Assessing the Impact of 2019 Registration-Based IPO System Reform of STAR Board on Private Equity Exit Strategies in China

by

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An honors thesis submitted in partial fulfillment

of the requirements for the degree of

Bachelor of Science

Business and Economics Honors Program

NYU Shanghai

May 2024

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Abstract

This study assesses the impact of the 2019 registration-based IPO system reform of STAR board on Private Equity and Venture Capital (PE/VC) exit strategies in China. Utilizing a comprehensive approach that combines regression analysis and industry interviews, the research explores the reform's effects on IPO exits, highlighting the differential impacts on high-tech industries compared to other sectors, and examining whether PE-backed companies exhibit distinct exit patterns post-reform. Findings reveal a significant structural shift in IPO exit strategies following the reform, with high-tech industries experiencing a more pronounced change in IPO exit percentages. However, the reform's influence on PE-backed companies compared to other firms was not significantly different, indicating nuanced effects of regulatory changes on the capital market's dynamics.

KEY WORD: Financial Market, Private Equity, Registration-based IPO

Acknowledgements

I want to extend my deepest gratitude to my thesis advisor, Professor David Yu, for his invaluable guidance in the realm of Private Equity and for his precise and insightful instructions that have greatly influenced my work. My sincere thanks also go to Mrs. Tracy Hu for graciously agreeing to be interviewed and for sharing her extensive knowledge about the industry and her company, enriching my research significantly.

Moreover, I am grateful to Professor Marti Subrahmanyam, Christina Wang, Wendy Jin and Ms. Xinyi Yang for their exceptional leadership in coordinating the Business and Economics Honors Program. Their efforts have created a nurturing and intellectually stimulating environment.

Last but certainly not least, my heartfelt thanks to all my peers within the program. Their constructive feedback, the sharing of their research methods and findings, and their collaborative spirit have been invaluable to the development and refinement of my work. Their camaraderie and support have been a cornerstone of my academic experience.

Content

1. Introduction

1.1 Overview of Private Equity industry with Chinese Context

Private equity (PE) refers to investment funds that acquire and manage private companies or assets with the goal of generating returns for their investors. The private equity industry has grown rapidly over the past few decades, driven in part by deregulation that has increased the supply of private capital to late-stage private companies (Demaria, 2013).

The private equity ecosystem involves several key players, including institutional investors who provide the capital, PE funds that raise and manage that capital, and the private companies or assets that the funds invest in. PE funds are typically organized as limited partnerships, with the fund managers responsible for fundraising, investment decisions, and portfolio company management.

The private equity market encompasses several different investment strategies, including venture capital (financing new company creation), growth capital (financing company expansion), leveraged buyouts (financing company acquisitions), and other specialized strategies like distressed debt and turnaround capital. Each of these strategies has distinct characteristics in terms of the types of companies targeted, the investment time horizons, and the use of leverage.

Investing in private equity presents both opportunities and challenges for institutional investors. While PE has the potential to generate attractive returns, it also requires specialized expertise and long holding periods that many investors lack. Researchers have debated the relative performance of PE investments compared to public markets, with some studies suggesting PE can outperform public market strategies with similar risk profiles (Yates & Hinchliffe, 2010).

1.2 Private Equity industry with Chinese Context

As the world's second largest economy, China has become a focal point for development, especially noted for its shift from traditional bank financing and public equity markets to a growing reliance on private equity. The history of China’s PE industry is relatively short: The first private equity organization in China, called China Venture Capital Investment Company, was founded in 1986 as a venture capital (VC) firm, by government bodies including the Ministry of Science and

Technology and the Ministry of Finance. The purpose was to finance and encourage the development of technology companies across China. (Wang 2017).

The private equity (PE) market in China is distinctly shaped by its regulatory environment. Regulatory bodies such as the Ministry of Commerce (MOC) and the China Securities Regulatory Commission (CSRC) exert a strong influence on private equity activities, particularly through their control over cross-border capital flows and currency exchanges, as well as their stringent control over IPO approvals. These regulations directly impact the strategies and operational flexibility of PE firms within the country.

The emergence and growth of RMB-denominated funds mark a significant trend within the Chinese PE market. These funds have been tailored to align with local investment preferences and regulatory requirements, differing significantly from USD-denominated funds. RMB funds typically focus on different segments and types of investments compared to their USD counterparts, influenced by factors such as local economic policies and the availability of capital within domestic markets.

Investment strategies within the Chinese PE sector predominantly emphasize growth investments. A significant portion of capital is directed towards sectors like technology and healthcare, which not only promise high growth potential but also traditionally have less access to other forms of financing. This focus reflects the broader economic priorities of China, aiming to stimulate sectors that are seen as pivotal for future economic transformation.

Moreover, the role of government and institutional investors in China's PE landscape cannot be overstated. State policies and government-backed funds are pivotal in directing PE activities, often with the goal of fostering innovation and supporting strategic sectors. Moreover, the involvement of large institutional investors such as insurance companies and pension funds has grown, bringing more sophistication and larger pools of capital to the PE market. These investors bring a level of stability and long-term investment perspective that was previously less common.

Exit strategies in China predominantly consist of trade sales, M&A or IPOs. Notably, there is a discernible preference among PE/VC funds for Initial Public Offerings (IPOs) as a primary exit strategy.

We can conclude that the Chinese private equity market remains immature compared to developed markets like the US, both from the market's perspective and the history of the industry. Being in this early-stage of development, the market can be widely impacted by policy changed in the financial market. Given the specific preference of exit via IPOs, changes in IPO regulations significantly impact private equity operations. The Shanghai and Shenzhen Stock Exchanges, established in the early 1990s, primarily served large state-owned enterprises, making it challenging for smaller or privately-owned companies to raise capital. Initially, private equity investments in China often exited overseas due to these limitations. The scenario began to change with the introduction of the Shenzhen Small and Medium Enterprises Board (SME Board) in 2004, which enabled smaller companies to pursue IPOs locally. The passage of the Partnership Company Law in 2006, allowing limited partnership structures common in international funds, marked the beginning of true private equity practices in China. This was highlighted by Shenzhen Coship Electronics, the first PE-backed company to successfully exit locally in 2006.

Further developments included the launch of ChiNext in 2009, a NASDAQ-like board that became a valuable exit route for PE-backed high-tech firms, leading to a significant increase in capital raised. However, the landscape shifted again in 2011 with economic inflation and tight monetary policies, followed by an IPO ban in 2013, which shifted the focus to trade sales as the primary exit channel. During this period, Chinese PE firms began focusing more on value creation through investment process and portfolio management.

