Impact of Demand Shocks on the Stock Market: Evidence from Chinese IPOs☆

Jennifer (Jie) Li[a], Neil D. Pearson[b,c], and Qi Zhang[d]

November 16, 2021

Abstract

The inelastic markets hypothesis states that the aggregate stock market price elasticity of demand is small, implying that flows have large impacts on prices. We exploit demand shocks created as investor funds are frozen and unfrozen during Chinese IPOs to estimate the impact of demand shocks on the Chinese stock market. Using brokerage account records, we observe the selling and buying as investors raise cash to subscribe for IPOs and then reinvest the funds that supported unsuccessful subscriptions. Using an instrumental variables estimator we find that a 10 bps demand shock increases stock prices by between 30 and 48 bps.

JEL Classifications: G11, G12, G18, G24

Keywords: Inelastic markets hypothesis, demand shocks, Chinese stock market, initial public offering

---

☆We gratefully thank Bong-Geun Choi, Hong Chen, Jintao Du, Rui Guo, Grace Hu, Kewei Hou, Zhiguo He, Lei Jiang, Wenjin Kang, Jun Liu, Kai Li, Jun Pan, Gordon Phillips, Yaxuan Qi, Shen Tao, Yongxiang Wang, Xueping Wu, Junbo Wang, Woody Wu, Lu Yao, Zhishu Yang, Hong Zhang, Ning Zhu, seminar participants at the City University of Hong Kong, Shanghai Advanced Institute of Finance, Tsinghua University School of Economics and Management, Renmin University Hanqing Institute, NYU Shanghai, Shanghai University of Finance and Economics, Birmingham Business School, Leeds School of Business, and participants at the 2019 China Financial Research Conference, and the 2019 China International Conference in Finance for helpful comments . We thank Kunpeng Zhou for excellent research assistance. Li acknowledges financial support from Shanghai Pujiang Talent Program and National Science Foundation of China (Grant NO. 71903124).

[a] Shanghai Advanced Institute of Finance, 211 West Huaihai Road, Shanghai, China 200030. Tel.: +86 21 62933591. E-mail: jli6@saif.sjtu.edu.cn.

[b] Department of Finance, University of Illinois at Urbana-Champaign, 1206 South Sixth Street, Champaign, Illinois, 61820, USA. Tel.: +1 (217) 244-0490. E-mail: pearson2@illinois.edu.

[c] CDI Research Fellow, Canadian Derivatives Institute, 3000, Chemin de la Côte-Sainte-Catherine, Montréal, Québec H3T 2A7, Canada.

[d] Department of Economics and Finance, Durham University Business School, Mill Hill Lane, Durham DH1 3LB, UK. Tel.: +44 191 3345376. E-mail: qi.zhang2@durham.ac.uk.

Impact of Demand Shocks on the Stock Market: Evidence from Chinese IPOs

November 16, 2021

Abstract

The inelastic markets hypothesis states that the aggregate stock market price elasticity of demand is small, implying that flows have large impacts on prices. We exploit demand shocks created as investor funds are frozen and unfrozen during Chinese IPOs to estimate the impact of demand shocks on the Chinese stock market. Using brokerage account records, we observe the selling and buying as investors raise cash to subscribe for IPOs and then reinvest the funds that supported unsuccessful subscriptions. Using an instrumental variables estimator we find that a 10 bps demand shock increases stock prices by between 30 and 48 bps.

JEL Classifications: G11, G12, G18, G24

Keywords: Inelastic markets hypothesis, demand shocks, Chinese stock market, initial public offering

1. Introduction

Government asset purchases have been important throughout the modern history of the Chinese stock market (Brunnermeier, Sockin, and Xiong 2018, Song and Xiong 2018). Similarly, the Japanese government currently holds 5% of the Japanese stock market. Recently, government interventions also have been important in western countries, for example quantitative easing policies in the U.S., Europe, and the U.K. (Krishnamurthy and Vissing-Jorgensen 2011, Bridges and Thomas 2012, Christensen and Rudebusch 2012, and Joyce, Miles, Scot and Vayanos 2012). Are government interventions in stock markets are effective? Should western countries consider quantitative easing policies in stock markets in addition to their bond markets? The magnitude of the aggregate stock market demand elasticity is a key parameter in evaluating the likely impact of such programs. Most rational and behavioral asset pricing models predict a very large price elasticity, suggesting that governments' stock purchases have little impact on prices.

In contrast, Gabaix and Koijen (2020b) propose the inelastic markets hypothesis. They begin with the observation that many investors are constrained by investment mandates that make their share demands inelastic. For example, investment mandates constrain equity mutual fund and pension fund managers to invest in equities regardless of market conditions. Hedge funds, which might be the natural arbitrageurs, hold only a small fraction of the aggregate stock market.[1] The model described by Gabaix and Koijen (2020b) captures this feature of financial markets and explains aggregate market inelasticity. In their model the sensitivity of prices to investor flows, the reciprocal of the elasticity, can be high. Thus investor flows in and out of the stock market have large impacts on prices and the model is able to generate stock market volatility that is high relative to the volatility in fundamentals.

Of course, the fact that many equity managers are constrained to remain invested in equities does not guarantee that their demands are inelastic. The shareholdings of constrained equity funds can change as the funds' ultimate investors increase or decrease their investments in the constrained funds. Thus, the magnitude of the impact of flows on prices is an empirical question, which so far remains largely unexplored.

[1] Gabaix and Koijen (2020b) point out that hedge funds hold only about 5% of the equity market and tend to reduce their equity allocations in bad times, possibly because of outflows or risk constraints (see Ben-David et al. (2012)).

This paper exploits institutional features of Chinese A-share initial public offerings (IPOs) that create large shocks to retail investor demands for shares of other listed companies, and uses these shocks to estimate how the level of the aggregate Chinese stock market responds to the demand shocks.[2] We estimate the impact of flows on prices in the Chinese market to be large, with a 10 basis point shock to demand altering the market price level by between 30 and 48 basis points.

This paper is among the first attempt to empirically estimate the aggregate stock market elasticity of demand. Contemporaneously, Gabaix and Koijen (2020b) provide another empirical estimation using U.S. data and the granular instrumental variables (GIV) approach described in Gabaix and Koijen (2020a), which exploits idiosyncratic shocks to the positions of large institutional investors. Gabaix and Koijen (2020b) estimate that buying 1% of the aggregate stock market increases its level by about 5%, or equivalently that the elasticity is about 0.2, which is about the same magnitude as our estimates.

Gabaix and Koijen's (2020b) estimates are from their new GIV approach, which relies on an identifying assumptions about the information sets of large institutional investors. We use traditional instrumental variables estimation that involves projecting the IPO demand shocks onto a set of plausibly exogenous instruments. Both estimates complement to each other in providing empirical support for the IMH.

The demand shocks we exploit are created by the interaction of several institutional features of Chinese A-share IPOs. Due to regulatory restrictions that cap the price/earnings (P/E) ratio at which shares may be offered, Chinese A-share IPOs are badly underpriced with first-day returns averaging over 100%.[3] From 1996 through the end of 2018, 95.2% of the 3,226 IPOs

[2] Chinese A shares are issued by mainland companies, listed on either the Shanghai or Shenzhen exchanges, and are traded by mainland Chinese investors using the Chinese yuan as the trading currency. Currently A shares may also be traded by certain foreign investors through the QFII, RQFII, and Stock Connect programs. B shares issued by mainland Chinese companies are listed in Shanghai or Shenzhen and are available to foreign investors, using the US dollar (Shanghai) or Hong Kong dollar (Shenzhen) as the trading currency. B shares may also be traded by certain mainland investors who have appropriate foreign currency accounts. H shares are listed in Hong Kong, use the Hong Kong dollar as the trading currency, and traded by Hong Kong and foreign investors. H shares may also be traded by certain QDII approved mainland investors and under the Stock Connect programs.

[3] According to Ritter (2011), the cap on the P/E ratio has been changed several times since 1996. From 1996 to 1999, the offer price was not permitted to result in a P/E ratio greater than 15. From July 2002 through the end of 2004, the P/E ratio was constrained to be not higher than 20. Starting from 2005, the cap on the P/E ratio was officially dropped, but in fact the CSRC did not approve IPOs with a P/E ratio greater than 23. Many researchers have documented the severe underpricing of Chinese IPOs, for example, Mok and Hui (1998), Su and Fleisher (1999), Su (2004), Chan et al. (2004), Wang (2005), Kimbro (2005), and Li (2006). In our data we confirm that the average IPO first-day return exceeds 100%.

experienced positive first-day returns. As a result of this underpricing, Chinese IPOs are typically very oversubscribed. From 1996 to 2018, the annual average ratio of IPO subscriptions by retail investors to available shares was 920. The median ratio was 800, and even in the year with the smallest average ratio, 2012, the mean subscription ratio was 108.

Second, during two periods running from December 26, 1996 through February 1, 2000 and from September 18, 2006 through January 5, 2016 the IPO process involved the freezing and unfreezing of investor funds. Specifically, for each investor IPO subscription cash in an amount equal to the value of the IPO shares requested was locked up or frozen and could not be used to purchase other securities for several days until the investor learned whether the subscription was successful. If the subscription was unsuccessful, the unused funds were unfrozen and available to be used to buy other securities. Through this process, investors had large needs for cash to subscribe for IPOs. For example, in 2015 the mean ratio of the amount of frozen funds to aggregate market capitalization on the trading date prior to the subscription date was 1.85%. In some years the mean ratio was smaller, for example 0.36% in 2012, and in some years much larger, for example 16.88% in 2006.

We use the investor trading and subscription records to show that many IPO investors sold shares in other companies on or shortly before the dates on which funds were frozen (the frozen dates) to obtain the cash necessary to back IPO subscriptions, and then purchased shares on and shortly after the unfrozen dates when their funds were released to them. While the amounts of the share sales and purchases were typically much smaller than the amounts of frozen and unfrozen funds—most of the funds used for IPO subscriptions came from sources other than share sales—the share sales (purchases) on the frozen (unfrozen) dates were still significant, averaging 0.036% (0.026%) of aggregate stock market capitalization.

We next explore the market returns on the frozen and unfrozen dates. We estimate regressions to explain market returns and account for the fact that a day can be both the frozen date of one IPO and the unfrozen date of another, which frequently happens. The coefficient estimates indicate that the market falls and rises by 22.0 and 31.6 basis points on the frozen and unfrozen dates, respectively. Combing these estimates with the sales and purchases of 3.6 and 2.6 basis points of aggregate stock market capitalization on the frozen and unfrozen dates, these estimates suggest that sales and purchases cause prices to fall or rise by several times the amounts of the net sales or purchases.

However, the share sales to raise the funds may be endogenous because investors' decisions to lock up funds to participate in the IPO and sell shares to raise the needed funds may depend on stock market conditions, including market liquidity, which in turn may be related to the price impact of the share sales and purchases. Thus simple comparisons of the share sales and purchases on the frozen and unfrozen dates to the price movements do not provide valid estimates of the price impact of the demand shocks. We address the endogeneity of investors' trading through an instrumental variables approach in which we first regress the amount of net trading in shares of other companies on industry indicator variables and other plausibly exogenous instruments. The industry indicator variables are useful instruments because investor interest in IPOs varies across industries. Together with indicator variables for the frozen and unfrozen date and the IPO sizes, they explain more than 40% of the variation in share sales and purchases on the frozen and unfrozen dates. We then include the fitted values from the first stage in second-stage regressions to estimate the impacts of the frozen amounts and net trading on the stock market indexes. Doing this we estimate that a demand shock of ten basis points of market capitalization alters the market price level by between 30 and 48 basis points.

These prices movements are unlikely to be due to information released on the frozen and unfrozen dates, as information about IPOs becomes public several months before the frozen dates. In addition, an IPO investor's wealth does not change as funds are frozen—rather the investor is temporarily unable to use some of his or her wealth to buy securities. Thus, the shocks to investor demand for shares of other companies are not associated with simultaneous releases of information or changes in wealth. Rather, each IPO amounts to the arrival of another investment opportunity that is so desirable due to the severe underpricing of IPOs that it leads to sales of shares of other companies to raise cash to participate in the IPO and then share purchases as the IPO funds are unfrozen.

Finally, we apply our results to estimate the impact of the Chinese National Team's purchases of shares during the third quarter of 2015 in response to the Chinese stock market collapse in June 2015. From the beginning to the end of the third quarter, the total market value of shares held by the National Team increased from 3.98% to 7.46% of the total market capitalization of the stocks listed on the Shanghai and Shenzhen exchanges. Our estimates of the price impact of demand shocks range from 2.998 to 4.781. Using the midpoint of this range of coefficient estimates, 3.89, we estimate that the National Team's buying during the third quarter of 2015 caused stock prices to be 3.89 × (7.46% – 3.98%) = 13.54% higher at the end of the quarter than they otherwise would have been.

Gabaix and Koijen (2020a, 2020b) are not the first to model aggregate stock market elasticity. Johnson (2006) studies endogenous variations in aggregate liquidity that arise in representative-agent endowment economies, focusing on the slope of the representative agent's demand curve. He finds that the price impact of demand shocks can be greater than one in several models. Johnson (2008) and Deuskar and Johnson (2011) also study aggregate market liquidity and the price impact of trading. Recent empirical literature provides implications on aggregate stock market elasticity using shocks to demands due to institutional changes. Da et al. (2018) study the impact of a financial advisory firm's recommendations of reallocations between equity and bond funds in the Chilean market, and finds that they create price pressure and volatility changes. Ben-David et al (2021) use Morningstar mutual fund rating system changes and show that advice-driven demand for mutual funds contributes to economically significant price fluctuations at the style level. Although the focus of the two papers is not to provide well-identified estimates of the aggregate stock market elasticity, some of their results are consistent with the inelastic markets hypothesis.

The next section of the paper describes the brokerage firm account records and other data we use. Section 3 describes the institutional setting, including the market for Chinese A-share IPOs, the IPO pricing policies, and the subscription mechanism that involves freezing and unfreezing subscription funds. It also shows that investors' net buying of shares of other companies is negative and positive on the frozen and unfrozen dates, respectively. In Section 4, we present the results showing that there are negative and positive market returns on the frozen and unfrozen dates, respectively. In Section 5, we describe and report the results of the main instrumental variables analyses showing that the demand shocks have statistically and economically significant impacts on the aggregate stock market. Section 6 discusses our estimates of the National Team's impact on the stock market during the summer of 2015, and Section 7 briefly concludes.

2. Data

Our instrumental variables analyses use information about IPO subscriptions and investor trading from a proprietary dataset of brokerage account records provided by a leading Chinese securities firm. These data include data on the investors' trades in stocks and other instruments, cash holdings, and IPO subscriptions. We also use data on IPOs and stock prices and returns from CSMAR and WIND, two leading Chinese data vendors.

2.1 Brokerage account data

The securities firm that provided the data is one of the largest in China. The brokerage account records come from a total of 310 branch offices located in 30 different regions across China, where a "region" can be either a province (e.g., Fujian), a municipality (e.g., Shanghai), or an autonomous region (e.g., Xinjiang). The data contain information about the investors' transactions and holdings in stocks, ETFs, and other securities during the period running from 2006 through 2018. There are 4,079,651 accounts of which 1,116,669 subscribed to one or more IPOs, consisting of 1,111,214 individual investors and 5,455 institutional investors. These "institutional investors" are not large financial institutions such as mutual funds, because during this period large Chinese institutional investors typically had direct access to the exchanges and did not trade through brokerage firms. We believe that many and probably most of the institutional investors whose trade records appear in the brokerage firm data are privately held companies or private equity funds.

