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The Short-Run Effects of the Cybersecurity Law on Venture Capital Investment in China

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The Short-Run Effects of the Cybersecurity Law on Venture Capital Investment in China[1]

Jingting Liu[*2] Ulrike Sengstschmid[*3] Liyu Dou[4]

Abstract

Despite active online discussions on the economic implications of the data regulations in China in recent years, empirical studies are scarce. We aim to fill this gap. In this paper, we examine the effects on venture capital investments of the enactment and enforcement of China's Cybersecurity Law in 2016 and 2017, respectively, using a difference-in-differences methodology. We find a significant and sizeable negative impact of the passage of the Cybersecurity Law on venture capital investment activity in China. On average, post-enactment and post-rollout, respectively, the number of venture capital deals dropped by more than 8% and 11% in the internet and software industries while the effects are muted for non-internet and non-software industries. This is because the CSL specifically regulates firms such as "providers of network products and services" and "application software download service providers." The reduction in the number of venture deals is more pronounced for early-stage investments and deals with foreign investors. Robustness tests using alternative specifications including synthetic difference-in-differences corroborate these results.

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1. Introduction

Data has become a quintessential input in our modern economy. However, the mass use of data brings with it concerns about threats to individuals' privacy, data breaches, or other misuses, because of which more and more countries have moved to regulate the use of personal data by companies. The most prominent example is the European Union's (EU) General Data Protection Regulation (GDPR) first published in 2016. Just one year later, China – one of the world's biggest producers and consumers of data – also moved to regulate personal data for both privacy and national security reasons. While such regulations often carry the policy objectives such as protecting users and national interests, they are also likely to have negative impacts on the economy through direct compliance costs to businesses as well as through broader indirect effects caused by an initial increase in uncertainty which potentially hinders investment spending.

The empirical literature on the effects of personal data protection regulation is still relatively young, and, so far, mostly focused on the EU's GDPR. The economic side effects of introducing privacy regulation found in the literature include (1) a negative impact on firm performance due to increased compliance costs and therefore lower profits (Chen et al., 2022; Koski & Valmari, 2020); (2) an increase in market concentration as smaller firms are disproportionately affected by compliance costs (Geradin et al., 2021; Johnson & Shriver, 2020; Peukert et al., 2020, 2022); (3) a negative effect on firms' innovation as less data is available that can be used for research and development (Bessen et al., 2020; Blind et al., 2022; Martin et al., 2019); and (4) a reduction of venture investments into firms affected by the data protection regulation (Jia et al., 2020, 2021).

We contribute to the literature by moving beyond the current EU focus to examine the effect of China's Cybersecurity Law (CSL) on the country's venture capital investments. To the best of our knowledge, we are the first to directly estimate the economic impact of China's data

regulations despite active discussions on the internet. Bauer et al. (2014) projected that China's GDP and investments will contract by 1.1% and 1.8%, respectively, due to potential legalisation of data regulations. While they used a GTAP framework, modelling the shock arising from the potential introduction of data regulations as a reduction in investment returns, we directly contrast the volume of venture capital investments in China against the rest of the countries before and after both the enaction and rollout of the CSL using the difference-in-differences method. Other studies of Chinese data regulations, however, are largely qualitative, and argue that the cost of compliance of Chinese data protection policies is significant, especially for foreign firms (Chander et al., 2021; Liu, 2021; Xie et al., 2023). We depart by formally quantifying the impact of China's CSL on foreign investments and joint investments in China.

We find a sizable and significant impact on the venture capital investment activities in China following the passage of CSL. On average, the number of monthly venture deals in the internet and software industries in China — the industries perhaps most directly affected by the CSL — dropped by between 8% to 36% in the post-CSL enactment period, and by between 11% and 18% post-CSL rollout across specifications. Within each specification, the negative effects are larger post-rollout than post-enactment. Our estimates are comparable to Jia et al. (2021), who find the GDPR-induced reduction in the monthly number of deals of data-reliant ventures in the EU relative to the US and the rest of the world to be 31%, and of consumer-facing venture deals to be 18%.