In 2013, the New Third Board (NEEQ) was expanded to include companies from all regions of China, making it a more viable exit option. The lifting of the IPO ban in 2014, alongside new reforms aimed at state-owned enterprises, rejuvenated interest among PE firms in exploring new opportunities.

1.3 Registration-based IPO system reform

Starting from 2019, China has been dedicating significant efforts to reform the secondary capital market, with the most prominent part being the registration system reform. This reform has substantially reduced the time required for an IPO and has created a more efficient pathway for primary market exits. In January 2019, the China Securities Regulatory Commission announced the implementation of the Science and Technology Innovation Board (STAR Market) at the Shanghai Stock Exchange, introducing a pilot registration system. This new system differs significantly from the existing approval system for the main board, with a key characteristic being its focus on information disclosure. It requires securities issuers to disclose company information truthfully, accurately, and completely, enabling investors to access the necessary information to evaluate the securities' value and make investment decisions. The regulatory authorities do not make substantive judgments on the value or price of securities. Establishing the STAR Market and piloting the registration system represents an incremental reform in the capital market, aiming to leverage the STAR Market's reform as a "test field" to develop replicable and promotable experiences. This reform will have a profound impact on exit strategies in the primary market: The registration system reform has lowered the difficulties for companies to IPO, making it highly significant to study how exit strategies in the primary market have changed due to this policy.

1.4 Research Question

In this study, the research question is to assess the Impact of the 2019 Registration Based IPO system reform of STAR Board on PE/VC's exit strategies in China.

There are 2 incentives to research into this question. First, from the regulatory perspective, The momentum of reform continued with the 2020 ChiNext reform, the establishment of the 2021 Beijing Stock Exchange, and the full implementation of the registration-based IPO system in 2023, each further transforming the private equity landscape. The establishment of the 2019 STAR board marks a crucial starting point for registration-system reforms, providing a valuable reference for ongoing and future reforms through 2023. This context underscores the significance of this study, as it captures a transformative period in China's approach to capital market regulation.

Apart from the regulatory perspective, it’s important to evaluate the industry incentive of this study. To gain a deeper understanding from an industry perspective regarding opinions on the registration-based reform on the STAR board, an interview is conducted with the managing partner

Chenhui Venture Partners, an early-stage VC in China. This can be regarded as a representative for considering Government-backed early stage institutional investors among my sampling. I interviewed the individual in order to understand the firm's general exit strategy, the determinants of exit strategy, and their perspective on whether the policy change has affected the exit strategy.

Several pivotal insights were garnered in this interview regarding the dynamics of investment exits, particularly in the context of the 2019 reform. First, it is highlighted that the fund has inherent pressure to exit investments within a designated time horizon, typically an 8-year window. This constraint necessitates strategic planning to optimize exit outcomes, often leading the firm to explore partial exits after a 3-4 year investment period to enhance the Internal Rate of Return (IRR).

Secondly, the firm expressed a distinct preference for exits via IPO, driven by the potential for higher valuations and returns. However, the pathway to an IPO is fraught with challenges, prompting the firm to consider M&A as viable alternatives when IPO prospects are dim. Moreover, the decision regarding which stock exchange board to target for an IPO is influenced significantly by the nature of the company's business and the liquidity of the exchange.

The 2019 registration-based IPO reform, intended to streamline the IPO process, was anticipated to have a profound impact on exit strategies. However, the firm's experience suggests that the reform has not decisively shifted their exit strategy. This is attributed to the fact that for VCs, the proportion of firms that reach the IPO stage is low historically, indicating that the primary focus remains on capturing value during the growth phase rather than navigating the nuances between primary and secondary market valuations. It is suggested that later stage investors like PE could be affected more by this policy change.

Given these insights, the research will delve deeper into the effects of the 2019 IPO reform on different industries, aiming to understand how sector-specific dynamics influence the efficacy and outcomes of the reform. Furthermore, the study will explore the differential impacts on various types of investors, particularly contrasting the effects on private equity (PE) firms versus early-stage investors. This nuanced approach seeks to unravel the complex interplay between regulatory changes, industry characteristics, and investor strategies, contributing to a more refined understanding of the investment landscape in the wake of significant regulatory reforms.

2. Literature Review

IPOs are considered to be one of the most attractive VC exit options (Ragozzino and Blevins, 2015) and also the most difficult since it is difficult to overcome information asymmetries in IPO. An exit through IPO is considered as a pinnacle of success for VCs as it allows them to raise a huge amount of capital and generate maximum returns for themselves (Cumming and Johan, 2008)

In the previous studies, scholars are using different models to model the exit decision of PEs. Gupta and Arora(2023) uses logistic regression and the dependent variable is taken to be the mode of exit categorized as IPOs and other exits. Stage of investment, industry, syndication size in and region of the have been taken as independent variables. Quarterly number of IPOs and GDP growth rate are also taken into account for market timing and macroeconomic conditions. Calafiore (2020) uses the names of the investors of the first 3 rounds of investment, the foundation date and the IPO date (if the company went public), the number of firms in each round, and the VIX index value on the round dates. However, these studies 1) focus on firm-level / deal-level prediction of exit strategies and does not provide insights from a market's perspective, and 2) limited to US or India private equity markets (due to limitations on datasets)

Apart from how we study PE's exit decisions, we would also want to see what is the established research about the effect on STAR board. He suggests that non-state-owned VC institutions yield slightly higher returns than state-owned ones, and the reputation of a VC institution, measured by years in operation and registered capital size, correlates positively with higher exit returns(2019). Moreover, VC exits in economically developed regions tend to have higher returns.Du and Geng (2023) suggests that IPO prices on the ChiNext Board are significantly higher than the estimated intrinsic value, indicating overpricing. However, some VCs do not exit the VCU when there's overvaluation of the IPO (Cumming and MacIntosh, 2003), and higher pricing does not have a clear correlation with the actual return by an IPO. This makes our study more meaningful if we can see if there's any correlation between the valuation of IPO and the choice of IPO. However, there is no research about how the reform affects the exit strategies.

3. Hypothesis & Methodology

3.1 Hypothesis

Following the research question on assessing the impact of registration-based IPO system reform of STAR board on PE/VC's exit strategies in China, 3 hypothesis were derived:

- **H1:** The percentage of firms exit by IPO significantly changed after the 2019 STAR board reform.
- **H2:** There is significant difference in the change of the percentage of firms exit by IPO among hi-tech industries than other companies
- **H3:** There is a significant difference between the change in the probability of exit by an IPO of companies supported by PE compared to other companies.