Each trade record includes the investor's account number, date, time, stock or ETF ticker symbol, buy/sell indicator, transaction price, number of shares, and share balance after the transaction. If we aggregate the buys and sells on a daily basis for each account and each listed stock and ETF, the dataset contains 1,359,768,052 observations indexed by account, stock or ETF, and date.

The data also include the investors' successful and unsuccessful IPO subscriptions, including their times, and the investors' daily cash holdings. The investors' cash balances allow us to determine the investors' transfers of funds into and out of their brokerage accounts, because any change in cash balances not explained by purchases and sales and associated commissions must be due to cash transfers in or out of the brokerage accounts. Thus, the data allow us to determine whether the funds used for IPO subscriptions come from pre-existing cash balances, sales of securities, or transfers from external sources.

Our main instrumental variable analyses use the data from the period running from September 18, 2006 through January 5, 2016. This is the intersection of the sets of dates for which we have the brokerage account data and the IPO process created shocks to investors' holdings of shares of other companies due to investors' needs to sell shares to raise cash to participate in the IPOs. There were a total of 1,486 IPOs during this period. Conditional on subscribing, the mean (median) investor subscribed for 40,059.72 (6,000) shares with mean (median) value of ¥421,330 (¥74,035) per IPO.

2.2 IPO and stock market data

While our instrumental variables analyses use the brokerage account data during the period running from September 18, 2006 through January 5, 2016, we also carry out some analyses using IPOs from before this period. For the broader sample, we start with all IPOs offered on the Shanghai and Shenzhen stock exchanges from 1996 to 2018, covering the entire history of the modern Chinese stock market through 2018. We use the IPO data starting from 1996 because the regulation of IPO subscriptions prior to 1996 was very preliminary, and we have not been able to determine the policies that were in effect. In addition, prior to 1996 some of the data that we need for our analyses are often missing from the databases maintained by Chinese financial data vendors.

The IPO and stock market data come from two sources: the China Stock Market and Accounting Research (CSMAR) database, which is available through Wharton Research Data Services (WRDS), and the Wind Financial Database (WIND), another leading Chinese data vendor. From CSMAR, we retrieve all available information about the subscriptions to IPO shares. For each IPO, the data include the numbers of shares issued online and offline, the number of online and offline subscribers, the online and offline subscription rates, and the fraction of online subscriptions that win the lottery used to allocate shares (the lottery rate). The data also include the number of shares allocated to strategic investors, and the lockup periods for institutional investors including mutual funds, insurance companies, and other strategic investors.

From WIND, we also retrieve data about the IPO issuance process and subscriptions, and additional variables including the IPO pricing and first-day performance and some information about the IPO roadshows. The variables related to the IPO subscriptions include the number of shares issued online and offline, the number of online and offline subscribers, the online and offline subscription rates, the online lottery rate, the number of shares allocated to strategic investors, the lockup periods for institutional investors, and the pre-determined P/E ratio. The WIND data also include the amounts of online and offline investors' funds that are frozen and unfrozen during the IPO process we describe in Section 3. We crosscheck the data from the two databases to ensure the accuracy of the information.

Some of our regression analyses use the CSMAR market sentiment index as a control variable. This sentiment index is constructed following Baker and Wurgler (2006) using principal component analysis to extract the common variation in six sentiment proxies. The six sentiment proxies are the closed-end fund discount, share turnover on the Shanghai and Shenzhen stock exchanges, the number of IPOs and their average first-day returns, the number of new accounts opened on the Shanghai and Shenzhen stock exchanges, and the consumer confidence index. The sentiment measure is computed at annual frequency from 2003 to 2018.

3. Chinese IPO market

Chinese A-share IPOs are heavily regulated by the China Securities Regulatory Commission (CSRC). A company must receive permission from the CSRC to go public, the application process is burdensome and lengthy, and the CSRC limits the number of IPOs. Conditional on eventually receiving permission to go public, it is normally several years from initial application to IPO. As a result, neither the issuing companies nor the securities firms that manage the process control the timing of the IPOs. Offering prices are also capped, as we describe below, leading to large first-day returns and very high subscription rates.

3.1 IPO pricing policy

Offering prices are constrained by caps on the trailing price/earnings (P/E) ratio at which shares may be offered. As described in Ritter (2011), during the early years of the modern Chinese stock market the maximum permitted P/E ratio varied between 13 and 15. From July 1999 through the end of June 2002, the CSRC conducted an experiment in which IPO prices were determined by auctions dominated by on-line bidding from retail investors. Starting from July 2002, the CSRC returned to capping offering prices, with caps of around 20. Starting from 2005, the restriction on the P/E ratios was officially dropped.[4] However, in practice, the CSRC

[4] On December 7, 2004, the CSRC issued a "Notice on Several Issues Concerning the Trial Inquiry System for Initial Public Offering" and the supporting document "Memorandum of Standards for Examination of Stock Issuance No. 18 - Regulatory Requirements on the Conditions and Behavior of Inquiry Objects for Initial Public Offering" formally introducing a new stock inquiry system to help determine IPO offering prices. The core of the inquiry system is to stipulate that the issuer and its sponsor shall determine the issue price by means of book building from institutional investors.

did not and still does not approve IPOs with a P/E ratio based on trailing earnings greater than 23.

Our instrumental variable analyses use data running from September 18, 2006 through January 5, 2016 when the P/E ratio was effectively capped at 23. During this period, institutional investors participated in a price-setting offline auction, with prices constrained by the cap on the P/E ratio. The cap was almost always binding, so shares were almost always sold at a price that resulted in a P/E ratio of 23. Retail investors subscribe to IPOs using an online mechanism. For IPOs on the Shanghai exchange investors subscribe in units of 1,000 shares, while for Shenzhen IPOs they subscribe in units of 500 shares. The maximum subscription amount for any investor account may not exceed 1/1,000 of the total number of shares offered. Each 1,000 (Shanghai) or 500 share (Shenzhen) subscription is separately entered into an IPO lottery that randomly selects the subscriptions that receive shares. The retail investors whose subscriptions are selected in the lottery then buy the shares at the price determined in the offline auction.

In the secondary market, Chinese stocks typically trade at P/E ratios well above 23. Thus, due to the caps on the P/E ratios IPOs have been severely underpriced throughout the modern history of the Chinese stock market (Mok and Hui, 1998; Su and Fleisher, 1999; Su, 2004; Chan et al., 2004; Wang, 2005; Kimbro, 2005; and Li, 2006), with average first day returns much larger than is typical of other markets, for example the United States.[5] Figure 1 confirms this underpricing by showing the number of Chinese A-share IPOs (left scale) and equal-weighted average first-day returns (right scale) during each calendar quarter from 1996 to 2018. The average first-day returns are 44% in the right-hand part of Figure 1 due to CSRC regulation that placed a limit of 44% on IPO first-day returns starting from 2014. The IPO underpricing is very high at the beginning of 1996. It then declines after 1996 but it is still much higher than that in the U.S. market. Figure 2 shows the number of IPOs during the 2006–2018 period with first-day returns falling in various intervals. The figure shows that only about 5% of all IPOs experienced a negative first day return. The large number of returns in the interval (25, 50] is a consequence of the 44% price limit on IPO first-day returns.[6]

[5]The literature documenting underpricing of U.S. IPOs includes McDonald and Fisher (1972), Logue (1973), Ibbotson and Jaffe (1975), Reilly (1977), Miller and Reilly (1987), Smith (1986), and Ritter (1984)).

[6] There is a 10% price limit on daily secondary market returns after the first trading day. If we use the return over the first three days then starting from 2014 the average returns in the right-hand part of Figure 1 are all close to 74.2% = 1.44×1.1^2. A large fraction of the returns over the first ten days are equal to 239.5% = 1.44×1.1^9

3.2 IPO subscription rates

In Table 1 we report some summary statistics describing the IPOs and their subscription rates for the years 1996–2018. Column (1) reports the number of IPOs in each year. In some years, the column contains two numbers, for example 55/135 for the year 2000. In these cases, the second number is the number of IPOs, while the first is the number of IPOs that followed the procedures in place during the period running from December 26, 1996 through February 1, 2000, which involved the freezing and unfreezing of subscription funds described below. Column (2) is the annual total gross proceeds of each year's IPOs divided by the total market capitalization of the Shanghai and Shenzhen stock exchanges as of the end of the previous year. It shows that in some years total IPO proceeds were a very large fraction of market capitalization. Unsurprisingly, this is the case in the early years of the Chinese stock market; for example, the IPO proceeds in 1996 were 26.98% of stock market capitalization as of the end of the previous year. Annual IPO proceeds were also large fractions of stock market capitalization during the stock market boom of 2006 and 2007, when the annual IPO proceeds were 19.10% and 20.24% of the stock market capitalization at the end of 2005 and 2006, respectively. The minimum ratio occurs in 2018, when the year's total IPO proceeds represented only 0.22% of stock market capitalization.

Column (3) shows, for each year, the equal-weighted average of the IPO size, where the size is measured as the ratio of the gross proceeds (offering price × shares sold) divided by the total market capitalization of the stocks listed on the Shanghai and Shenzhen stock exchanges on the last trading date of the previous year. The mean of the annual means is 0.0006 or 0.06%, i.e. the average IPO raised funds equal to 0.06% of aggregate stock market capitalization at end of the previous year.

The next two columns (4) and (5) show the fractions of shares that were sold through the online and offline mechanisms. In each case, the number in the table is the equal-weighted mean of the ratio across the IPOs during the year. The mean online and offline portions often do not sum to one because some shares are sold through the market value allotment mechanism described below. For example, during 2003–2005 all shares were sold through this mechanism, so the online and offline fractions were zero during this period. Except during this period, the bulk of IPO shares were sold using the online retail investor lottery.

The subscription rates reported in the rightmost four columns measure the extent to which the IPOs were oversubscribed. The online (offline) subscription rate is the ratio of the total number of shares requested through the online (offline) auction to the total number of shares allocated for online (offline) sale. The four rightmost columns report the annual equal-weighted means and medians of these ratios. The online subscription rate is the more important one because the bulk of the shares were sold through the online mechanism. These columns show that the subscription rates were consistently very high, except during 2003–2005 when all IPO shares were sold using the market value allotment mechanism. Given the high oversubscription ratio, the probability of winning each IPO lottery is low. Even with a low probability of gaining an extremely positive return, the expected returns are low so that it appears not rational for investors to subscribe.[7] During 2006, the first year for which we have the brokerage firm data, the average IPO size was 0.00273, or 0.273% of aggregate stock market capitalization on the previous trading day. During 2015, the last full year for the sample used in our main analyses, the average IPO size was only 0.00002, or 0.002% of market capitalization.

3.3 Freezing and unfreezing of subscription funds

Starting from 1996, we can identify four different regulatory regimes governing Chinese IPOs. Two of these four regimes required the freezing and unfreezing of IPO subscription funds. As indicated above, this freezing and unfreezing created shocks to investors' demands for shares as investors sold shares to raise funds to subscribe for IPOs and then reinvested in the stock market when their funds were unfrozen.

From December 26, 1996 through February 1, 2000, the subscription process involved the freezing and unfreezing of funds. On the subscription date T, investors submit orders to purchase IPO shares. On the next day ($T + 1$), the China Securities Depository and Clearing Corporation (CSDC) freezes the subscription funds in an amount equal to the value (offering price × quantity) of the IPO shares requested.[8] Thus, on the subscription date investors must either already have cash at least equal to the value of the IPO shares requested in their brokerage accounts, transfer funds in from some outside source, or sell other securities to raise the needed

[7] Hu et al. (2019) frame investor IPO subscription as lottery-like experiences and find that winning the IPO lottery increases investors' subsequent gambling propensity.

[8] If the subscription funds cannot be recorded in time due to the bank settlement system, it shall provide the remittance voucher through the electronic interbank system of the People's Bank of China on $T + 1$ and ensure that the subscription funds are recorded in the account on the morning of $T + 2$.

cash. On $T + 2$, the lead underwriter, together with its accountants and the CSDC, check the availability of subscription funds. On the third day after the subscription date ($T + 3$), the lead underwriter organizes the lottery over the subscriptions and announces the winning subscriptions. On the fourth day after the subscription date ($T + 4$) the funds backing the winning subscriptions are used to pay for the IPO shares and the other funds are unfrozen. Throughout this process, the freezing of funds does not change an investor's wealth as the frozen funds remain the property of the investor. They are either used to pay for IPO shares or made available to the investors on the fourth trading date following the subscription date.

During a second period running from February 1, 2000 through September 17, 2006, the subscription policy was mixed in that some the IPOs still followed the subscription policy in effect during the previous period while other IPOs follow a procedure referred to as "market value allotment" that did not involve the freezing of funds. In the market value allotment procedure, investors may submit orders for IPO new shares based on the market value of the securities they hold.[9] Specifically, each investor holding securities with a market value of ¥10,000 on date $T – 2$ is permitted to apply to purchase 1,000 IPO shares for each ¥10,000 of market value, and the subscription amount must be an integer multiple of 1,000 shares. Investors holding securities with market value less than ¥10,000 may not apply for IPO shares. Investors are informed of the winning subscriptions on date $T + 2$, and then pay for the shares on $T + 3$, without any freezing of subscription funds. Gradually, the old subscription policy was abandoned and all IPOs followed the market value allotment. In our analyses below, we include the IPOs that took place during the period running from February 1, 2000 through September 17, 2006 but followed the procedures of the previous period with the IPOs that took place during the first period.

The market returned to a procedure that involved the freezing and unfreezing of funds during a third period running from September 18, 2006 through January 5, 2016. During this period there was a hybrid system that combined an offline tranche sold to institutional investors using a price-setting auction together with an online tranche for which retail investors placed orders without specifying a price. For retail investors, the subscription policy during this period was very similar to that from the first period except that the unfrozen date changed from the

[9] The securities that are used to calculate the market value include stocks, mutual funds and convertible bonds.

fourth to the third trading date (T + 3) after the subscription date. Specifically, retail investors submit orders and pay for the requested shares on the subscription date. To do this, investors must have the full amount of funds available on the subscription date. On T + 1, the issuer and its lead underwriter, together with its accountants and the China Securities Depository and Clearing Corporation (CSDC), check the availability of subscription funds. On date T + 2, the CSDC determines the extent to which the offering is oversubscribed and then after the close of trading informs the brokerage firms participating in the IPO the fraction of share subscriptions that can be fulfilled. On the third trading day (T + 3) after the subscription date, the CSDC deducts the subscription funds from the accounts of the winning bidders and unfreezes the remainder of the subscription funds. Starting from 2009, CSRC also required that the maximum online subscription amount for each stock account shall not exceed 1/1,000 of the total number of shares offered through the online process.[10]

During a fourth period starting from January 6, 2016 the market reverted to the market value allotment used during the second period. Differences are that the allotments are based on the average holdings form date $T-22$ to $T-2$, investors are informed of the winning subscriptions on date T + 1, and then pay for the shares on T + 2. Thus, there is no freezing and unfreezing of funds, investors do not need to raise large amounts of cash to subscribe for IPOs and there no shocks to investor share demands on the frozen and unfrozen dates.