We further show that the effect of the CSL is heterogeneous across different categories of venture deals: Generally, the negative effects are muted for non-internet and non-software industries. More specifically within the internet and software industries, the negative effects of the CSL are more pronounced for venture investments in the early stage, and investments from

foreign investors. The number of monthly venture deals from home investors in China, however, exhibits no reduction due to CSL.

The remainder of the paper is structured as follows: Section 2 presents the institutional background around China's personal data protection policies. In Section 3 we discuss our choice of data, and we show basic evidence of the impact of CSL in Section 4. Section 5 presents our empirical strategy and the findings are discussed in Section 6. In Section 7 we conduct several robustness checks, before concluding in Section 8.

2. Institutional Background

The Cybersecurity Law was passed in November 2016 and took effect in June 2017. It regulates personal data protection and defines the data security obligations of internet service providers and so-called critical infrastructure operators, including provisions on data localization. Importantly, and contrasting to other personal data protection regulations such as the EU's GDPR, the underlying motivation for this law is not the right of data subjects but larger national security interests (Creemers, 2022; Qi et al., 2018). This generally makes it more difficult for businesses, especially non-Chinese ones, to operate under such a law as it requires measures like security assessments or even a complete ban on data exports in certain sectors (Xie et al., 2023).

In the CSL, a few types of service providers and organizations are explicitly mentioned, including "providers of network products and services", "electronic information distribution service providers", "application software download service providers", "internet industry organizations", and "network-related industry organizations", which motivated us to examine the impact of CSL on the investments in the internet and software industries separately from the rest.

Subsequently, China implemented both the Data Security Law (DSL) and the Personal Information Protection Law (PIPL) in September and November 2021, respectively, further extending data localisation requirements. While the DSL and the PIPL may entail more wide-ranging effects, we focus on the effects of the CSL to avoid potential contamination due to the COVID-shock and elevated geopolitical tensions during the same period.

3. Data

Our primary data source is the Preqin database, a global venture capital dataset. We collect data on all venture capital deals in all countries, including China. Deal-specific information includes deal date, deal size (in USD millions), investor, investor country, portfolio company, portfolio company country, industry classifications, and venture financing rounds. We sort venture deals into three stages: early, main, and late stage. Early stage deals include those in the angel, pre-IPO, and seed rounds. Main stage deals include Series A, Series B, and Series C investments. Late stage deals are those in the Series D to Series L rounds, and private investment in public equity, secondary stock purchases, and venture debts. Stage classification follows Jia et. al. (2021).

We focus on venture investment deals, instead of other types of investments, because venture deals are for more nascent firms, which arguably would be more prone to changing regulatory environment and the associated uncertainty, and venture capital investment data is of high frequency with daily transaction records allowing a very specific study of particular events like the introduction of new regulations. Further, venture capital investments are a sizable financing source for Chinese firms besides loans. Table 1 compares the cumulative value of venture investment deals in China between Nov 2015 and Jun 2018 with other sources of financing. Over this period, the cumulative value of venture investments equals around 6% of the value of credit issued to non-financial corporations, or total bank loans. Additionally, the value of venture investments is comparable to the sum of foreign credit flows to China, and is near half

of all the foreign direct investments and three times the foreign investments in Chinese firms-issued bonds over the same period.

Table 1: Cumulative value of investments in China Between Nov 2015 and Jun 2018

Type of Investment	Cumulative Value (million USD)
Venture capital investments	230,205
Credit to non-financial corporations (core debt)	3,557,000
Foreign credit	217,427
Foreign debt securities	61,990
Foreign direct investment	532,221

Notes: Credit to non-financial corporation (core debt), foreign credit, and foreign debt securities are from BIS, and foreign direct investment data is from The State Administration of Foreign Exchange of China collected from CEIC.