3.2 Methodology

Hypothesis 1: Structural break after the 2019 reform

This study uses chow test to test whether there is a structural break in the time series data of percentage of exit by IPO. The breakpoint, according to the official date of STAR board reform, is July 22nd, 2019.

The regression for the chow test is defined as follows:

- Restricted Model:

  $IPO\_exit\_percentage = \beta_0 + \beta_1\, investment\_horizon + \beta_2\, monthly\_investments + \beta_3\, fund\_vintage + \Sigma(\beta_{fund}\, fund\_percentage) + \Sigma(\beta_{ind}\, industry\_percentage) + \beta_4\, fundraise + \beta_5\, stock\_index + \beta_6\, lag\_IPO\_exit\_percentage + \delta_1 D + \delta_2 (D \times investment\_horizon) + \delta_3 (D \times monthly\_investments) + \delta_4 (D \times fund\_vintage) + \Sigma(\delta_{fund} (D \times fund\_percentage)) + \Sigma(\delta_{ind} (D \times industry\_percentage)) + \delta_5 (D \times fundraise) + \delta_6 (D \times stock\_index) + \delta_7 (D \times lag\_IPO\_exit\_percentage) + \epsilon$

- Unrestricted Model:

  $IPO\_exit\_percentage = \beta_0 + \beta_1\, investment\_horizon + \beta_2\, monthly\_investments + \beta_3\, fund\_vintage + \Sigma(\beta_{fund}\, fund\_percentage) + \Sigma(\beta_{ind}\, industry\_percentage) + \beta_4\, fundraise + \beta_5\, stock\_index + \beta_6\, lag\_IPO\_exit\_percentage + \epsilon$

Where:

IPO_exit_percentage	the percent of exit by IPO among all exits
investment_horizon	average investment horizon for each exit
fund_vintage	Average vintage of funds
monthly_investments	number of primary market investments, with lag = 36
fund_percentage	percentage of each type of fund in all exits
industry_percentage	percentage of each industry in all exits
fundraise	number of funds starting fundraising in the period
stock_index	SSEC stock index
lag_IPO_exit_percentage	IPO_exit_percentage with lag = 1

In the unrestricted model, D is the dummy variable, D=1 when time of exit > 2019.7.22, D = 0 otherwise.

All variables are in its first difference form, due to the fact that the original data is not stationary. This will be further discussed in section 3.3 data transformations. The lags in the data will be discussed in section 4 Results.

This regression incorporates variables from 3 different perspectives:

- Secondary(stock) market condition: stock_index is the SSEC stock index, which reflects the stock market condition
- Primary market condition: monthly_investments, fundraise reflects the activeness of primary market
- Exit condition: breakdown exit conditions into the

Then use the F statistics calculated for the restricted and unrestricted model to see if there's a structural break in the IPO exit strategy.

Hypothesis 2: Hi-tech Industries vs. Other Industries

This study uses the Diff and Diff method to test for this hypothesis. Treatment group is the hi-tech industries, which includes IT, hi-end manufacturing, new materials, renewable energy and healthcare. Other industries are regarded as control groups. The breakpoint is also July 22nd, 2019. The regression is defined as:

$$IPO\_Percentage_t = \beta 0 + \beta_1 \times Is\_Target\_Industry + \beta_2 \times Post_t + \beta_3 \times TreatmentXPost_t + \epsilon_t$$

Where:

- $IPO\_Percentage_t$ is the dependent variable representing the log-transformed percentage of IPO exits out of total exits, adjusted with log(value+1)to accommodate zero values and make the distribution more normal, for month t.
- Is_Target_Industry is a binary independent variable indicating whether an industry is a target industry (1 if it is one of '医疗健康', 'IT 及信息化', or '先进制造', and 0 otherwise).
- $Post_t$ is a binary time dummy variable indicating the period after July 2019 (1 for months after July 2019, and 0 for months before and including July 2019).
- $TreatmentXPost_t$ is an interaction term between Is_Target_Industry and Post t , designed to capture the differential effect of the time period on the IPO exit percentage for the target industries compared to other industries.

Finally we would see if the coefficient of treatmentXPost is statistically significant. If this coefficient is significant, we can conclude that the change in the percentage of firms exit by IPO among hi-tech industries is significantly bigger than other companies.

Hypothesis 3: PE-Supported companies VS other companies

Samely as hypothesis2, we use the Diff and Diff method to test. Treatment group is the PE exits, Other fund type exits are regarded as control groups. The breakpoint is also July 22nd, 2019. Regression definition:

$$IPO\_Percentage_t = \beta 0 + \beta_1 \times Is\_PE + \beta_2 \times Post_t + \beta_3 \times TreatmentXPost_t + \epsilon_t$$

Where:

- $IPO\_Percentage_t$ is the dependent variable representing the log-transformed percentage of IPO exits out of total exits, adjusted with log(value+1)to accommodate zero values and make the distribution more normal, for month t.
- Is_PE is a binary independent variable indicating whether the exit is from a PE or other type of investors. (1 if it is a PE exit, and 0 otherwise).
- $Post_t$ is a binary time dummy variable indicating the period after July 2019 (1 for months after July 2019, and 0 for months before and including July 2019).
- $TreatmentXPost_t$ is an interaction term between Is_Target_Industry and Post t , designed to capture the differential effect of the time period on the IPO exit percentage for the target industries compared to other industries.

Finally we would see if the coefficient of treatmentXPost is statistically significant. If this coefficient is significant, we can conclude that the change in the probability of exit by an IPO is significantly bigger in companies supported by PE than other companies.

4. Data

4.1 Scope and Source

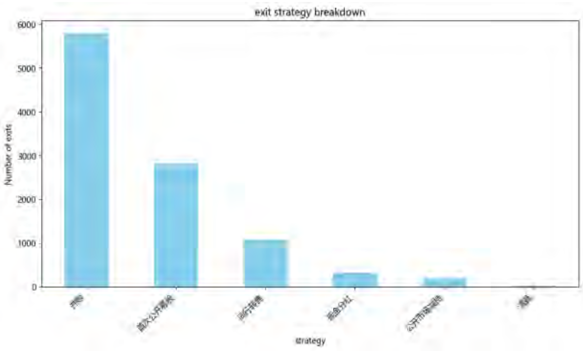
CVSource is chosen as the main dataset. Its data collection methods include news sources with quarterly questionnaires to ensure the data's timeliness and accuracy. This dataset outperforms other major sources particularly in the domains of Mergers & Acquisitions (M&A) and management sales information. Additionally, the dataset demonstrates a lower incidence of duplicate entries, enhancing the precision and usability of the data for research purposes.