Our main analyses use the shocks to investor shareholdings created by the freezing and unfreezing of funds and require the brokerage account data, which are available starting from 2006. Thus, our main analyses use data from the third period running from September 18, 2006 through January 5, 2016. During this period there were 1,461 A-share IPOs and 597 distinct frozen dates, and the unfrozen date was the third trading date after the frozen date.

Due to the very high subscription rates shown in Table 1, during the first and third periods the frozen and unfrozen amounts were often significant fractions of the aggregate market capitalization of the Shanghai and Shenzhen stock exchanges. We report statistics describing the frozen funds in Table 2. The first four columns show the year, the number of IPOs in each year, and the annual mean online and offline subscription rates. The next six columns report statistics about the online, offline, and total frozen funds. In each case, the frozen amount consists of the

[10] http://www.csrc.gov.cn/pub/zjhpublic/G00306201/200906/t20090612_107417.htm.

subscriptions through the sales channel (online, offline, or the total of online and offline), divided by the aggregate stock market capitalization of the Shanghai and Shenzhen exchanges on the trading date prior to the subscription date. The statistics reported are either the annual equally-weighted means or the annual medians, as indicated by the column headings. The frozen funds are zero during the years when the IPO process did not involve freezing and unfreezing of funds.

Scanning down the rightmost two columns reporting the annual mean and median total frozen funds for the other years, it is clear that the frozen amounts can be large. For example, in 2002 the frozen funds for a typical IPO were about 23% of aggregate stock market capitalization on the day before the subscription date, and the annual mean exceeded 10% in seven of the years. The frozen amounts have become smaller fractions of market capitalization in recent years, but even in 2015 the mean and median frozen amounts were 1.85% and 1.35% of aggregate stock market capitalization.

The unfrozen amounts are similar to the frozen amounts, and thus are not reported. They differ only in that the frozen funds backing winning subscriptions are used to pay for the shares and thus are not unfrozen. Due to the very high subscription ratios, the unreturned frozen funds are only small fractions of the frozen funds.

We next use the brokerage firm data to compute estimates of the total cash balances of IPO subscribers in event time around the frozen dates, which is date zero. For each IPO, we start with the total cash balances of the brokerage firm IPO subscribers eight days before the frozen date. For each date from –7 to +8 we increment the initial cash balances of the IPO subscribers by either the net transfers into the brokerage accounts from external sources or the sum of the net transfers from external sources and the net proceeds from trading stocks, ETFs and mutual funds. To scale up to the market level, we divide the two amounts by the IPO subscriptions of the brokerage firm investors and multiply by the total IPO subscriptions for the entire market. The results are estimates of the total cash balances of all IPO subscribers. Finally, we divide these estimates by the market capitalization of stocks on the Shanghai and Shenzhen exchanges on date –9 to express the cash balances as a percentage of aggregate stock market capitalization. Figure 3 displays the cross-sectional means of these two series, in event time. Note that most of the cash balances are frozen on dates 0, 1, and 2; these frozen amounts are included in cash balances displayed in the figure.

The solid black line in Figure 3 shows that there is a large increase in investors' cash balances on the frozen date 0; on that date the cash balances increased from 2.79% to 4.13% of the total market capitalization of stocks listed on the Shanghai and Shenzhen exchanges. The dashed line, which excludes the changes in cash balances due to trading securities, is only slightly below the solid line, indicating that most of the increases in cash balances were due to cash transfers into the account from external sources rather than from stock, ETF, and mutual fund sales. Cash balances then do not change much on dates 1 and 2, which is to be expected because most of the date 0 cash balances are frozen as the investors subscribe for IPOs. Cash balances then fall sharply on the unfrozen date 3 as funds are unfrozen and investors both use unfrozen funds to buy shares and transfer unfrozen cash out of their brokerage accounts, and then fall again, though by smaller amounts, on day 4. While it is not visually apparent in Figure 3, the difference between the solid and dashed lines increases from date –1 to date 0 and decreases from date 2 to date 3. This indicates that security trading contributed to the increase and decreases in cash balances on date 0 and 3, respectively.

To highlight the effects of security trading on cash balances, we next use the brokerage account data to explore the IPO subscribers' net trading around the frozen date in more detail. Specifically, in Figure 4 we show the net buying from eight days before to eight days after the frozen date, which is date zero, during the 2006–2016 period. To construct this figure, for each IPO frozen date we first aggregate net trading (including net trading of stocks, ETFs and mutual funds) across all IPO subscribers on each of the dates –8, –7, …, 8. For each IPO we then scale the net buying up to the market level by dividing by the total IPO subscriptions of the brokerage firm investors and multiplying by the total amount of subscription funds for the entire market. We then express the net buying as a fraction of aggregate stock market capitalization by dividing by the total market capitalization of stocks listed on the Shanghai and Shenzhen exchanges on date -9. For each IPO the result of this calculation is a sequence estimates of (scaled) net buying for the event dates –8, –7, …, 8. Finally, for each date we then compute the mean and median across dates, and present the means and medians in Figure 4.

Figure 4 shows net selling increasing gradually around one week before the frozen date, with much more selling on date –1 and then even more on the unfrozen date 0. The mean (median) value of net buying on the frozen date is about –0.037% (–0.015%) of the total market capitalization of the Shanghai and Shenzhen exchanges. The mean and median values of net trading are close to zero on dates 1 and 2, and then becomes positive on the unfrozen date 3 and the following date 4. On the unfrozen date, the mean (median) value of net buying is 0.027% (0.008%) of the total market capitalization of the stocks in the Shanghai and Shenzhen composite indexes.

4. Stock market returns on the frozen and unfrozen dates

The net selling (buying) shown in Figure 4 leads us to predict negative (positive) market returns on the frozen (unfrozen) dates of the IPOs that followed the procedures of the first and third periods that involved freezing and unfreezing of subscription funds. [11] There were 1,764 such IPOs but only 843 distinct frozen and unfrozen dates because there was often more than one IPO on the same date. During the first and third periods, the unfrozen date was four or three days after the frozen date, respectively.

Shi, Sun, and Zhang (2018) have previously found that there were negative returns on the Shanghai and Shenzhen stock market indexes on the frozen dates using data from part of our sample period. We also examine the stock returns on the unfrozen dates, and take account of the fact that many dates are both frozen and unfrozen dates.

Our sample period for this analysis consists of the dates running from Dec. 26, 1996 through January 5, 2016. This period includes all of the IPOs that involved the freezing and unfreezing of funds. One issue is that a date t can be both the frozen date of one IPO and the unfrozen date of another. We address this using a regression in which the dependent variable is the aggregate market return computed as the value-weighted return on the Shanghai and Shenzhen indexes on date t. The covariates consist of indicator variables for dates that are the frozen or unfrozen dates of one or more IPOs and additional indicator variables for some of the dates around the frozen and unfrozen dates. Specifically, we define the following indicator variables. $F_{-2}(t) = 1$ if t is two days before the frozen date of an IPO; $F_{-1}(t) = 1$ if t is one day before a frozen date of an IPO; $F(t) = 1$ if t is a frozen date of an IPO; $F_{+1}(t) = 1$ if date t is the first date after the frozen date of an IPO; $F_{+2}(t) = 1$ if date t is the second or third (second) date after an frozen date during the first (third) period; $U(t) = 1$ if t is the unfrozen date of an IPO;

[11] Testing these hypotheses does not require the brokerage account data. Thus, for these tests we include the IPOs from the first period when the brokerage account data are not available.

$U_{+1}(t) = 1$ if t is the day after the unfrozen date of an IPO; and $U_{+2}(t) = 1$ if t is two days after the unfrozen date of an IPO. For many days, more than one indicator variable equals one. Then we estimate a regression in which the left-hand side variable is the market return and the right-hand side variables are the indicator variables together with a constant.

We report the regression results in Table 3. The estimates for the frozen and unfrozen dates are –0.22% (t-statistic = –3.12) and 0.316% (t-statistic = 4.46) respectively, implying that market returns are significantly negatively and positively related to the frozen and unfrozen date indicator variables, respectively, as expected.[12] These results indicate that something happened on the frozen and unfrozen dates to affect the aggregate stock market.

5. Instrumental Variables Regressions

We now turn to estimating the impact of the frozen and unfrozen date share sales and purchases on the level of the aggregate stock market. We address the possible endogeneity of the share sales using instrumental variables regressions in which we estimate first stage regressions that use a set of plausibly exogenous instruments to predict the share sales and purchases. We then estimate second-stage regressions that use the fitted values from the first stage to explain the stock market returns. We estimate three sets of such instrumental variables regressions. The first set uses trading and returns data from the frozen and unfrozen dates, while the second set uses data from short windows that include those dates, and the third set uses data from longer windows that include the frozen and unfrozen dates.

The unit of observation is a date. The sample for the first set of regressions consists of the trading dates that are the frozen or unfrozen dates of one or more IPOs with subscription dates during the period running from September 18, 2006 through January 5, 2016. This is the intersection of the periods for which the IPO process involved the freezing and unfreezing of funds and we have brokerage firm data that includes the subscription amounts and trading records that allow us to compute the investors' net trading. During this sample period, the

[12] The sample period running from September 18, 2006 through January 5, 2016 includes three years (2003–2005) during which none of the IPOs involved the freezing and unfreezing of funds. We obtain similar results if we restrict the regression to the first and third periods, i.e. if the sample consists of the dates running from December 26, 1996 through February 1, 2000 together with the dates running from September 18, 2006 through January 5, 2016. During this period there were 1,727 IPOs and 746 distinct frozen dates. The estimated coefficients on the indicator variables for the frozen and unfrozen dates are –0.223% (t-statistic = –2.66) and 0.344% (t-statistic = 4.11), respectively.

unfrozen date was always three days after the frozen date. This period includes 1,461 IPOs but only 597 distinct frozen dates, of which 233 are also unfrozen dates of earlier IPOs. Thus we have in total 961 (= 2 × 597 − 233) dates that are either frozen or unfrozen dates.

The sample for the second set of regressions consists of the trading dates that are either the frozen date of an IPO, the trading date before the frozen date, the unfrozen date, or the trading date after the unfrozen date. This sample includes 1,295 such dates. The sample for the third set of regressions consists of all trading days that include five days before a frozen date, dates between a frozen and an unfrozen date, and three days after an unfrozen date. This sample includes 1,594 such dates.

5.1 First-stage regressions that explain net trading on the frozen and unfrozen dates

The dependent variable $NetTrad(t)$ is a measure of net trading on date *t* constructed from the brokerage account data, scaled up to the market level. For each frozen or unfrozen date *t*, we first compute the net trading of the brokerage firm investors whose funds are frozen or unfrozen on that date. For each investor at date *t*, the net trading is the sum of net stock trading, net ETF trading, and the impact from purchases and redemptions of mutual funds at date *t*. If the investor holds more than one mutual fund, we estimate the impact by calculating total purchases net of total redemptions, which is multiplied by the percentage of stock holdings in each fund portfolio, as disclosed in the most recent financial report of the mutual fund before date *t*. The total impact from mutual funds for each investor is the sum of net impact across all funds held by the investor on date *t*.

We then normalize each investor's net trading amounts by the total subscriptions of the brokerage firm investors for the IPOs for which her funds were frozen or unfrozen on date *t*, i.e. the IPOs for which she subscribed on dates *t* or *t* – 3. If date *t* is only a frozen (unfrozen) date, we scale her net trading by the total brokerage firm subscriptions of the IPOs for which she subscribed on date *t* (date *t* – 3); if date *t* is both a frozen date and an unfrozen date, and she participated in some IPOs that froze funds on date *t* and some other IPOs that unfroze funds on date *t*, then we scale her net trading by the sum of the total brokerage subscriptions for all of these IPOs. We next scale her net trading up to the market level by multiplying it by the total market wide subscription funds for the IPOs for which her funds were frozen or unfrozen on date *t*. We then sum the scaled net trading of the brokerage firm investors whose funds are frozen or unfrozen on date *t*, yielding an estimate of the market-wide net trading of investors whose subscription funds were frozen and unfrozen on that date. Finally, we express the net trading as a fraction of aggregate market capitalization by dividing by the total market capitalization of stocks on the Shanghai and Shenzhen exchange on trading date $t - 1$, the trading date prior to t.

Our principal instruments are indicator variables that equal one for the frozen and unfrozen dates and industry indicator variables. These are exogenous and explain net trading on the frozen and unfrozen dates because investors sell and buy on the frozen and unfrozen dates, respectively, and interest in IPOs differs across industries. We also estimate alternative specifications of the first-stage regressions that include additional instruments.

Complications arise from the fact that the unit of observation is a date but some of the covariates are IPO characteristics and often there is more than one IPO on the same date. We account for this by computing size-weighted characteristics of the IPOs on each relevant date, as follows.

Let $M(t)$ denote the number of IPOs with frozen date t, and $M(t-3)$ the number of IPOs with frozen date $t-3$. The characteristics of IPOs with frozen date $t - 3$ appear as date t covariates because t is the unfrozen date of these IPOs and we expect the net buying on the unfrozen date to be related to the characteristics of the date $t - 3$ IPOs. Let $S_{t,m}$ be the amount to be raised by the *m*th IPO on date t divided by the total stock market capitalization across both the Shanghai and Shenzhen exchanges on the preceding date $t - 1$. We expect net trading to be related to the total funds IPO firms are trying to raise. Thus, the regression specifications include the size variables $S_t = \sum_{m=1}^{M(t)} S_{t,m}$ and $S_{t-3} = \sum_{m=1}^{M(t-3)} S_{t-3,m}$, the total sizes of the date t and date $t - 3$ IPOs.

The industry indicator variables are based on the CSRC's 2012 standard industry classification scheme. The first-level industry classification is too crude but the two-level classification is too fine outside manufacturing because there are few IPOs in most two-level industries other than manufacturing. Thus we use the first-level classification for non-manufacturing firms, and the two-level classification for manufacturing firms (those for which the first-level classification is C).[13] We also merge categories that contain fewer than five IPOs.

[13] Our industry classifications are based on the CSRC's 2012 standard industry classifications. We convert IPOs from before 2012 to the 2012 standard.

We merge industries Q (health and social work) and H (accommodation and catering) into one category because industries Q and H have only three and two IPOs, respectively; we merge industry C25 (petroleum processing, coking and nuclear fuel processing) into C26 (chemical raw materials and chemical products manufacturing), and merge industry C42 (comprehensive utilization of waste resources) into C41 (other manufacturing industries), because C25 and C42 contain only two and one IPO, respectively. After these modifications to the CSRC's industry classifications we have 41 different industries. We then construct and include IPO-size-weighted industry indicator variables $D_{h,t} = \sum_{m=1}^{M(t)} D_{h,t,m} S_{t,m}$ and $D_{h,t-3} = \sum_{m=1}^{M(t-3)} D_{h,t,m} S_{t,m}$, where $D_{h,t,m}$ equals one if the mth IPO with subscription date t is in industry h, and equals zero otherwise.

