control group in the CSI 1000. As shown in the graph, the confidence interval encompasses zero in all quarters except for the third and the fourth quarter of 2015 from 2014 to 2016. This suggests that during this quarter, when the national team strongly influenced the market, the number of shareholders in the CSI 500 group decreased, while it increased for the CSI 1000 group. This finding aligns with our empirical results in Part C, suggesting that small shareholders may have sold their entire holdings to the national team and exited the market.

In addition to the cumulative changes in Ln(number of shareholders), we also examine the cumulative changes in turnover differences between the two groups. As shown in the Panel C, during the former period, the turnover difference was negative, indicating higher turnover in the control group. This is not surprising, as small investors are more likely to engage in day trading than the National Team. In 2018, as the Chinese stock market experienced another crash, turnover was higher in the CSI 500 group than in the CSI 1000. Overall, however, the turnover change differences between the two groups were generally insignificant, suggesting that the national team likely had no prior information about turnover when they injected the rescue funds. Turnover appears to reflect the market's reaction to the crash rather than any information available to the national team before their intervention. Panel D depicts the cumulative change in the dividend rate. As shown in the graph, there is no significant difference between the treated and control groups by the end of 2015. While the treated group exhibited a higher dividend rate in 2016, overall, there is no significant difference between the two groups.

In our investigation of the volatility of the sample stocks, we aimed to assess whether the introduction of exogenous cash flows would lead to changes in volatility. The graph in Panel E illustrates that, from the third quarter of 2015 to the third quarter of 2017, there are no significant differences in the volatility changes between the two groups. Although we observe some notable differences in the last quarter of 2017 and throughout 2018, this period is distanced from the actions of the national team. Therefore, it is insufficient to conclude that the team has the ability to anticipate such future differences in volatility.

We further investigate the labor market impact due to the exogenous purchase and inflated asset price. Since we can only collect annual data on the number of employees, we compare the employee numbers from 2015 onward for the treated group in the CSI 500 and the control group in the CSI 1000. As shown in the Panel F, the difference in Ln(number of employees) changes between the CSI 500 and CSI 1000 groups is not statistically significant after the rescue fund entered the market. Figure 10 has two sets of indications. First, the National Team's purchase is largely orthogonal to the intention of preserving employments, as treated groups are not employing more workers than the control group. Second, a 6.4% exogenous boost in asset prices is not enough to provide significantly more jobs.

In Panels G and H, which display R&D spending and the capital expenditure rate, the shaded area consistently encompasses zero. This indicates no significant difference in these variables between the treated and control groups, suggesting that the cash flow did not lead to a substantial increase in spending on innovation or capital investment.

Regarding delisting probability, 99 stocks in the treated group and an equal number in the control group were still actively traded as A-shares in July 2020. This indicates that the inflated prices did not significantly change the delisting probability for the sample stocks.

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). Regardless of the policymaker's intention, we find that the inflated asset prices, however, did not lead to higher employment, capital expenditure, ROA, or lowered delisting probability in the following years.

APPENDIX A

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

APPENDIX B

Sample Stocks: 100 stocks in CSI 500 (Treated Group) vs. 100 stocks in CSI 1000 (Control Group)

Treated Group			
600983	600780	600509	600826
000422	000735	600325	600195
600801	002430	600425	002392
000823	600864	600059	600064
600997	600851	000921	603366
600971	002277	600389	002317
600141	000417	000962	002140
600720	002194	002705	000631
600596	002225	002557	600351
000877	600657	002048	600329
000726	600488	600884	601999
601101	002237	000488	002254
600284	600073	600761	600773
000951	002342	000418	000762
600563	600702	601965	002233
002393	002118	002490	000667
000525	002122	600199	002011
600456	000552	000501	000680
601678	002281	000919	002029
000780	000636	600067	600122
000572	600460	000830	603001
000900	600586	601208	600251
000926	600743	000426	002482
600636	601126	000969	000099
002028	601233	600298	600750

Control Group			
600230	000731	000701	600386
000597	300110	000589	002126
600449	002483	600467	600708
600279	600830	000551	600162
002386	300129	002521	002671
300080	002060	600368	600973
002328	002597	000570	600630
601798	600237	000886	600084
000789	002510	002668	300127
601677	300193	600459	300375
000521	600979	000553	600360
600322	000419	300082	000153
000935	002286	600192	600328
002628	002033	002394	300154
000968	002035	600982	601616
600723	002567	002083	002300
000159	000949	600740	600116
002566	600081	600469	601007
000404	002255	600382	002182
002457	600523	600197	300050
600303	600354	002144	600843
603123	600683	600858	000752
600668	300102	601996	300304
600308	000571	600082	600680
002355	002449	002561	600822

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