The dataset encompasses exit data spanning from September 2000 to January 2024, recording 45,056 exits. Investment data spanned from September 2001 to January 2024, with 133,252 investments recorded. Exit and investment data is organized into three primary categories: company information, exit investor information, and deal information. Fund data spanned from October 1880 to January 2024, recording in total 19,315 fund information. Attributes include fund founding dates, the date of starting fundraising, etc.

4.2 Data Cleaning

Rows containing missing data are dropped, including 1,625 rows in investment data, 539 rows in exit data, and 3,126 rows in fund data. Due to poor data recording issues, all data before 2008 are dropped as well, which leaves the sample to contain data spanning from January 2008 to January 2024 (192 months). Then all data are grouped by month and are aligned with the time index. Industry data contains multiple levels, and are pulled to the highest industry level to simplify the analysis.

4.3 Descriptive Statistics



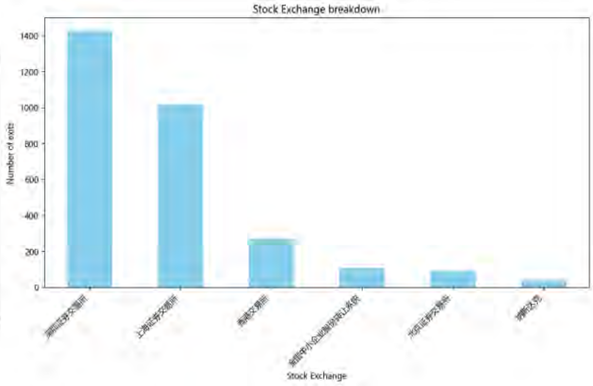


Figure 2: Exit Strategy Breakdown

Figure 3: IPO Stock exchange breakdown

Figure 3 shows the distribution of different exit strategies in the sample. The most common exit strategy is M&A, and IPO is the second common exit strategy. Figure 4 shows the stock exchange to list on among all IPO exits. The Chinese stock exchange, including Shenzhen Stock exchange and Shanghai Stock Exchange is the most common choice, suggesting the preference of going IPO locally.

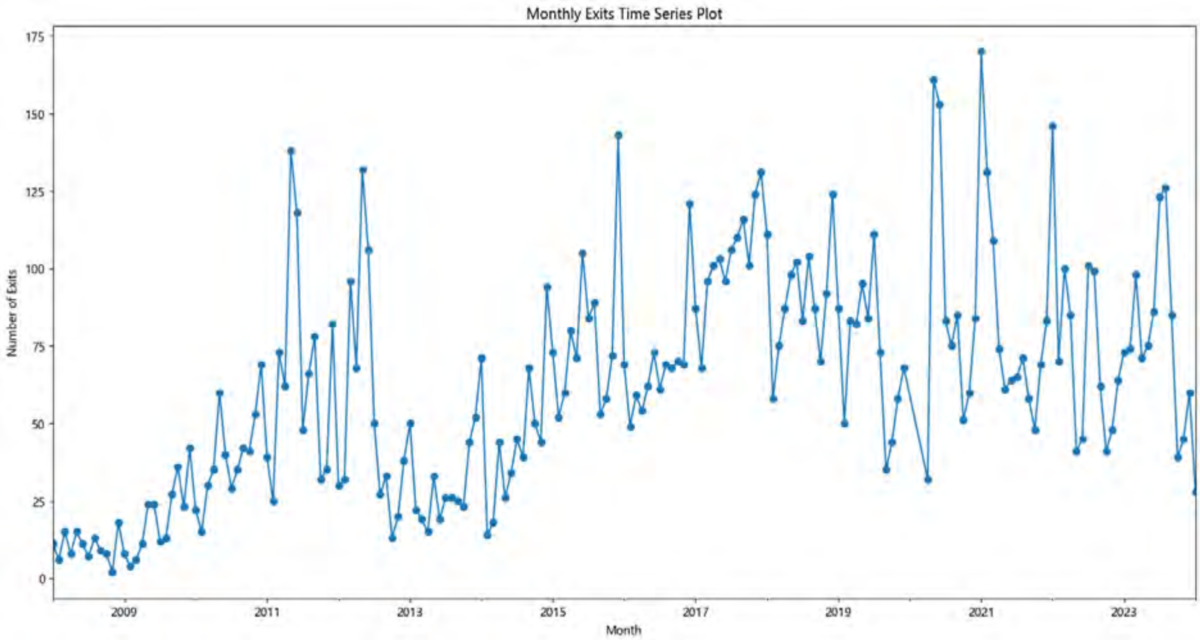


Figure 4: Number of exits (by month)

Figure 5 shows the number of exits during 2008 to 2024, grouped by month. There are several spikes in the data, including 2011, 2016, and 2020-2022, leading to potential non-stationary problems. Detailed regression analysis will be discussed in section 4.

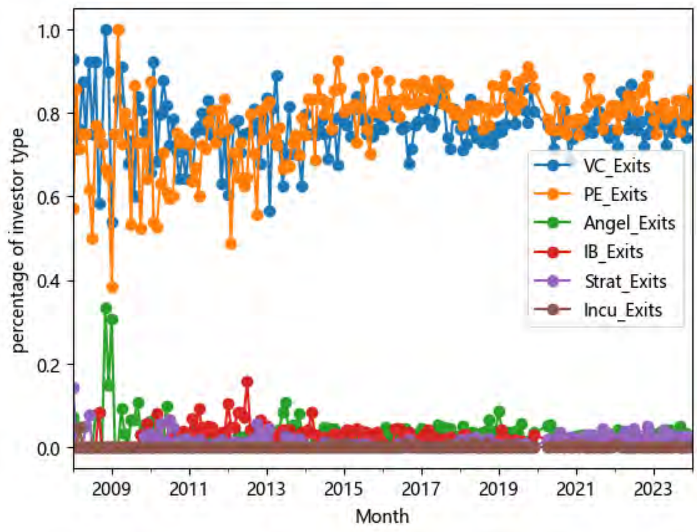


Figure 5: Percentage of investor type among all exits

Figure 6 clearly shows that PE and VC are the major players in the data samples, which corresponds to the previous introduction. Data does not sum to 1 for each period, since funds can demonstrate both PE and VC characteristics and will be counted in both samples.