Demand for IPO shares may be related to the expected price at which the IPO shares will trade after the IPO. We use the market-adjusted P/E ratios of listed firms in the same industry as the IPO firm to proxy for this, based on the industry classifications described above. Specifically, for each frozen date t we construct an IPO size-weighted market-adjusted industry P/E ratio of the date t IPO firms as follows. For each IPO in the sample, we first compute the industry P/E ratio as of the IPO date as the sum of the market capitalizations of firms in the same industry as the IPO firm divided by the sum of the firms' most recent four quarterly announced earnings prior to the IPO, and then winsorize the industry P/E ratios at the top and bottom 1%. We then compute market-adjusted industry P/E ratios by subtracting the market P/E ratio for the appropriate date from each industry P/E ratio, where the market P/E ratio is the sum of the market capitalizations of all firms listed on the Shanghai and Shenzhen exchanges, divided by the sum of their most recent four quarterly announced earnings prior to the IPO. Then, if there are $M(t)$ IPOs on trade date t and $PE_{t,m}$ is the market-adjusted industry P/E ratio for the mth date t IPO, we construct the size-weighted market-adjusted P/E ratio $PE_t = \sum_{m=1}^{M(t)} PE_{t,m} S_{t,m}$, where $S_{t,m}$ is the size of the mth IPO on date t, and use the size-weighted ratio as the explanatory variable. This assumes that for date t the impact of the mth IPO P/E ratio is proportional to the size $S_{t,m}$ of the mth IPO, which is reasonable—if the mth IPO on date t is small so that $S_{t,m} \approx 0$ then we expect that this IPO will contribute little to the net trading. We also include the size-weighted P/E ratio $PE_{t-3} = \sum_{m=1}^{M(t-3)} PE_{t-3,m} S_{t-3,m}$ for the IPOs with frozen date $t - 3$ and unfrozen date t.

We include the average first-day returns of the most recent ten IPOs before date *t*, $Past1stDayIPORet_t$.[14] This variable is a characteristic of the date rather than of an IPO firm. However, when we include it we multiply it by the total size variables $S_t = \sum_{m=1}^{M(t)} S_{t,m}$ and $S_{t-3} = \sum_{m=1}^{M(t-3)} S_{t-3,m}$ because we expect the net trading to be increasing in the total IPO sizes as investors raise more cash to participate in larger IPOs. Thus, the regression specification includes the variables $IPORet_t = Past1stDayIPORet_t \sum_{m=1}^{M(t)} S_{t,m}$ and $IPORet_{t-3} = Past1stDayIPORet_{t-3} \sum_{m=1}^{M(t-3)} S_{t-3,m}$.

These additional instruments satisfy the exclusion restriction because the dependent variable in the second stage is the market return on either the frozen or unfrozen date, and the instruments are unlikely to predict daily aggregate market returns other than through the first stage.[15]

We must allow the signs of the coefficients to differ for the frozen and unfrozen dates because we expect IPO investors to be net sellers on the frozen dates and then reinvest unfrozen funds on the unfrozen dates. We also allow the magnitudes of the coefficients to differ for the frozen and unfrozen dates. On the unfrozen dates investors may not reinvest all of the cash that they raised by selling on or shortly before the frozen date, or they may invest some of the other funds that they transferred into their account to participate in the IPOs. We do this as follows.

Let $I(t)$ be an indicator variable that equals one if *t* is the frozen date of an IPO; thus if *t* is the unfrozen date of an IPO $I(t-3) = 1$. For some dates *t* we will have $I(t) = 1$ and $I(t-3) = 0$, for some $I(t) = 0$ and $I(t-3) = 1$, for some $I(t) = I(t-3) = 1$, and for some $I(t) = I(t-3) = 0$. We construct the covariates by interacting the various explanatory variables, including the intercept, with $I(t)$ and $I(t-3)$. This allows the effect of the explanatory variables to differ on the frozen and unfrozen dates.

Taking account of the above, the regression model is

$$NetTrad(t) = I(t) \times \left[a_0^f + b_0^f S_t + b_1^f PE_t + b_2^f IPORet_t + \sum_{h=1}^{H} c_h^f D_{h,t} \right] + I(t-3) \times$$

[14] If the tenth most recent IPO occurs on a date on which there were multiple IPOs then we include the first-day returns of all of the IPOs on the date in the average. Thus, sometimes this variable is an average of the first-day returns of more than ten IPOs.

[15] A caveat is that the covariates may be correlated with market risk premia. However, at the daily horizon risk premia are small, so the possibility that P/E ratios and past returns may be correlated with aggregate risk premia is of no consequence.

$$\left[a_0^u + b_0^u S_{t-3} + b_1^u PE_{t-3} + b_2^u IPORet_{t-3} + \sum_{h=1}^{H} c_h^u D_{h,t-3}\right] + e_j. \qquad (1)$$

There are two sets of regression coefficients, a_0^f , b_0^f, b_1^f , b_2^f, and c_h^f and a_0^u , b_0^u, b_1^u, b_2^u, and c_h^u that capture the impacts of IPOs with frozen or unfrozen date *t*, respectively. The covariates S_t, PE_t, $IPORet_t$, and $D_{h,t}$ are for the IPOs with frozen date *t*, and the covariates S_{t-3}, PE_{t-3}, $IPORet_{t-3}$, and $D_{h,t-3}$ are for IPOs with frozen date t – 3 and thus unfrozen date *t*.

We report the results of these first-stage regressions in Table 4, Panel A. The column headed (1) contains the results of a specification that includes all variables, while the column headed (2) presents the results of a specification that includes only size, the indicator variables for the frozen and unfrozen dates, and the size-weighted industry indicator variables. The column headed (3) shows the results of a specification that includes all variables excluding the size-weighted industry indicator variables. This specification results in an adjusted R^2 of 0.372, lower than the other two specifications, with the adjusted R^2 of 0.453 for the specification that includes all variables and 0.444 for the specification in Column (2). Thus, size, the indicator variables for the frozen and unfrozen dates, and the size-weighted industry indicator variables, account for most of the explained variation in net trading.

In both columns the highly significant negative and positive coefficients on the indicator variables $I(t)$ and $I(t-3)$, respectively, indicate that there is net selling on the frozen date and net buying on the unfrozen date, as expected. The results in Column (1) show that net trading on the frozen date is significantly (at the 10% level) negatively related to the average first-day returns of past recent IPOs, as expected. The average first-day returns of past recent IPOs are negatively and significantly (at the 1% level) related to the net trading in Column (3) with coefficient estimate –0.0918. This is consistent with the hypothesis that higher first-day returns of recent IPOs lead investors to sell stock on the frozen date in order to free cash to subscribe to IPOs. The point estimate on past returns is positive for the unfrozen date as investors use the unfrozen cash to purchase stocks, but insignificant.

5.2 First-stage regressions using additional dates

The specifications described above are likely to result in the most powerful tests because the greatest amounts of net selling and buying occur on the frozen and unfrozen dates, respectively. We also estimate additional specifications that also include the net trading on the date before the frozen date and the date after the unfrozen date because the results shown in Figure 4 indicate that IPO-related selling and buying also occurs on those dates.

The idea in these additional specifications is that for each date t, the net trading $NetTrad(t)$ depends on the IPOs with frozen date t, the IPOs with frozen date $t + 1$ (because investors might sell some shares one day before the frozen date), the IPOs with frozen date $t - 3$ (because t is the unfrozen date of these IPOs), and the IPOs with frozen date $t - 4$ (because t is the date after the frozen date of these IPOs, and investors might buy shares one day after the unfrozen date). We similarly construct the dependent variable $NetTrad(t)$ as the scaled net trading as in the last section. For each investor who participated in IPOs with their frozen dates on either t, $t + 1$, $t - 3$, $t - 4$ (i.e. date t is zero or one days ahead of, or three or four days after, the frozen date of an IPO), we calculate her net trading (including net stock trading, net ETF trading, and net mutual fund trading) on date t. We then divide her net trading by the sum of total brokerage subscriptions for all IPOs she participated on either t, $t + 1$, $t - 3$, $t - 4$, and multiply by the total amount of subscription funds of these IPOs for the entire market. We sum up the scaled net trading on date t for all investors whose funds were frozen on either t, $t + 1$, $t - 3$, $t - 4$, and finally divide by the total market capitalization on the Shanghai and Shenzhen Composite on the date before date $t - 2$, yielding the dependent variable $NetTrad(t)$.[16]

The regression model must also include the explanatory variables for all IPOs falling during the windows. Thus, we estimate the regression model

$$
\begin{aligned}
NetTrad(t) = {} & \\
& I(t) \times \left[a_0^f + b_0^f S_t + b_1^f PE_t + b_2^f IPORet_t + \sum_{h=1}^{H} c_h^f D_{h,t}\right] + \\
& I(t+1) \times \left[a_0^f + b_0^f S_{t+1} + b_1^f PE_{t+1} + b_2^f IPORet_{t+1} + \sum_{h=1}^{H} c_h^f D_{h,t+1}\right] + \qquad (2) \\
& I(t-3) \times \left[a_0^u + b_0^u S_{t-3} + b_1^u PE_{t-3} + b_2^u IPORet_{t-3} + \sum_{h=1}^{H} c_h^u D_{h,t-3}\right] + \\
& I(t-4) \times \left[a_0^u + b_0^u S_{t-4} + b_1^u PE_{t-4} + b_2^u IPORet_{t-4} + \sum_{h=1}^{H} c_h^u D_{h,t-4}\right] + e_t.
\end{aligned}
$$

[16] If the investor participated in some IPOs that froze funds on date t and some other IPOs that unfroze funds on date t, then we scale her net trading by the sum of the total brokerage subscriptions for all of these IPOs.

where the various covariates were defined previously.

We report the results in Table 4, Panel B. As in Panel A the column headed (1) contains the results of a specification that includes all variables, while the column headed (2) presents the results of a specification that includes only the size-weighted industry dummy variables. The column headed (3) shows the results of a specification that includes all variables excluding the size-weighted industry indicator variables. Similar to Panel A, they show that the date and industry indicator variables, along with the size variables, account for most of the explained variation in net trading. The specification with just the size variables and the date and industry indicator variables has an R^2 of 45.2%, which increases only slightly to 45.7% in the specification with all variables. Turning to the other covariates, the net trading on the frozen and unfrozen dates is negatively and positively related to the past IPO returns, as expected, though the coefficient estimates are insignificant in Column (1). In the specification excluding the industry indicators, the average first-day returns of past recent IPOs are negatively and significantly (at the 1% level) related to the net trading. The coefficient estimate on the P/E ratio variable $PE_{t-3} + PE_{t-4}$ is also positive and significant, as expected.

Furthermore, we estimated a specification where the net trading $NetTrad(t)$ depends on all the IPOs with frozen date $u \in [t-6, t+5]$, (i.e. date t was within [-5, +6] days around the frozen date of an IPO, in other words, date t is within five days before a frozen date, between a frozen and an unfrozen date, or within three days after an unfrozen date). We calculate the net trading on date t for each investor who participated in IPOs with frozen date within $[t-5, t+6]$, and divide by the subscription funds of the IPOs that the investors participated in, and multiplied by the total amount of subscription funds of these IPOs for the entire market. We then sum up the scaled net trading from all these IPO investors with frozen date within $[t-5, t+6]$, and finally, divide the sum by the total market capitalization on the Shanghai and Shenzhen Composite ondate $t-6$, yielding the estimate of $NetTrad(t)$.

We include four sets of coefficients in this specification: with a_0^f , b_0^f, b_1^f, b_2^f, and c_h^f and a_0^u , b_0^u, b_1^u, b_2^u, and c_h^u that capture the impacts of IPOs with frozen or unfrozen date t, respectively, we include a_0^b , b_0^b, b_1^b, b_2^b, and c_h^b captures the impacts of IPOs for the pre-frozen dates, and a_0^a , b_0^a, b_1^a, b_2^a, and c_h^a captures the impacts of IPOs for the post-unfrozen dates. The model becomes

$$
\begin{aligned}
&NetTrad(t) \\
&\sum_{j=1}^{5}\left[I(t+j)\times\left(a_0^b+b_0^bS_{t+j}+b_1^bPE_{t+j}+b_2^bIPORet_{t+j}+\sum_{h=1}^{H}c_h^b\,D_{h,t+j}\right)\right]+ \\
&\qquad I(t)\times\left(a_0^f+b_0^fS_t+b_1^fPE_t+b_2^fIPORet_t+\sum_{h=1}^{H}c_h^f\,D_{h,t}\right)+ \\
&\qquad I(t-3)\times\left(a_0^u+b_0^uS_{t-3}+b_1^uPE_{t-3}+b_2^uIPORet_{t-3}+\sum_{h=1}^{H}c_h^uD_{h,t-3}\right)+ \\
&\sum_{j=4}^{6}\left[I(t-j)\times\left(a_0^a+b_0^aS_{t-j}+b_1^aPE_{t-j}+b_2^aIPORet_{t-j}+\sum_{h=1}^{H}c_h^aD_{h,t-j}\right)\right]+e_t, \qquad (3)
\end{aligned}
$$

We report the results in Table 4, Panel C. As in Panel A and B, the column headed (1) contains the results of a specification that includes all variables, while the column headed (2) presents the results of a specification that includes only the size-weighted industry dummy variables. The column headed (3) shows the results of a specification that includes all variables excluding the size-weighted industry indicator variables. The R^2s of these regressions are lower because including trading over the longer windows introduces more noise in the dependent variable. The specification with just the size variables and the date and industry indicator variables has an R^2 of 41.3%, which increases only slightly to 42.4% in the specification with all variables.

In all three columns, the highly significant negative and positive coefficients on the indicator variables $I(t)$ and $I(t-3)$, respectively, indicating that there is net selling on the frozen date and net buying on the unfrozen date. The dummy variables that represent pre-frozen dates ($\Sigma_{j=1}^{5}I(t+j)$) and post-unfrozen dates ($\Sigma_{j=1}^{5}I(t-j)$) are negatively and positively correlated with net trading, consistent with net selling before frozen dates and net buying after the unfrozen dates. The average first-day returns of past recent IPOs on the pre-frozen dates are negatively and significantly (at the 1% level) related to the net trading, as expected. In Column (3), the coefficient on the market-adjusted P/E ratio is negative, though insignificant during the pre-frozen dates, and positive and highly significant during the post-unfrozen dates. These results are consistent with the hypothesis that a higher market-adjusted P/E ratio of firms in the same industry as the IPO firms leads investors to sell more stock on the frozen date in order to free more cash to subscribe to the current IPO, and then buy back stock on the unfrozen date as the cash of unsuccessful IPO investors is unfrozen. The size of IPOs is negative on the frozen dates and positive on the unfrozen dates with both highly significant coefficients. These results imply that larger IPOs motivate investors to sell more stocks on the frozen dates and then buy back on the unfrozen date.

5.3 Second-stage regression that explain market returns

For the second-stage regressions, we use either (i) the frozen and unfrozen dates, or (ii) the frozen and unfrozen dates, together with the dates immediately before a frozen date or immediately after an unfrozen date, , or (iii) all dates within [-5, +6] window around a frozen date. In all three cases we estimate the following second stage regression

$$MktReturn(t) = \beta_0 + \beta_1 \times PredNetTrad(t) + \gamma X_t + t, \tag{4}$$

where the dependent variable *MktReturn*(*t*) is the value-weighted average of the returns on the Shanghai and Shenzhen composite indices on date *t*. The key explanatory variable $PredNetTrad(t)$ is the predicted net trading from the one of first stage regressions described above. According to IMH, we expect predicted net trading causes positive market returns. .