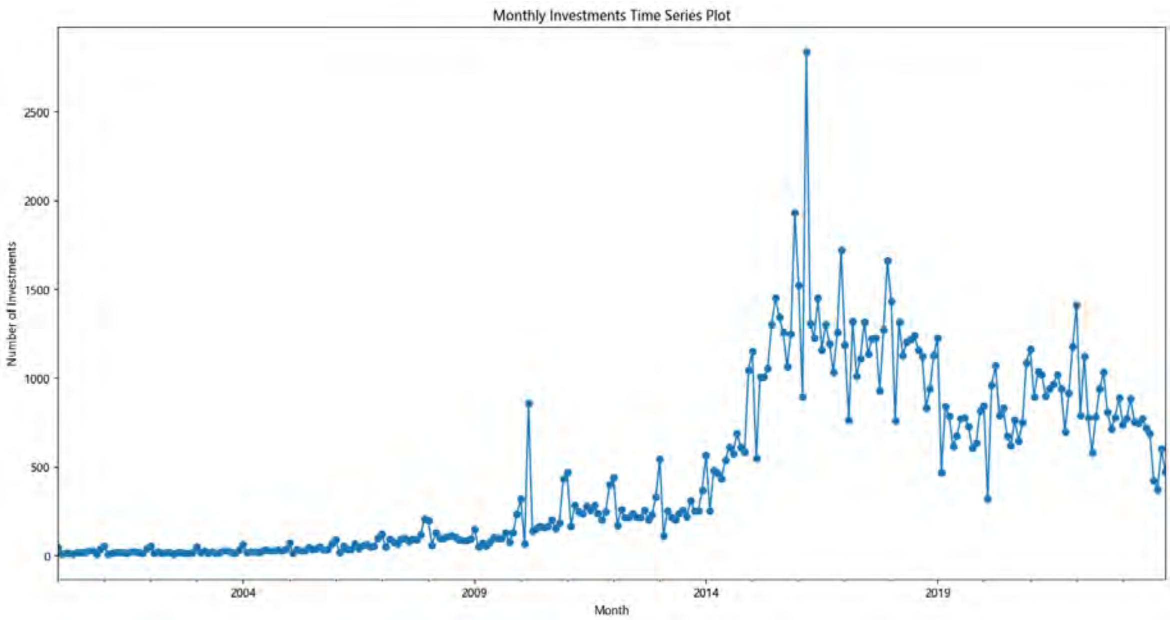


Figure 6: Number of investments (by month)

Samely as exit data, there are multiple spikes in investment data, suggesting potential non-stationarity problems.

4.4 Variable Calculation and Transformation

IPO_exit_percentage(Y in regression)

IPO_exit_percentage = IPO counts during the period / total exits during the period

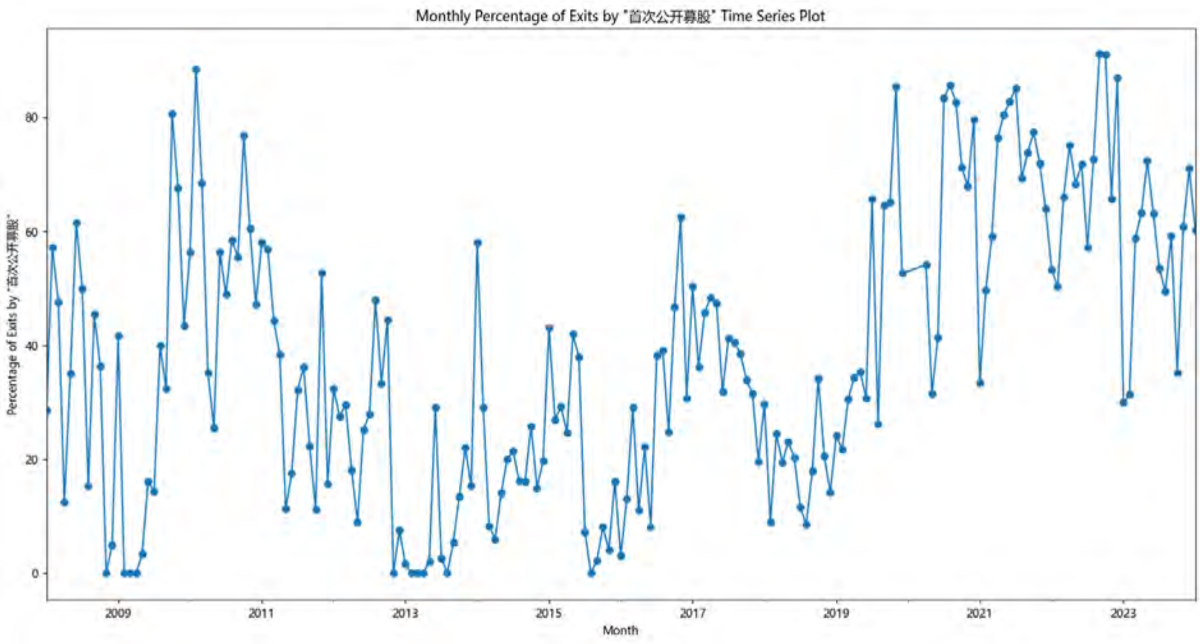


Figure 7: Percentage of exit by IPO among all exits (by month)

Then we conduct an ADF test to test for its stationarity. The F-statistic of the ADF test is -2.35035 (p-value = 0.1562 > 0.05). This indicates that this time series data is not stationary on the 5% level. After taking the first difference of this time series data and reconducting the ADF test, the F statistic is -4.4102 (p-value = 0.00028 < 0.05), which indicates that the first difference data is stationary.

In order to ensure consistency in analysis, all data are transformed into its first difference in the following variable definition.

Average investment horizon

Investment horizon = date of exit - date of initial investment

Avg_horizon = sum(investment horizon) / number of investment

Average vintage of funds

$$Vintage = 2024.1 - date\ of\ establishment$$

$$Find\_vintage = sum(vintage) / number\ of\ funds$$

Industry percentage

$$Indsutry\_percentage = exit\ counts\ for\ selected\ industry / total\ exit\ counts$$

Selected industry include IT, manufacturing, healthcare,corporate service, AI, blockchain, software and IT, scientific development, electronics and information, hi-end manufacturing, which covers the industry preference of the STAR board.

Fund type

$$Fund\_type= exit\ counts\ for\ selected\ fund\ type/ total\ exit\ counts$$

Fund type includes: PE, VC, Investment Banking (IB), Strategic investor(Strat), angel investor(angel), incubators (Incu).

Monthly investment

Considering the monthly_investment data, investment would affect exit but only after a certain time period, given the fact that funds have to wait for the company to grow. In the data, the average investment horizon is 3 years (36 months), so lag = 36 is applied to the original investment data following this logic.

Descriptive statistics of all variables after transformations:

	mean	std	min	25%	50%	75%	max
IPO_exit_percentage	0.167564	18.0642	-57.0295	-9.67498	0	10.09524	48.16458
lag_IPO_exit_percentage	-0.10698	30.2881	-100	-12.7647	0	12.64785	100
VC_Exits	-0.00045	0.090262	-0.36154	-0.04531	0	0.044815	0.272727
PE_Exits	0.001495	0.096271	-0.33654	-0.04673	0	0.040412	0.365385
Angel_Exits	-0.00031	0.046478	-0.30769	-0.01665	0	0.015528	0.333333
IB_Exits	6.34E-05	0.024552	-0.11708	-0.00976	0	0.010614	0.086466
Strat_Exits	-0.00063	0.018491	-0.14286	-0.00657	0	0.006755	0.05
Incu_Exits	1.37E-20	0.00559	-0.04762	0	0	0	0.047619
investment_horizon	1.321053	222.4873	-852	-134.25	12	129	646
month_investments	4.155378	243.4868	-1531	-28	3	36	1941
stock_index	4.73526	214.6304	-1082.99	-76.15	10	95.08	747.79
fund_vintage	-0.05395	2.954122	-13.7027	-0.63624	-0.1011	0.626047	12.525
fundraising	7.588933	167.1251	-791	-21	0	27	745
IT	0.000749	0.091615	-0.37308	-0.0443	0	0.06298	0.260409
manufacturing	0.00082	0.134997	-0.43939	-0.05878	0	0.082051	0.530303
Social media	-0.00047	0.054404	-0.18333	-0.02286	0	0.026891	0.242424
Healthcare	0.000188	0.067687	-0.2	-0.0301	0	0.028741	0.169892
Corporate service	-0.00022	0.032084	-0.1952	-0.00173	0	0.002533	0.178744
AI	-0.00023	0.02899	-0.21729	0	0	0	0.235582
Blockchain	-8.60E-05	0.001216	-0.01422	0	0	0	0.005851
software	-0.00068	0.025434	-0.22614	0	0	0	0.122244
Scientific research	-3.40E-04	0.006945	-0.06296	0	0	0	0.045534
electronics	-0.00022	0.025719	-0.13964	-0.00032	0	0.00071	0.140014
semiconductor	0.000589	0.045284	-0.21452	0	0	0	0.387155
Hi-end manufacturing	-0.00045	0.011632	-0.1035	0	0	0	0.07329

Figure 8: Descriptive statistics

All data are transformed to its first difference for a coherent analysis. The standard deviation of fundraising, investment_horizon, IPO_exit_percentage is relatively high, suggesting that the investment and exit strategies are not consistent for all funds and companies on a high level.

5. Empirical Analysis

5.1 Structural Break After the 2019 STAR Board Reform

Lag of monthly_investment and IPO_exit_percentage are used in regressors. For the IPO exit data, AR(1) data is added to the regression as a regressor. Without this variable, the R squared of the model would drop from 51.6% to 24.5%. The coefficient of lag_IPO_exit_percentage is also significant on the 5% level. We first conduct a VIF test to test for multicollinearity in the regressors.

Feature	VIF
lag_IPO_exit_percentage	1.293429
VC_Exits	1.239881
PE_Exits	1.54769
Angel_Exits	1.368902
IB_Exits	1.298419
Strat_Exits	1.37745
Incu_Exits	1.335123
avg_horizon	1.474468
month_investments	1.120576
stock_index	1.15081
vintage	1.708935
fundraising	1.788967
IT	1.331354
Manufacturing	1.809582
Social media	1.326104
Healthcare	1.451819
Corporate service	1.185478
AI	1.355213
Blockchain	1.197535
software	1.140863
Scientific research	1.563921
electronics	2.167552
semiconductor	1.066001
Hi-end manufacturing	1.015613

Since every VIF is less than 5, there are no significant multicollinearity issues in the dataset.

Unrestricted Model

The R squared of this regression is 51.6%, with an adjusted R squared = 34.8%. The F statistic of the regression model is 2.148(p-value = 0.000123 < 0.05), which indicates that the model is statistically significant.

Variable	Coefficient	Standard Error	t-value	P>|t|	95% CI Lower	95% CI Upper
const	-13.491	10.602	-1.273	0.205	-34.467	7.485
lag_percentage	-0.2571	0.083	-3.107	0.002	-0.421	-0.093
VC_Exits	-36.7623	14.428	-2.548	0.012	-65.309	-8.216
PE_Exits	-63.3624	15.027	-4.217	0	-93.093	-33.632
Angel_Exits	-41.0084	28.741	-1.427	0.156	-97.874	15.857
IB_Exits	-83.5489	53.381	-1.565	0.12	-189.165	22.067
Strat_Exits	-101.8414	80.906	-1.259	0.21	-261.916	58.233
Incu_Exits	224.7357	244.265	0.92	0.359	-258.548	708.019
avg_horizon	-0.0028	0.007	-0.395	0.694	-0.017	0.011
month_investments	0.0002	0.005	0.037	0.971	-0.01	0.01
stock_index	-0.0006	0.003	-0.246	0.806	-0.006	0.004
vintage	0.7035	0.447	1.573	0.118	-0.181	1.588
fundraising	0.0055	0.004	1.341	0.182	-0.003	0.014
IT	-3.0725	17.009	-0.181	0.857	-36.726	30.581
Social media	27.8802	27.18	1.026	0.307	-25.897	81.657
manufacturing	24.7387	14.699	1.683	0.095	-4.343	53.821
healthcare	38.8971	23.836	1.632	0.105	-8.263	86.057
Corporate service	-73.2069	38.785	-1.888	0.061	-149.944	3.53
electronics	28.1108	53.97	0.521	0.603	-78.671	134.892
AI	4.3924	100.622	0.044	0.965	-194.691	203.476
Blockchain	-765.3599	1044.007	-0.733	0.465	-2830.953	1300.233
software	-188.6781	65.29	-2.89	0.005	-317.855	-59.501
Scientific research	-164.7787	144.004	-1.144	0.255	-449.693	120.136
semiconductor	9.4552	16.546	0.571	0.569	-23.281	42.192
Hi-end manufacturing	-32.5241	52.611	-0.618	0.538	-136.617	71.569
D	5.3308	12.162	0.438	0.662	-18.731	29.393
VC_Exits_D	-128.1976	77.697	-1.65	0.101	-281.923	25.528
PE_Exits_D	295.1227	138.288	2.134	0.035	21.516	568.729
Angel_Exits_D	146.7776	313.048	0.469	0.64	-472.595	766.151
IB_Exits_D	-746.8387	398.54	-1.874	0.063	-1535.361	41.683
Strat_Exits_D	467.7832	264.012	1.772	0.079	-54.571	990.137
Incu_Exits_D	-5935.3704	1898.367	-3.127	0.002	-9691.335	-2179.405
vintage_D	0.0316	0.021	1.474	0.143	-0.011	0.074
month_investment_D	0.0143	0.011	1.284	0.202	-0.008	0.036
stock_index_D	0.0025	0.007	0.362	0.718	-0.011	0.016
vintage_D	-1.0859	0.826	-1.314	0.191	-2.721	0.549
lag_percentage_D	-0.0252	0.224	-0.113	0.91	-0.467	0.417
fundraising_D	-0.0054	0.011	-0.487	0.627	-0.028	0.017
IT_D	21.9327	40.958	0.535	0.593	-59.104	102.969
Social media_D	141.2447	158.019	0.894	0.373	-171.4	453.889
manufacturing_D	-55.2498	38.976	-1.418	0.159	-132.364	21.864
healthcare_D	31.8169	49.507	0.643	0.522	-66.134	129.768