The vector X_t consists of the control variables. These are the lagged market returns over the preceding day, week, month, and two months, denoted *MktReturn*[−1], *MktReturn*[−1week], *MktReturn*[−1 month], *and MktReturn*[−2 months]; the absolute values of the four lagged market returns; and the value of the CICSI Chinese market sentiment index from CSMAR. The CICSI sentiment index is constructed using the Baker and Wurgler (2006) matrix of coefficients.

We report the regression results in Table 5. Columns (1)–(3) show the results explaining market returns when the sample consists of the frozen and unfrozen dates, Columns (4)–(6) displays the results when the sample also includes the dates immediately before a frozen date or immediately after an unfrozen date, while Columns (7) – (9) show the results with all dates within [−5, +6] window around a frozen date.

The results in Table 5 show that the key variable *PredNetTrad* is positively significantly correlated with stock market return in all specifications. The coefficient estimates range from a low of 2.998 (*t*-statistic = 2.937) in column (4) to a high of 4.781 (*t*-statistic = 3.662) in column (4). The coefficient estimates are larger in columns (1)–(3) that focus on the frozen and unfrozen dates compared to those in columns (4)–(9) that use trading over longer intervals.

The estimates of the coefficient on the trading variable *PredNetTrad* are economically significant. The midpoint of the range [2.998, 4.781] of these coefficient estimates is 3.89. Using this value, and recalling that net trading is measured relative to aggregate stock market capitalization, the interpretation is that an exogenous demand shock equal to ten basis points of stock market capitalization increases the level of the aggregate stock market by $3.89 \times 10 = 38.9$ basis points. Our estimates of between 2.998 and 4.781 are consistent with the corresponding value of about five estimated by Gabaix and Koijen (2020b) and their inelastic market hypothesis. As pointed out by Gabaix and Koijen (2020b), estimates of this magnitude are inconsistent with the implication most other models. Even the smallest coefficient on *PredNetTrad* we estimate, 2.998 in column (4), is inconsistent with the implications of most other models.

5.4 Discussion

Our instrumental variables estimates use data from IPO frozen and unfrozen dates and the dates immediately before the frozen date and immediately after the unfrozen date. The estimates are thus conditional on the occurrence of the IPOs, i.e. we estimate the impact of the shocks on market prices during periods when IPOs occur. This raises the question of whether the price impacts estimated using data from those dates are representative of other dates. For example, do the issuers or the securities firms who manage the IPO process offer shares when the market is either more or less liquid than typical? This seems unlikely. Conditional on being eventually allowed to issue shares, the time elapsed from initial application to the CSRC to the IPO is typically two to three years or longer, and is not under the control of the issuing companies or the securities firms that manage the process for the issuers. Thus, issuers and the securities firms have no or at most very little ability to time IPOs.

However, the regulators suspend IPOs from time to time, and it is possible that the periods when IPOs are suspended have either high or low liquidity. Figure 6 shows the level of an aggregate market index constructed from value-weighted averages of the Shanghai and Shenzhen Composite index returns along with the market turnover ratio, defined as the ratio of yuan trading volume to total stock market capitalization. The grey-shaded areas represent periods when the Chinese government suspended IPOs. IPOs occurred during most of our sample period, and there is no obvious pattern to the periods when IPOs were suspended. As we can see from Figure 6, IPOs were suspended in 2006 when turnover was high, in 2009 when turnover was higher than average (though not near its peak level during the 2007 market boom) and the market was steadily rising, during 2013 when the market was stable and turnover was lower than average, and during the period of high volatility subsequent to the 2015 stock market collapse. Because IPOs took place throughout most of our sample period, and there is no apparent pattern to the periods when IPOs were suspended, it seems unlikely that regulatory decisions to suspend IPOs from time to time have important impacts on our estimates. Even if they do, it is highly unlikely that correcting our coefficient estimates for any possible bias would alter the conclusion that our results about the impact of demand shocks on stock prices are consistent with the inelastic markets hypothesis and inconsistent with most other models.

6. Impact of National Team Buying During the Third Quarter of 2015

In this section, we combine our estimate of the price impact of demand shocks with estimates of the buying by the Chinese "National Team" during the third quarter of 2015 to estimate the direct (that is, non-informational) impact of the National Team's buying on the aggregate stock market. Asset purchases can also have indirect effects on prices through the information they convey to investors (e.g., Brunnermeier, Sockin, and Xiong 2018), which may be important.

From December 31, 2014 to June 12, 2015, the Shanghai Composite Index increased by 60% and the Shenzhen Composite Index surged by 122%. The Shanghai Composite Index reached its maximum of 5178.19 points on June 12, while the Shanghai and Shenzhen 300 Index reached 5380.43 points on June 9. However, by 8–9 July 2015 the Shanghai stock market had fallen 30 percent over three weeks as 1,400 companies, or more than half of those listed, filed for trading halts in an attempt to prevent further declines.

The Chinese government enacted various actions to stem the stock market turbulence, including suspending IPOs, restricting short selling, and restricting share sales by large shareholders. In addition, in early July 2015 the Chinese government established a "National Team" that included 21 securities firms led by China Securities Finance Corporation Limited (CSF), CSF funds, Central Huijin (HJ), and the SAFE investment platforms, and directed the National Team members to purchase stocks. CSF lent money to the 21 securities firms to facilitate this, and CSF and HJ directly purchased stocks of more than 1,000 companies.

The National Team's buying began on July 6, 2015 and was heaviest during the week of July 6–10. We estimate the National Team's buying during the third quarter of 2015 using data from Wind, which provides the holdings of the National Team members China Securities Finance Corporation Limited (CSF), CSF funds, China Central Huijin Investment Limited (HJ), and the SAFE investment platforms. Each quarter, all listed companies report their top ten shareholders in their quarterly reports, and Wind calculates the holdings of the National Team members based on these reports. At the end of the second quarter of 2015, the members of the National Team appeared as one of the top ten shareholders for only eight listed companies, while at the end of the third quarter the National Team members appeared among the top ten shareholders of 1,404 listed companies.

At the end of the second quarter, the National Team held 3.98% of the total market capitalization of stocks listed on the Shanghai and Shenzhen exchanges. The National Team's holdings increased to 7.46% of total market capitalization by the end of the third quarter.[17] We estimate the direct impact of the National Team's buying using a coefficient of 3.89, which is the midpoint of the range of coefficient estimates on *PredNetTrad* reported in Table 5. Using the estimate of 3.89, the National Team's buying during the third quarter of 2015 caused stock prices to be $3.89 \times (7.46\% - 3.98\%) = 13.54\%$ higher at the end of the quarter than they otherwise would have been.

We also estimate the impact of the daily trading of the National Team during the week of July 6–10. For each stock, we take the increase in the National Team's stock holdings from June 30, 2015 to September 30, 2015 as the total amount of shares that the National Team purchased. We allocate the purchases to each trading day using the "large transaction" data provided by RESSET, which sums all transactions above 10 million yuan for each stock on each day. Figure 6 plots the daily large transactions during the third quarter of 2015. One can see a sharp rise in large transactions during July 6–10.

We estimate the National Team's daily trading by assuming that the distribution of its trading across days is the same as the distribution of large transactions. Specifically, for each stock and date during the third quarter of 2015 we calculate the daily ratio of the shares traded in

[17] If we compute the value of the holdings at the end of the third quarter using the positions at the end of the third quarter but prices from the end of the second quarter we obtain an estimate of 7.49% of market capitalization.

large transactions to the total number of shares traded in large transactions during the quarter. We then multiply this ratio by the number of shares purchased by the National Team between June 30 and September 30, resulting in an estimate of the National Team's stock trading for each stock and date. Next for each date we multiply the estimated number of shares by the intraday average stock price (calculated as the total value of shares purchased divided by total number of shares purchased) to obtain an estimate of the National Team's purchases of each stock on each day, and then sum across stocks to yield an estimate of the total National Team buying on each date. Finally, we scale the estimates of the National Team's daily buying by the total market capitalization of the stocks listed on the Shanghai and Shenzhen exchanges as-of the close of trading on the previous day. Figure 7 plot the resulting daily series for the third quarter of 2015.

We estimate the impact of the National Team's buying during the week of July 6–10, 2015 by summing the daily estimates of buying during the week and multiplying by 3.89, the estimate we used above. We estimate that the National Team bought shares with total value equal to 1.33% of total market capitalization during the week of July 6–10, 2015, and caused prices at the end of the week to be 3.89 × 1.33% = 5.17% higher than they otherwise would have been. The estimates of daily buying on the five days of the week ranged from 0.20% to 0.44% of market capitalization, and the price impact of the daily buying ranged from ranged from 0.778% to 1.712% of market capitalization.

7. Conclusion

We exploit the fact that the Chinese IPO procedures in effect up until early 2016 involved the freezing and unfreezing of investors' funds and important shocks to their stock trading. An investor who subscribed for IPO shares was required to have cash in his or her brokerage account greater than or equal to the value of the requested shares. Investors often sold shares in other companies to raise the funds to participate in the IPOs, and then investors whose subscriptions were unsuccessful would buy shares when their funds are unfrozen.

We use brokerage account records to estimate the magnitudes of the net trading on the frozen and unfrozen dates. Net selling (buying) on the frozen (unfrozen) dates averaged 0.039% (0.026%) of aggregate market capitalization. Using the value-weighted return on the Shanghai and Shenzhen indexes, we show that the aggregate stock market fell 22.0 basis points on the frozen dates when investors sold shares, and rose by 31.6 basis point on the unfrozen dates when investors bought shares.

In our main analyses, we estimate the impact of stock trading on the level of the aggregate stock market using an instrumental variables approach that exploits the fact that investor trading on the frozen and unfrozen dates is well predicted by a set of plausibly exogenous instruments. We first regress investors' net trading on the instruments, and then use the fitted values in a second stage regression to estimate the impacts on the stock market indexes. We find that a shock to demand equal to ten basis points of market capitalization causes a return of between 29.98 and 47.81 basis points. As pointed out by Gabaix and Koijen (2020b), impacts of these magnitudes are consistent with the inelastic markets hypothesis and inconsistent with most other theories. We also find that shocks to investors' available funds do not impact the level of the stock market other than through their impact on investors' net trading.

References

Brunnermeier, M. K., and L. H. Pedersen. 2008. Market liquidity and funding liquidity. *Review of Financial Studies* 22(6): 2201‒2238.

Brunnermeier, M. K., and Y, Sannikov. 2014. A macroeconomic model with a financial sector. *American Economic Review* 104(2): 379‒421.

Brunnermeier, M. K., M. Sockin, and W. Xiong, W. 2020. China's model of managing the financial system. Working Paper, Princeton University.

Chang, Y. C., H. Hong, and I. Liskovich. 2014. Regression discontinuity and the price effects of stock market indexing. *Review of Financial Studies* 28(1): 212‒246.

Chakrabarti, R., W. Huang., N. Jayaraman, and J. Lee, 2005. Price and volume effects of changes in MSCI indices–nature and causes. *Journal of Banking & Finance* 29(5): 1237‒1264.

Chen, G., M. Firth, and J. Kim. 2000. The post-issue market performance of initial public offerings in China's new stock markets. *Review of Quantitative Finance and Accounting* 14, 319‒339.

Chan, K., H.W. Kot, and G.Y. Tang. 2013. A comprehensive long-term analysis of S&P 500 index additions and deletions. *Journal of Banking Finance* 37(12), pp.4920-4930.

Chen, H., G. Noronha, and V. Singal. 2004. The price response to S&P 500 index additions and deletions: Evidence of asymmetry and a new explanation. *Journal of Finance* 59(4): 1901‒1930.

Denis, D.K., J.J. McConnell, A.V. Ovtchinnikov, Y. Yu. 2003. S&P 500 index additions and earnings expectations. *Journal of Finance* 58(5): 1821-1840.

Deuskar, Prachi and Timothy C. Johnson. 2011. Market liquidity and flow-driven risk *Review of Financial Studies* 24(3): 721‒753

Dhillon, U. and H, Johnson. 1991. Changes in the Standard and Poor's 500 list. *Journal of Business* 64(1): 75‒85.

Gabaix, Xavier. 2012. Variable rare disasters: An exactly solved framework for ten puzzles in macro-finance. *Quarterly Journal of Economics* 127, No. 2, 645-700.

Gabaix, Xavier, and Ralph Koijen. 2020a. Granular instrumental variables. Working paper, Harvard University and the University of Chicago.

Gabaix, Xavier, and Ralph Koijen. 2020b. In Search of the origins of financial fluctuations: The inelastic markets hypothesis. Working paper, Harvard University and the University of Chicago.

Garleanu, N., and Lasse H. Pedersen. 2011. Margin-based asset pricing and deviations from the law of one price. *Review of Financial Studies* 24(6): 1980‒2022.

Goetzmann, W.N. and M. Garry. 1986. Does delisting from the S&P 500 affect stock price? *Financial Analysts Journal* 42(2): 64–69.

Harris, L. and E. Gurel. 1986. Price and volume effects associated with changes in the S&P 500 list: New evidence for the existence of price pressures. *Journal of Finance* 41(4): 815–829.

Hau, H., M. Massa, and J. Peress. 2009. Do demand curves for currencies slope down? Evidence from the MSCI global index change. *Review of Financial Studies* 23(4): 1681-1717.

He, Z., and A. Krishnamurthy. 2013. Intermediary asset pricing. *American Economic Review* 103(2): 732–770.

Ibbotson, R. G., and J.F. Jaffe. 1975. “Hot issue” markets. *Journal of Finance* 30(4): 1027–1042.

Johnson, Timothy C. 2006. Dynamic liquidity in endowment economies. *Journal of Financial Economics* 80(3): 531–562.

Johnson, Timothy C. 2008. Volume, liquidity, and liquidity risk. *Journal of Financial Economics* 87(2): 388–417.

Kimbro, M. B. 2005. Managing underpricing? The case of pre-IPO discretionary accruals in China. *Journal of International Financial Management & Accounting* 16(3): 229–262.

Kaul, A., V. Mehrotra, V. and R. Morck. 2000. Demand curves for stocks do slope down: New evidence from an index weights adjustment. *Journal of Finance* 55(2): 893-912.

Kraus, A. and Stoll, H.R., 1972. Price impacts of block trading on the New York Stock Exchange. Journal of Finance, 27(3), pp.569-588.

Logue, D. E. 1973. On the pricing of unseasoned equity issues: 1965–1969. *Journal of Financial and Quantitative Analysis* 8(1): 91–103.

Li, L. 2006. Can corporate governance variables explain short-term IPO returns? A study of the Chinese market. *Accounting, Accountability & Performance* 12(1): 64.

Li, J., Liao, L., and Shen, H. (2013). Price Elasticity for Stocks: Evidence from China's Split-Share Structure Reform. Available at SSRN 2362257.

Liu, C. and B. Wang. 2020. Do demand curves for stocks slope down in the long run? PBCSF-NIFR Research Paper,

Mok, H. M., and Y.V. Hui. 1998. Underpricing and aftermarket performance of IPOs in Shanghai, China. *Pacific-Basin Finance Journal*, 6(5): 453–474.

Loderer, C., J.W. Cooney, and L.D. Van Drunen. 1991. The price elasticity of demand for common stock. *Journal of Finance*, 46(2): 621-651.

Lynch, A.W. and R. R. Mendenhall. 1997. New evidence on stock price effects associated with changes in the S&P 500 index. *Journal of Business* 70(3): 351–383.

McDonald, J. G., and A.K. Fisher. 1972. New-issue stock price behavior. *Journal of Finance*, 27(1): 97–102.

Miller, R. E., and F. K. Reilly. 1987. An examination of mispricing, returns, and uncertainty for initial public offerings. *Financial Management*, 33–38.

Ofek, E. and M. P. Richardson. 2000. Large the IPO lock-up period: Implications for market efficiency and downward sloping demand curves. Available at SSRN 207908.

Petajisto, Antti. 2009. Why do demand curves for stocks slope down? *Journal of Financial and Quantitative Analysis* 44(5): 1013–1044.

Reilly, F. K. 1977. New issues revisited. *Financial Management* 6(4): 28–42.

Ritter, J. R. 1984. The “hot issue” market of 1980. *Journal of Business* 57(2): 215–240.

Scholes, Myron. 1972. The market for securities: Substitution versus price pressure and the effects of information on share price. *Journal of Business* 45(2): 179–211

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

Song, Zheng and Wei Xiong. 2018. Risks in China’s financial system. *Annual Review of Financial Economics* 10: 261–286.

Su, D. 2004. Adverse-selection versus signaling: Evidence from the pricing of Chinese IPOs. *Journal of Economics and Business* 56: 1−19.

Su, D., and B. M. Fleisher. 1999. An empirical investigation of underpricing in Chinese IPOs. *Pacific-Basin Finance Journal* 7(2): 173–202.

Shi, Song, Qian Sun, and Xin Zhang. 2018. Do IPOs affect the market price? Evidence from China. *Journal of Financial and Quantitative Analysis* 53(3): 1391–1416.

Wang, C. 2005. Ownership and operating performance of Chinese IPOs. *Journal of Banking & Finance* 29, 1835−1856.

Wurgler, J. and E. Zhuravskaya. 2002. Does arbitrage flatten demand curves for stocks? *Journal of Business* 75(4): 583–608.

Figure 1
Numbers of Chinese A-share IPOs and average IPO first-day returns, by quarter. This figure shows the number of Chinese A-share IPOs during each calendar quarter from 1990 to 2018 and the equal-weighted average first day return of the IPOs in each quarter. Starting from January 2014, CSRC set price limits that constrained IPO first-day returns to be less than or equal to 44%.

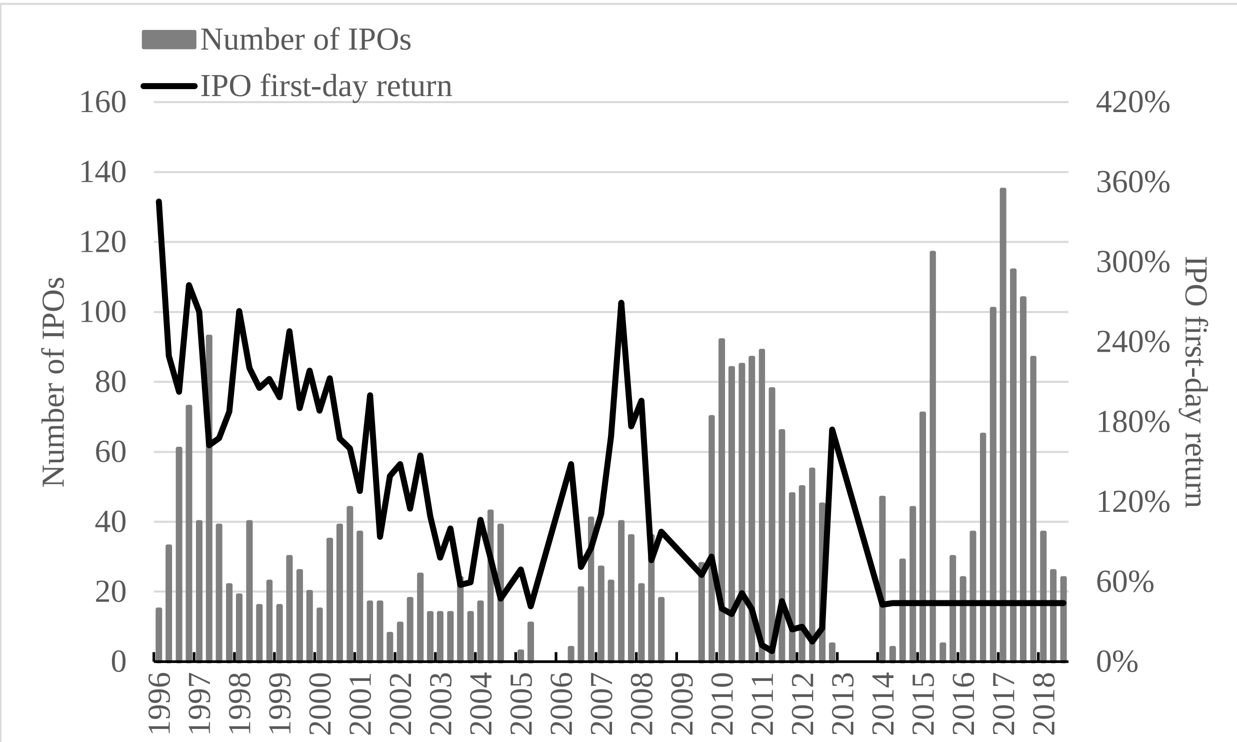

Figure 2
Distribution of first-day returns following Chinese A-share IPOs. Starting from January 2014, CSRC set price limits of 44% on IPO first-day returns. The figure shows the number of IPOs with initial returns falling in each interval. The sample consists of Chinese A-share IPOs during the period running from 1996 through 2018. The vertical shows the number of IPOs and the horizontal axis shows the return intervals, where the returns are in percent.

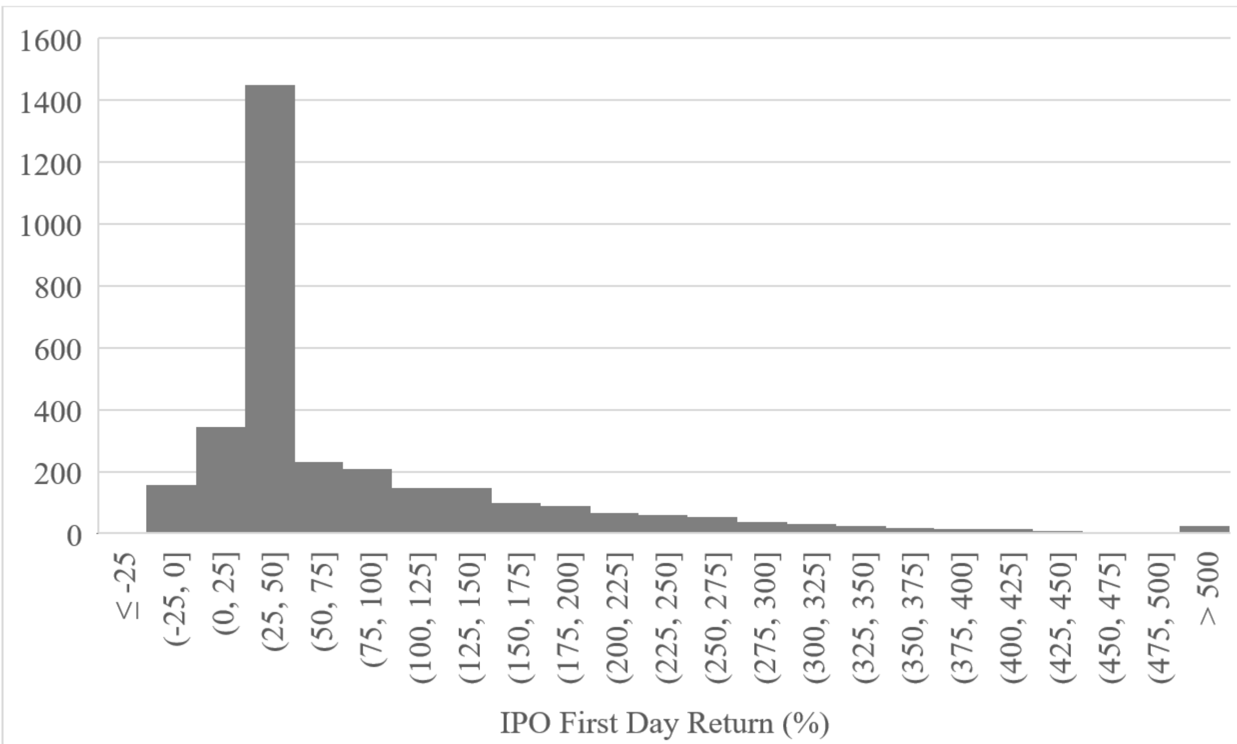

Figure 3
Investors' cash balances around the frozen dates of Chinese A-share IPOs. The figure displays the cumulative changes to cash balances of the IPO subscribers in the brokerage firm, in event time where the frozen (subscription) date is date zero, around IPO frozen dates. The sample consists of Chinese A-share IPOs during the period running from September 18, 2006 through January 5, 2016. There were a total of 1,461 IPOs during this period but only 597 distinct frozen dates. For each date that is an IPO subscription date, we start with the total investor cash balances on event-time date –8. Each day we increment the initial cash balance by the net transfers into the brokerage accounts from external sources shown in dashed line. Or we increment the initial cash balance by the sum of the net transfers from external sources and also the proceeds from net trading (including selling of stocks, ETFs, and mutual funds), which is shown in the black line. We divide the accumulated cash transfers into account, and cash from net trading for the IPO subscribers by their IPO subscription funds, and multiply by the total amount of subscription funds for the entire market and finally scaled by the total market capitalization of stocks on the Shanghai and Shenzhen exchange on the preceding date -9. The figure displays the cross-sectional means of these two series.

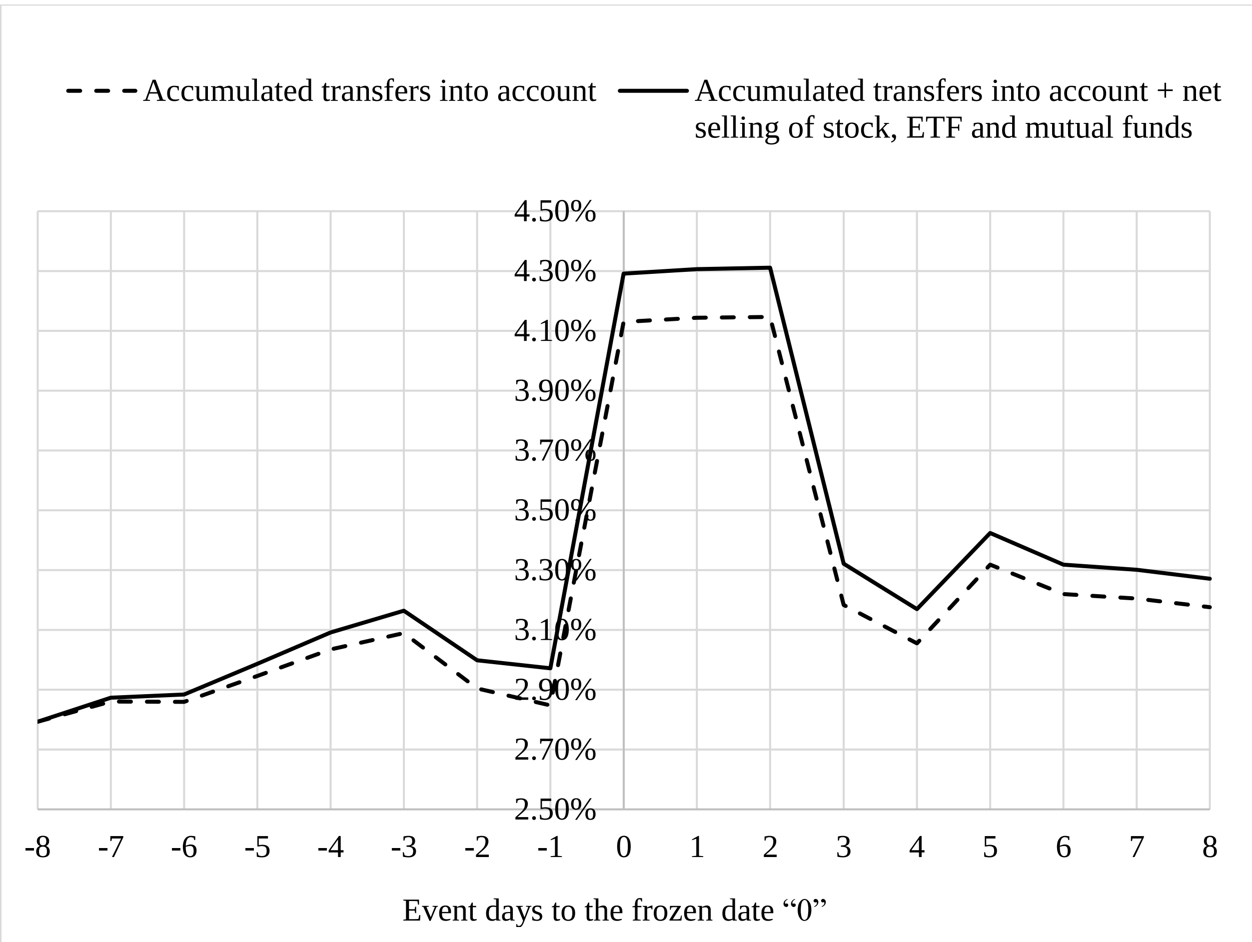

Figure 4
Net trading of the IPO subscribers in the brokerage firm around the frozen (subscription) dates of Chinese A-share IPOs. The sample consists of Chinese A-share IPOs during the period running from September 18, 2006 through January 5, 2016. There were a total of 1,461 IPOs during this periods but only 597 distinct frozen dates. For all investors who participated in IPOs, we calculate their aggregate net trading (including net trading of stocks, net trading of ETFs and net purchases of mutual funds) on each date. We divide their net trading by the sum of total brokerage subscriptions for all IPOs, and multiply by the total amount of subscription funds of these IPOs for the entire market. For investors who subscribe for more than one IPO, we divide the net buying by the brokerage firm subscriptions of the IPOs they subscribe and multiply by the total subscriptions of these IPOs in the entire market to obtain the scaled net buying for these investors. Finally, we sum up the scaled net buying from all these groups of investors and divide by the total market capitalization on the Shanghai and Shenzhen Composite on the date -9 to scale up to the market level. The figure displays the cross-sectional mean and median net trading in event time, where date 0 is the frozen date.