Corporate service_D	11.2424	209.386	0.054	0.957	-403.033	425.518
electronics_D	-119.4822	197.839	-0.604	0.547	-510.911	271.947
AI_D	-296.4387	153.966	-1.925	0.056	-601.064	8.187
blockchain_D	-109.8743	4965.783	-0.022	0.982	-9934.798	9715.05
software_D	-188.6781	65.29	-2.89	0.005	-317.855	-59.501
Scientific research_D	-164.7787	144.004	-1.144	0.255	-449.693	120.136
semiconductor_D	9.4552	16.546	0.571	0.569	-23.281	42.192
Hi-end manufacturing_D	-32.5241	52.611	-0.618	0.538	-136.617	71.569

Restricted Model

The R squared of this regression is 35.8%, with an adjusted R squared = 21.6%. The F statistic of the regression model is 2.522 (p-value = 5.38e-05 < 0.05), which indicates that the model is statistically significant.

Variable	Coefficient	Standard Error	t-value	P>|t|	95% CI Lower	95% CI Upper
const	-6.1778	8.426	-0.733	0.465	-22.82	10.465
VC_Exits	-30.5669	14.185	-2.155	0.033	-58.584	-2.549
PE_Exits	-60.383	14.859	-4.064	0	-89.732	-31.034
Angel_Exits	-41.0418	28.946	-1.418	0.158	-98.213	16.13
IB_Exits	-93.8085	53.367	-1.758	0.081	-199.214	11.597
Strat_Exits	-40.2395	72.983	-0.551	0.582	-184.389	103.91
Incu_Exits	172.3549	237.671	0.725	0.469	-297.066	641.776
avg_horizon	-0.0058	0.006	-0.919	0.36	-0.018	0.007
month_investments	0.0023	0.004	0.525	0.601	-0.006	0.011
stock_index	-0.0004	0.002	-0.179	0.858	-0.005	0.004
vintage	0.3402	0.329	1.033	0.303	-0.31	0.99
lag_percentage	-0.269	0.072	-3.741	0	-0.411	-0.127
fundraising	0.003	0.004	0.837	0.404	-0.004	0.01
IT	7.7317	14.576	0.53	0.597	-21.057	36.52
Social media	18.8198	26.323	0.715	0.476	-33.171	70.81
manufacturing	29.6883	12.512	2.373	0.019	4.976	54.401
healthcare	43.4774	19.068	2.28	0.024	5.817	81.138
Corporate service	-69.8037	38.126	-1.831	0.069	-145.106	5.499
electronics	62.0712	52.145	1.19	0.236	-40.92	165.062
AI	-9.7707	41.982	-0.233	0.816	-92.689	73.148
Blockchain	-928.1312	981.892	-0.945	0.346	-2867.459	1011.197
software	1.4631	54.963	0.027	0.979	-107.094	110.02
Scientific research	-279.0151	236.966	-1.177	0.241	-747.044	189.014
semiconductor	10.7971	25.486	0.424	0.672	-39.541	61.135
Hi-end manufacturing	-41.6799	96.847	-0.43	0.668	-232.961	149.601

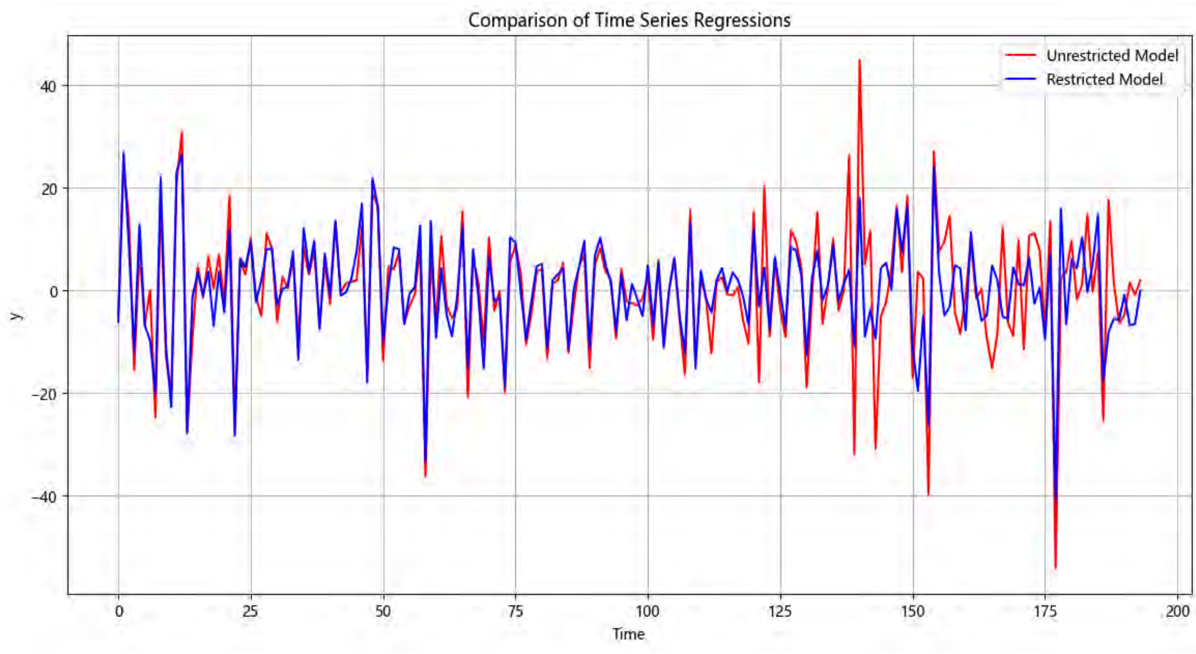
From this regression, we calculated the Chow test statistic is 3.0484, and the critical F-value is 1.516. Since 3.0484 > 1.516, we reject the null hypothesis, and there is a significant change in firms exit by IPO significantly after the 2019 STAR board reform.