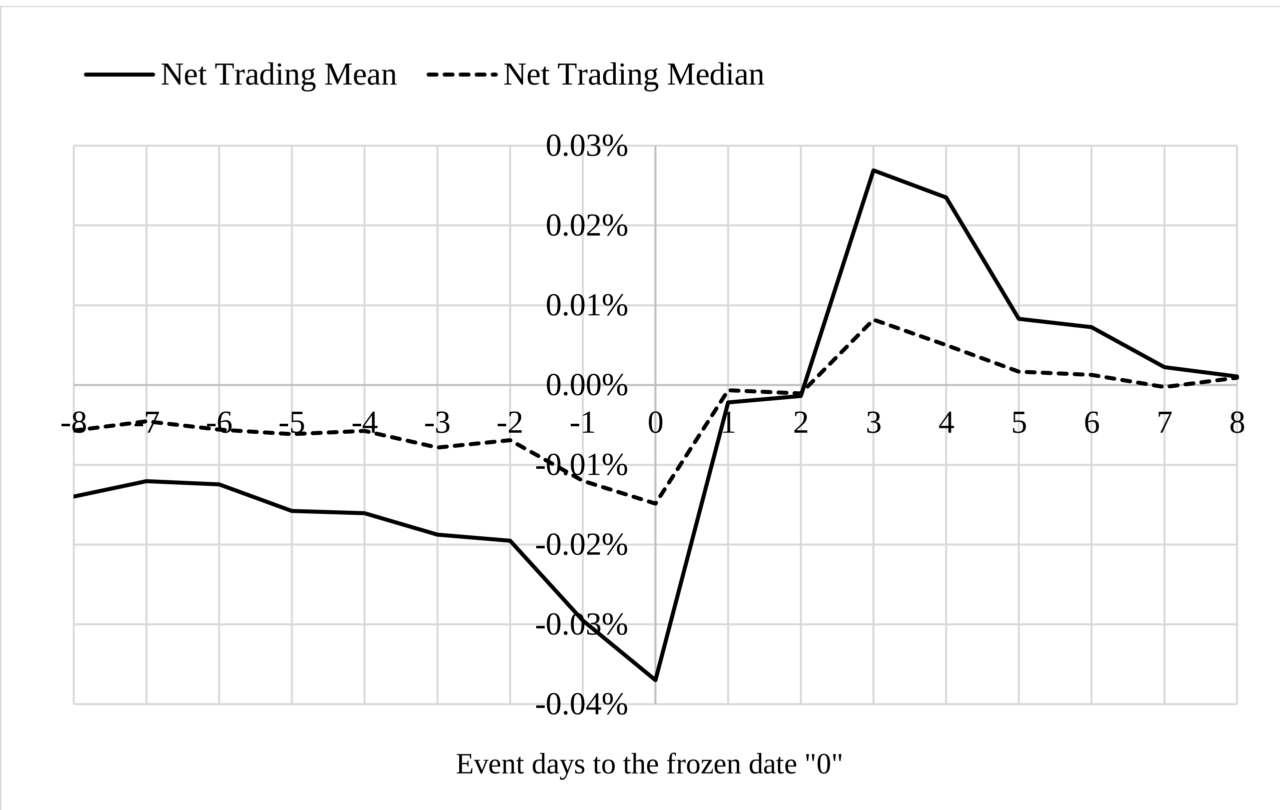

Figure 5
IPO suspension and non-suspension periods during the period running from 2006 through 2016. The figure shows an aggregate Chinese stock market index and the market turnover ratio, defined as trading volume/total market capitalization. The aggregate stock market index is constructed by compounded on the daily returns on the value-weighted average of the Shanghai and Shenzhen composite indexes, starting from an index value of 100 on January 2, 1996. The grey areas indicate periods during which Chinese A-share IPOs were suspended.

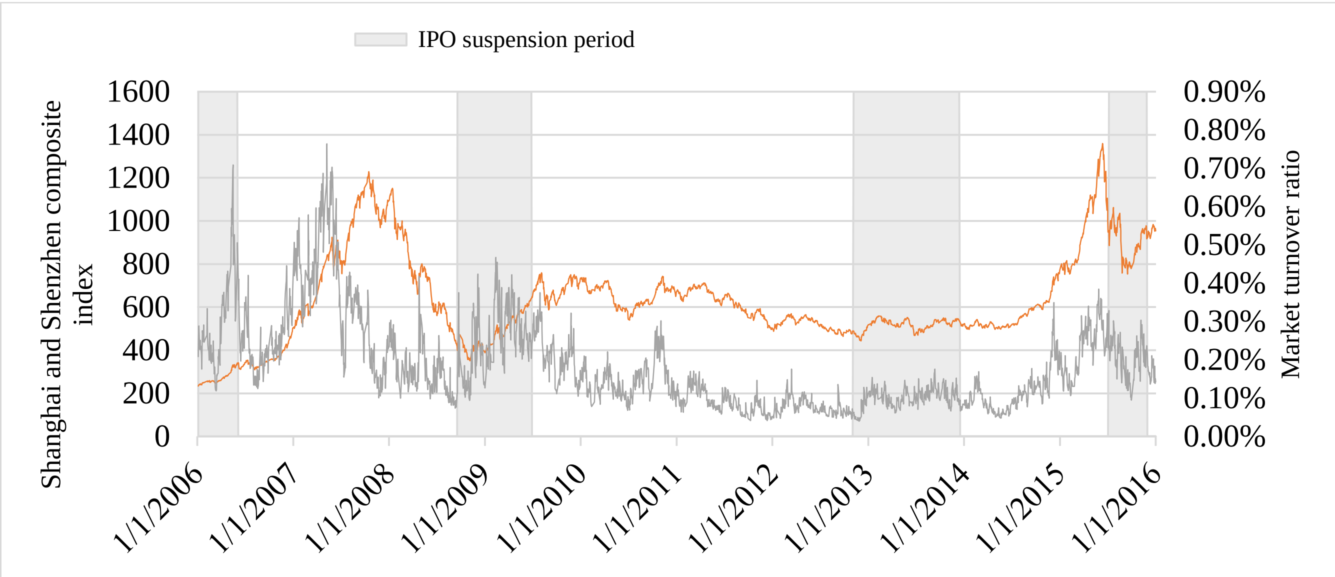

Figure 6
The distribution of daily scaled large transactions during 2015 Quarter 3. The scaled large transaction is calculated as the total value of large transactions above 10 million yuan divided by the lagged one-day total market capitalization of the stocks listed on the Shanghai and Shenzhen exchanges.

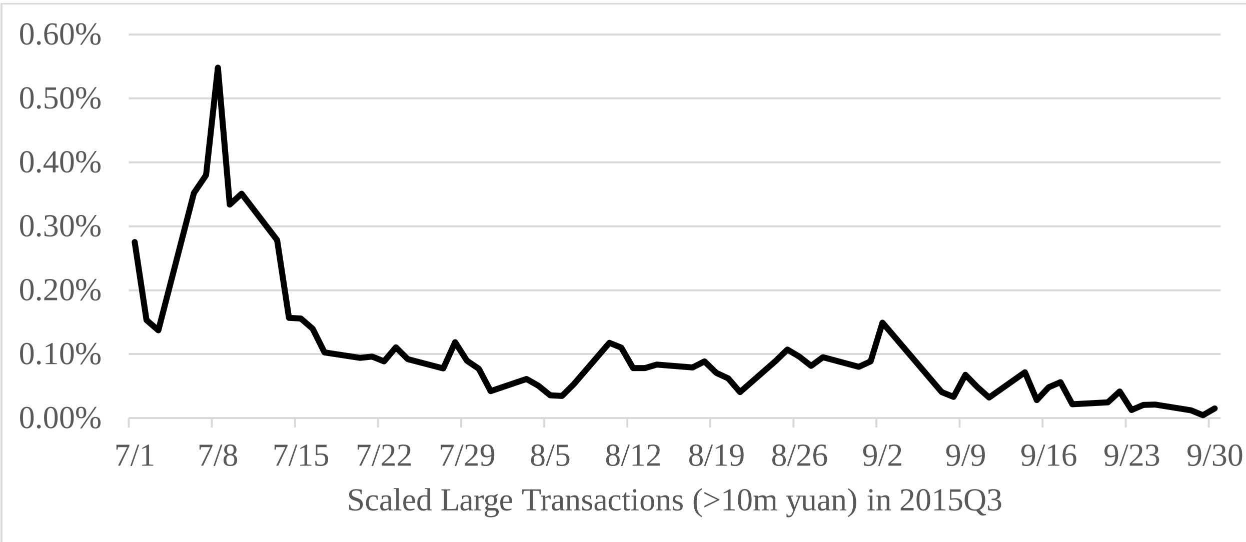

Figure 7
The distribution of daily predicted scaled stock trading by the National Team during the third quarter of 2015. The predicted scaled stock trading is calculated as follows: for each stock, we calculate the daily amount of large transactions above 10 million yuan as a proportion of all large transactions between June 30 and September 30. We then multiply this ratio by the total shares purchased by the National Team between June 30 and September 30, resulting in a daily prediction of stock trading for each stock. Next, we multiply the number of shares by the intraday-average stock price (calculated as total value of traded shares divided by total number of traded shares), yielding an estimate of the investment in each stock on each day. Finally, for each day we sum the investments across stocks, and then scale the daily total investment by the total market capitalization of the stocks listed on the Shanghai and Shenzhen exchanges on the previous trading date.

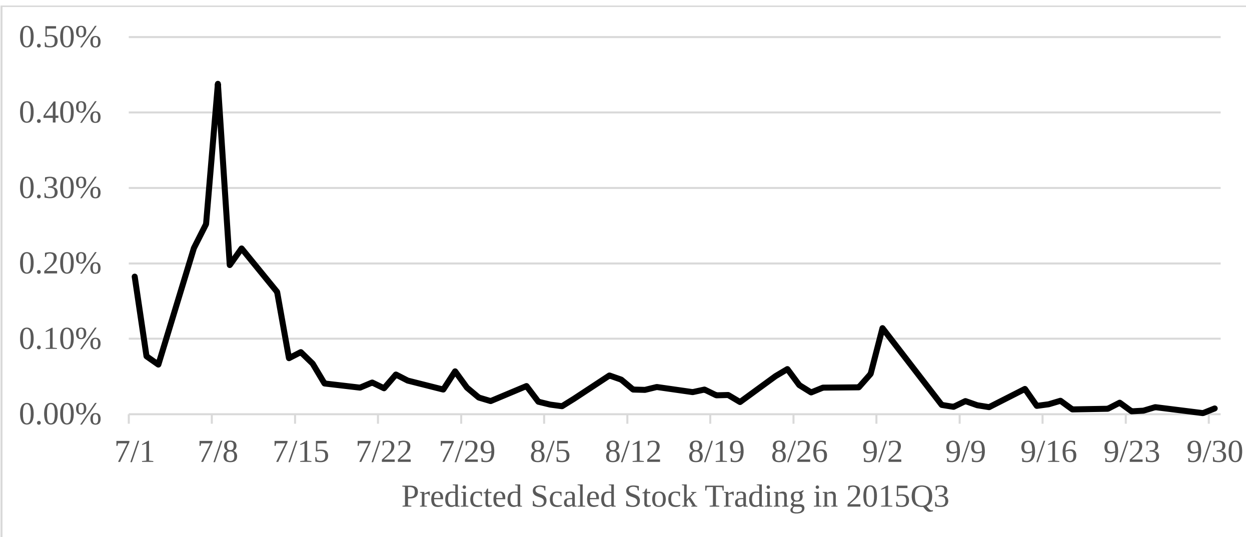

Table 1 Summary statistics describing IPOs and subscription rates

Statistics describing IPOs during 1996–2018. In some years column (1) displaying the number of IPOs contains two numbers, for example 55/135 for 2000. The first number is the number of IPOs that involved the freezing and unfreezing of funds described in Section 3, while the second is the total number of IPOs during the year. IPO proceeds is the gross proceeds given by the product of the offering price and the number of shares sold; the column shows the annual total divided by the total market capitalization of the stocks listed on the SSE and SZSE at the end of the previous year. IPO size is the ratio of the gross proceeds divided by the total market capitalization of the stocks listed on the SSE and SZSE at the end of the previous year. The online and offline portions are the fractions of shares that were sold through the online and offline mechanisms described in Section 3. The online and offline subscription rates are the ratios of the total number of shares requested through the online and offline mechanisms to the numbers of shares allocated to the two mechanisms.

Year	No. of IPOs (1)	IPO proceeds as fraction of agg. market cap. (annual total) (2)	IPO size as fraction of agg. mkt. cap. (annual mean) (3)	Online portion (ann. mean) (4)	Offline portion (ann. mean) (5)	Online subscription rate (annual mean) (6)	Online subscription rate (annual median) (7)	Offline subscription rate (annual mean) (8)	Offline subscription rate (annual median) (9)
1996	157	0.2698	0.00172	0.8595	0	143.03	114.79	0	0
1997	176	0.2385	0.00136	0.9184	0	126.32	96.33	0	0
1998	97	0.0789	0.00081	0.8992	0	294.46	287.08	0	0
1999	86	0.0846	0.00098	0.9031	0.0051	253.67	236.31	0	0
2000	55/135	0.1052	0.00078	0.7256	0.0352	407.72	357.34	0	0
2001	18/67	0.0383	0.00057	0.9016	0.0153	639.16	431.01	0	0
2002	15/66	0.0388	0.00059	1	0	710.74	550.72	0	0
2003	0/65	0.0407	0.00063	0	0	0	0	0	0
2004	0/97	0.0280	0.00029	0	0	0	0	0	0
2005	0/14	0.0049	0.00035	0	0	0	0	0	0
2006	70	0.1910	0.00273	0.7570	0.2018	491.87	398.82	90.69	90.74
2007	118	0.2024	0.00172	0.7708	0.2069	1080.74	605.75	198.72	193.27
2008	76	0.0121	0.00016	0.7984	0.2016	1741.04	1509.72	244.28	247.89
2009	110	0.0441	0.00040	0.7918	0.2082	287.58	209.62	145.61	132.45
2010	344	0.0337	0.00010	0.7916	0.2046	162.45	154.48	62.51	57.28
2011	275	0.0147	0.00005	0.7972	0.2028	115.99	96.43	16.32	12.75
2012	149	0.0063	0.00004	0.7299	0.2659	107.89	84.66	23.21	9.17
2014	124	0.0035	0.00003	0.7795	0.2165	141.33	141.43	384.76	286.23
2015	220	0.0043	0.00002	0.8908	0.1092	270.15	236.99	908.39	741.86
2016	248	0.0034	0.00001	0.9217	0.0783	3,350.18	2,981.80	15,048.56	1,3606.07
2017	419	0.0049	0.00001	0.9210	0.0790	4,167.85	3,761.42	9,334.91	8,196.72
2018	82	0.0022	0.00003	0.9089	0.0874	2,988.49	2,700.05	6,045.85	5,813.95

Table 2 Summary statistics describing IPO frozen amounts

Statistics describing characteristics of IPOs during1996–2018. In some years column (2) displaying the number of IPOs contains two numbers, for example 55/135 for the year 2000. The first number is the number of IPOs that involved the freezing and unfreezing of funds described in Section 3, while the second is the total number of IPOs during the year. The online and offline subscription rates in columns (2) and (3) are the ratios of the total number of shares requested through the online and offline mechanisms to the numbers of shares allocated to the two mechanisms. Columns (4)–(9) report statistics about the online, offline, and total frozen funds. In each case, the frozen amount consists of the subscriptions through the sales channel (online, offline, or the total of online and offline), divided by the aggregate stock market capitalization of the stocks listed on the SSE and SZSE on the trading date prior to the subscription date. These columns display either the annual mean or median of the variable, as indicated by the column heading.