5.2 Hi-tech Industries vs. Other Industries

The r squared of the regression is 34.8%, and the f statistic of the regression is 69.35(p-value = 3.16e-37 < 0.05), which indicates that the model is significant.

Variable	Coefficient	Standard Error	t-value	P>|t|	95% CI Lower	95% CI Upper
const	0.6938	1.016	0.683	0.495	-1.297	2.685
Is_Target_Industry	-2.103	1.768	-1.189	0.234	-5.57	1.364
Post	4.5158	1.858	2.431	0.015	0.874	8.157
TreatmentXPost	-11.9284	3.105	-3.841	0	-18.016	-5.841

For the DID test, The t statistics of TreatmentXPost variable is -3.841, with a p-value = 0.000 < 0.05. Therefore, we reject the null hypothesis and conclude that the change in the percentage of firms exit by IPO among hi-tech industries is significantly bigger than other companies.



This graph shows the prediction of the restricted model and the unrestricted model. It can be clearly identified that after the reform, the prediction between the 2 models are different.

5.3 PE-supported Companies vs. Other Companies

The R squared of the DID regression model is 29.7%, and the f statistic is 30.75(p-value = 8.58e-18 < 0.05). So the model is statistically significant.

Variable	Coefficient	Standard Error	t-value	P>|t|	95% CI Lower	95% CI Upper
const	3.0189	0.09	33.696	0	2.843	3.195
Treatment	-0.0043	0.126	-0.034	0.973	-0.253	0.244
Post	1.0875	0.178	6.114	0	0.738	1.437
TreatmentXPost	0.0381	0.251	0.151	0.88	-0.456	0.532

The t statistics of TreatmentXPost variable is 0.151 with a p-value = 0.880 > 0.05. So there is no evidence to reject the null hypothesis. There is not enough evidence to say that the exit strategy of PE changed more significantly compared to other firms.

A potential explanation for the non-significant treatment effect could be attributed to the composition of IPO exits, which often involve a combination of PE and other types of funds. The dataset permits funds to be classified under multiple types (e.g., PE and VC simultaneously). Additionally, exits may involve multiple funds of different types. For data analysis, we exclusively calculated exits that consisted of "PE" type funds, which accounted for more than 80% of total exits. The regression result further confirms this explanation, since the coefficient of Treatment is not significant while the coefficient of Post is significant. This suggests that the treatment and control groups were not distinctly separated prior to the intervention but exhibited significant differences post-intervention, supporting Hypothesis 1.

An alternative data-splitting method—using exits that only contain PE investors as the control group and comparing them to exits without any PE investors—yielded less than 10 samples per period for PE investor exits. This sampling limitation represents one of the constraints of this study and could be reevaluated in the future with more extensive data availability.

6. Discussion and Conclusion

For the first hypothesis, the negative coefficients for VC_Exits and PE_Exits in the unrestricted model suggest that both venture capital and private equity exits were associated with a decrease in IPO exit percentages, possibly reflecting a preference for other exit strategies or market conditions not conducive to IPOs at the time. The significant positive coefficient for PE_Exits_D in the unrestricted model suggests that the relationship between private equity exits and IPO exit percentages became more positive after the reform, indicating a potential shift in how these exits interact with market conditions post-reform.

The large negative coefficient for Incu_Exits_D indicates a significant decrease in IPO exits associated with incubator exits post-reform, suggesting that companies exiting incubation were less likely to go public or were negatively impacted by the reform.

Overall, several conclusions can be drawn from the empirical analysis. First, The consistent presence and significance of market condition variables (like stock_index) across hypotheses suggest that overarching market trends play a critical role in IPO exits, more so than specific reforms or industry characteristics in some cases.

Second, The differential impact on hi-tech industries and the significant coefficients related to specific sectors like software and IT highlight that sector-specific factors are crucial. Reforms and market changes do not impact all sectors uniformly, and some sectors may face unique challenges or benefits from such changes.

Moreover, the varying impact of PE and VC exits on IPO percentages, particularly the shift post-reform, underscores the complex role that different types of investment play in guiding a company towards an IPO. The reform might have altered the landscape for these investors, but not uniformly across all types of investor support.

Overall, these insights suggest that while structural reforms like the STAR board reform can significantly impact IPO exit strategies, the effects are nuanced, with sector-specific impacts and differing roles of investor support. Understanding these dynamics requires a close examination of the interplay between market conditions, sector characteristics, and types of investor support.

7. Limitation

To conduct a more comprehensive study on the changing exit strategies of private equity in China, Hypothesis 1 posits that the percentage of exits by IPO relative to the total number of exits serves as the dependent variable. A multivariable logistic regression can be implemented, where each predictor variable corresponds to a specific type of exit. This approach will allow for a nuanced analysis of the factors influencing different exit strategies.

Regarding Hypothesis 3, as noted in Section 5.3, the current limitations in data availability have precluded satisfactory outcomes. Future research could benefit significantly from enhanced data records, which would enable a more complete understanding of how private equity is influenced by policy changes.

This study primarily employs econometric and regression analyses due to the availability of a relatively comprehensive data set. Moving forward, the construction of a machine learning model could provide an alternative method to assess changes in exit percentages. However, the interpretability of such a model may present a challenge, necessitating careful consideration.

The ultimate aim of this study is to derive implications that are valuable to policymakers and practitioners in the private equity industry. The findings could foster meaningful discussions within the industry and inform policy formulation, thereby bridging the gap between empirical research and practical application.

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