Year	No. of IPOs (1)	Online subscr. rate (annual mean) (2)	Offline subscr. rate (annual mean) (3)	Online frozen funds (annual mean) (4)	Online frozen funds (annual median) (5)	Offline frozen funds (annual mean) (6)	Offline frozen funds (annual median) (7)	Total frozen funds (annual mean) (8)	Total frozen funds (annual median) (9)
1996	157	143.03	0	0.0343	0.0357	0	0	0.0343	0.0357
1997	176	126.32	0	0.0799	0.0710	0	0	0.0799	0.0710
1998	97	294.46	0	0.1577	0.1552	0	0	0.1577	0.1552
1999	86	253.67	0	0.0696	0.0322	0	0	0.0696	0.0322
2000	55/135	407.72	0	0.1118	0.0991	0	0	0.1118	0.0991
2001	18/67	639.16	0	0.1287	0.1392	0	0	0.1287	0.1392
2002	15/66	710.74	0	0.2338	0.2284	0	0	0.2338	0.2284
2003	0/65	0	0	0	0	0	0	0	0
2004	0/97	0	0	0	0	0	0	0	0
2005	0/14	0	0	0	0	0	0	0	0
2006	70	491.87	90.69	0.1515	0.1358	0.0173	0.0072	0.1688	0.1487
2007	118	1080.74	198.72	0.1378	0.1107	0.0207	0.0045	0.1585	0.1195
2008	76	1741.04	244.28	0.1343	0.1184	0.0077	0.0038	0.1420	0.1204
2009	110	287.58	145.61	0.0425	0.0411	0.0105	0.0051	0.0530	0.0453
2010	344	162.45	62.51	0.0244	0.0239	0.0031	0.0024	0.0275	0.0269
2011	275	115.99	16.32	0.0074	0.0061	0.0004	0.0002	0.0078	0.0065
2012	149	107.89	23.21	0.0033	0.0028	0.0003	0.0001	0.0036	0.0030
2014	124	141.33	384.76	0.0064	0.0049	0.0022	0.0012	0.0086	0.0062
2015	220	270.15	908.39	0.0125	0.0097	0.0060	0.0033	0.0185	0.0135
2016	248	3,350.18	15,048.56	0	0	0	0	0	0
2017	419	4,167.85	9,334.91	0	0	0	0	0	0
2018	82	2,988.49	6,045.85	0	0	0	0	0	0

Table 3 Regression estimates of market returns around the frozen and unfrozen dates

This table presents regression estimates of the market returns on dates surrounding the dates on which funds were frozen or unfrozen for at least one IPO. The sample consists of the dates during the period running from Dec. 26, 1996 through January 5, 2016. During this period there were a total of 1,764 IPOs that involved the freezing of funds but only 843 distinct frozen and unfrozen dates, because in many cases there was more than one IPO on the same date. The covariates consist of indicator variables, defined as follows: $F_{-2}(t) = 1$ if t is two days before a frozen date of an IPO; $F_{-1}(t) = 1$ if t is one day before the frozen date of an IPO; $F(t) = 1$ if t is the frozen date of an IPO; $F_{+1}(t) = 1$ if date t is the first date after the frozen date of an IPO; $F_{+2}(t) =1$ if t is the second or third date after the frozen date of an IPO in the first period or if t is the second date after the frozen date of an IPO in the third period; $U(t) = 1$ if t is the unfrozen date of an IPO; $U_{+1}(t) = 1$ if t is the day after the unfrozen date of an IPO; and $U_{+2}(t) = 1$ if t is two days after the unfrozen date of an IPO. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	Coefficient estimate	Std. error	t-statistic	Prob. > $\|t\|$
Intercept	0.0624	0.0329	1.90	0.058
$F_{-2}(t)$	–0.0114	0.0703	–0.16	0.8707
$F_{-1}(t)$	–0.0130	0.0704	–0.19	0.8531
$F(t)$	**-0.2205*****	0.0706	–3.12	0.0018
$F_{+1}(t)$	–0.1323*	0.0700	–1.89	0.0587
$F_{+2}(t)$	–0.0325	0.0645	–0.50	0.6138
$U(t)$	**0.3156*****	0.0707	4.46	< 0.0001
$U_{+1}(t)$	0.0243	0.0703	0.35	0.7294
$U_{+2}(t)$	–0.01012	0.0703	–0.14	0.8856
No of obs.	4,605			
R^2	0.0068			
Adj. R^2	0.0050			

Table 4
First-stage regressions that explain stock trading

This table presents the first stage regressions that explain net trading of IPO subscribers. Panel A presents the results of regressions that explain net trading on the dates on which funds were frozen or unfrozen for at least one IPO during the period running from September 18, 2006 through January 5, 2016. This period includes 1,461 IPOs but only 597 distinct frozen dates, of which 233 are also unfrozen dates of earlier IPOs. Panel B displays the results of regressions that explain net trading on dates that are the frozen or unfrozen date of at least one IPO, the day before a frozen date, or the day after an unfrozen date. Panel C displays the results of regressions that explain net trading on dates within [-5, +6] window of at least one IPO. The explanatory variables are defined in Section 5.1. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Sample consists of frozen and unfrozen dates

Explanatory variable	$NetTrad(t)$		
	(1)	(2)	(3)
$I(t)S_t$	1.183	1.295	-0.0479
	(0.707)	(0.772)	(-1.334)
$I(t)PE_t$	0.00363		0.00173
	(1.148)		(0.760)
$I(t)IPORet_t$	-0.0555*		-0.0918***
	(-1.822)		(-3.396)
$I(t-3)S_{t-3}$	0.280	0.00905	0.126***
	(0.169)	(0.00545)	(3.502)
$I(t-3)PE_{t-3}$	-0.00587*		-0.00335
	(-1.843)		(-1.476)
$I(t-3)IPORet_{t-3}$	0.0296		0.0269
	(0.971)		(0.997)
$I(t)$	-0.000305***	-0.000306***	-0.000343***
	(-8.683)	(-8.690)	(-13.08)
$I(t-3)$	0.000292***	0.000295***	0.000287***
	(8.298)	(8.352)	(10.97)
$I(t)D_{h,t}$	Yes	Yes	No
$I(t-3)D_{h,t-3}$	Yes	Yes	No
No. of obs.	961	961	961
R^2	0.453	0.444	0.372

Panel B. Sample consists of frozen and unfrozen dates, the day before a frozen date, and the day after an unfrozen date

Explanatory variable	$NetTrad(t)$ (1)	(2)	(3)
$\{I(t)S_t, I(t+1)S_{t+1}\}$	1.324	1.409	-0.0570**
	(1.094)	(1.167)	(-2.203)
$\{I(t)PE_t, I(t+1)PE_{t+1}\}$	0.00328		0.000575
	(1.406)		(0.351)
$\{I(t)IPORet_t, I(t+1)IPORet_{t+1}\}$	-0.0357		-0.0588***
	(-1.574)		(-3.024)
$\{I(t-3)S_{t-3}, I(t-4)S_{t-4}\}$	0.794	1.045	0.102***
	(0.625)	(0.822)	(3.952)
$\{I(t-3)PE_{t-3}, I(t-4)PE_{t-4}\}$	0.00386*		0.00310*
	(1.710)		(1.889)
$\{I(t-3)IPORet_{t-3},$	0.0276		0.0245
$I(t-4)IPORet_{t-4}\}$	(1.262)		(1.260)
$\{I(t), I(t+1)\}$	-0.000257***	-0.000258***	-0.000290***
	(-11.11)	(-11.15)	(-16.64)
$\{I(t-3), I(t-4)\}$	0.000212***	0.000208***	0.000251***
	(9.189)	(9.027)	(14.35)
$\{I(t)D_{h,t}, I(t+1)D_{h,t+1}\}$	Yes	Yes	No
$\{I(t-3)D_{h,t-3}, I(t-4)D_{h,t-4}\}$	Yes	Yes	No
No of obs.	1,295	1,295	1,295
R^2	0.457	0.452	0.380

Panel C. Sample consists of all dates within [-5, +6] window of any frozen date

Explanatory variable	$NetTrad(t)$ (1)	(2)	(3)
$\{I(t+j)\}_{j=1,\ldots,5}$	-0.0000768***	-0.0000779***	-0.000102***
	(-5.369)	(-5.430)	(-9.917)
$\{I(t+j)\times S_{t+j}\}_{j=1,\ldots,5}$	0.268	0.219	-0.0167
	(0.328)	(0.266)	(-1.033)
$\{I(t+j)\times PE_{t+j}\}_{j=1,\ldots,5}$	-0.000611		-0.00124
	(-0.402)		(-1.175)
$\{I(t+j)\times IPORet_{t+j}\}_{j=1,\ldots,5}$	-0.0297**		-0.0370***
	(-2.104)		(-3.085)
$I(t)$	-0.000176***	-0.000176***	-0.000195***
	(-4.494)	(-4.477)	(-6.404)
$I(t)\times S_t$	4.261**	4.694**	-0.0964***
	(2.292)	(2.518)	(-2.628)
$I(t)\times PE_t$	0.00756**		0.00210
	(2.300)		(0.905)
$I(t)\times IPORet_t$	0.0231		-0.0293
	(0.727)		(-1.047)
$I(t-3)$	0.000257***	0.000261***	0.000245***
	(6.555)	(6.640)	(8.143)
$I(t-3)\times S_{t-3}$	2.788	2.969*	0.112***
	(1.578)	(1.676)	(3.023)
$I(t-3)\times PE_{t-3}$	-0.00198		-0.00375
	(-0.608)		(-1.623)
$I(t-3)\times IPORet_{t-3}$	0.100***		0.0432
	(3.120)		(1.539)
$\{I(t-j)\}_{j=4,5,6}$	0.0000774***	0.0000714***	0.000118***
	(3.702)	(3.535)	(7.874)
$\{I(t-j)\times S_{t-j}\}_{j=4,5,6}$	1.424	1.529	0.0739***
	(1.285)	(1.376)	(3.357)
$\{I(t-j)\times PE_{t-j}\}_{j=4,5,6}$	0.00194		0.00434***
	(0.967)		(3.208)
$\{I(t-j)\times IPORet_{t-j}\}_{j=4,5,6}$	-0.0275		-0.0548***
	(-1.336)		(-3.274)
$\{I(t+j)\times D_{h,t+j}\}_{j=1,\ldots,5}$	Yes	Yes	No
$I(t)D_{h,t}$	Yes	Yes	No
$I(t-3)D_{h,t-3}$	Yes	Yes	No
$\{I(t-j)\times D_{h,t-j}\}_{j=4,5,6}$	Yes	Yes	No
No of obs.	1,594	1,594	1,594
R^2	0.424	0.413	0.298

Table 5 Second-stage regressions that explain market returns

This table presents the results of second-stage regressions that explain aggregate stock market returns during the period running from September 18, 2006 through January 5, 2016. Columns (1) to (3) show the results of regression that explain aggregate stock market returns on the frozen and unfrozen dates. Columns (4) to (6) display the results of regression that explain aggregate stock market returns on dates that are frozen or unfrozen dates, the day before a frozen date, or the day after an unfrozen date. Columns (7) to (9) display the results of regression that explain aggregate stock market returns on all dates within [-5, +6] window of any IPO frozen date. For each date, the aggregate stock market return is the value-weighted average of the returns on the Shanghai and Shenzhen composite indexes. In each column, the predicted net trading variable *PredNetTrad*(*t*) is the fitted value of net trading estimated from the first stage regressions. The control variables are lagged market returns over the previous day, week, month, and two months (*MktReturn*[−1], *MktReturn*[−1week], *MktReturn*[−1month], and *MktReturn*[−2month]), their absolute values, and the CSMAR sentiment index. *t*-statistics are in parentheses below the coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	MktReturn(*t*)								
Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PredNetTrad(*t*)	4.204***	4.213***	4.781***	2.998***	3.219***	3.103***	3.929***	4.104***	4.090***
	(3.561)	(3.536)	(3.662)	(2.937)	(3.134)	(2.773)	(3.739)	(3.848)	(3.251)
MktReturn[−1]	-0.00502	-0.00533	-0.00346	0.0735**	0.0730**	0.0742**	0.0259	0.0256	0.0279
	(-0.131)	(-0.139)	(-0.0901)	(2.255)	(2.236)	(2.276)	(0.872)	(0.862)	(0.937)
MktReturn[−1week]	0.0451**	0.0454**	0.0448**	0.00753	0.00721	0.00793	0.0199	0.0196	0.0215
	(2.298)	(2.312)	(2.277)	(0.450)	(0.431)	(0.474)	(1.319)	(1.296)	(1.424)
MktReturn[−1month]	0.0176**	0.0176**	0.0177**	0.00859	0.00866	0.00813	0.0143**	0.0144**	0.0137**
	(2.109)	(2.108)	(2.110)	(1.188)	(1.198)	(1.126)	(2.210)	(2.230)	(2.112)
MktReturn[−2month]	0.00306	0.00303	0.00286	0.00179	0.00172	0.00203	0.00227	0.00213	0.00281
	(0.449)	(0.444)	(0.419)	(0.303)	(0.291)	(0.344)	(0.422)	(0.394)	(0.522)
| *MktReturn*[−1]|	0.0968*	0.0965*	0.0951*	0.168***	0.168***	0.167***	0.102**	0.101**	0.0991**
	(1.858)	(1.852)	(1.821)	(3.789)	(3.776)	(3.767)	(2.488)	(2.466)	(2.420)
| *MktReturn*[−1week]|	0.0399	0.0404	0.0397	0.0131	0.0130	0.0119	0.0161	0.0166	0.0154
	(1.423)	(1.440)	(1.412)	(0.545)	(0.543)	(0.496)	(0.736)	(0.760)	(0.703)
| *MktReturn*[−1month]|	-0.00809	-0.00825	-0.00810	0.00190	0.00199	0.00180	0.00208	0.00205	0.00226
	(-0.609)	(-0.621)	(-0.608)	(0.164)	(0.172)	(0.156)	(0.204)	(0.201)	(0.222)
| *MktReturn*[−2month]|	0.000834	0.000798	0.000528	-0.00716	-0.00741	-0.00722	-0.00687	-0.00714	-0.00627
	(0.0724)	(0.0692)	(0.0458)	(-0.720)	(-0.744)	(-0.725)	(-0.764)	(-0.794)	(-0.696)
Sentiment	-0.0000814	-0.0000821	-0.0000667	-0.0000814	-0.000166	-0.000158	-0.000135	-0.000138	-0.000121
	(-0.672)	(-0.677)	(-0.549)	(-0.672)	(-1.574)	(-1.499)	(-1.421)	(-1.456)	(-1.274)
Constant	0.00205	0.00207	0.00156	0.00205	0.00496	0.00468	0.00434	0.00450	0.00379

	(0.416)	(0.422)	(0.317)	(0.416)	(1.153)	(1.089)	(1.129)	(1.170)	(0.988)
No. of obs.	961	961	961	1,295	1,295	1,295	1,594	1,594	1,594
R^2	0.035	0.034	0.035	0.030	0.031	0.030	0.022	0.023	0.020
First-stage covariates	All	Size, date & industry indicators	All except industry indicators	All	Size, date & industry indicators	All except industry indicators	All	Size, date & industry indicators	All except industry indicators