We conjecture that internet and software related industries will be more affected by the Cybersecurity Law, given such services providers and organizations are explicitly mentioned in the law. We therefore separately examine the venture investment activities in the internet and software industries. To visualize what type of portfolio firms fall under such industries in China, we identify the highest frequency words in these firms' industry verticals. Industry verticals are short descriptions of the specializations of each firm in the Preqin dataset. The word cloud in Figure 1 below shows that most of the venture investment deals in the internet and software industries in China specialize in mobile apps and software-as-a-service (Saas), followed by e-commerce, machine learning and cloud computing.

Macroeconomic control variables, including GDP and interest rates are collected from CEIC. Quarterly GDP data are linearly interpolated to monthly frequency, and are scaled by the annual population size obtained from the World Bank to calculate GDP per capita, assuming population remains constant throughout the year. Whenever possible, interest rates at monthly frequency are collected, and interest rates of lower frequencies are interpolated.[5] Finally, unemployment rates at annual frequency are collected from the ILOSTAT database and interpolated to monthly frequency.

[5] Interest rate of Myanmar is at annual frequency and interest rate of Bahrain is at quarterly frequency, both are linearly interpolated to monthly frequency.

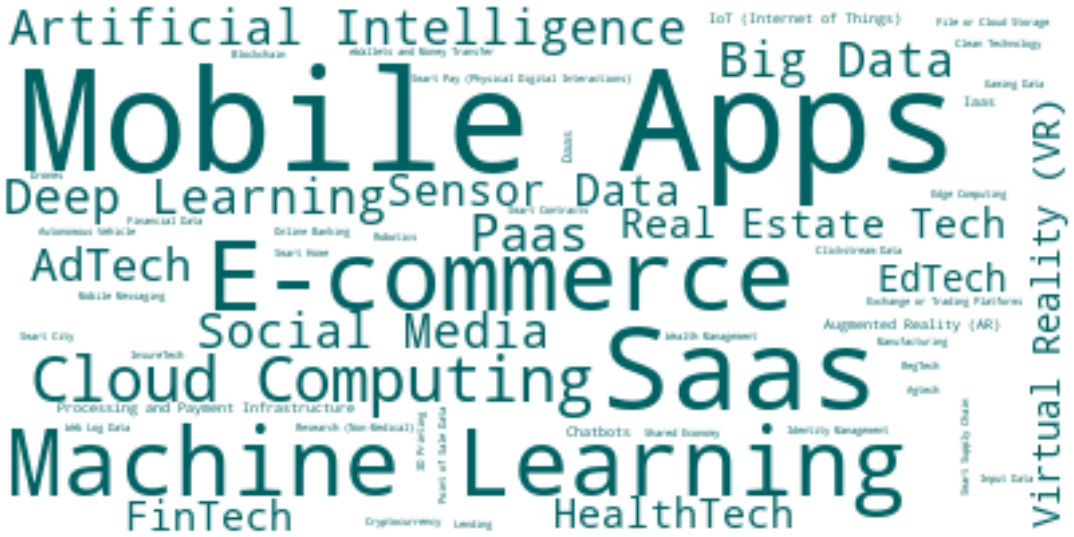

Figure 1: Keyword word cloud on the internet and software industry. Sample period: Nov 2015 – Jun 2018

4. Basic Evidence

Before empirically examining the effects of Chinese data regulations on venture capital investments, we first identify prominent trends in the Chinese venture capital market to check whether our main sample period coincides with any other major shifts in the market. The top panel of Figure 2 plots the monthly number of venture capital investment deals in China from January 2010 to December 2022 against those of the US. Over most of the period, both countries have a comparable number of investment deals. Venture investments in China grew exponentially entering 2014, surpassing that of the US in volume in 2015, and remained relatively stable until around mid-2018 when the US-China trade war began, with the number of venture investment deals subsequently declining substantially.

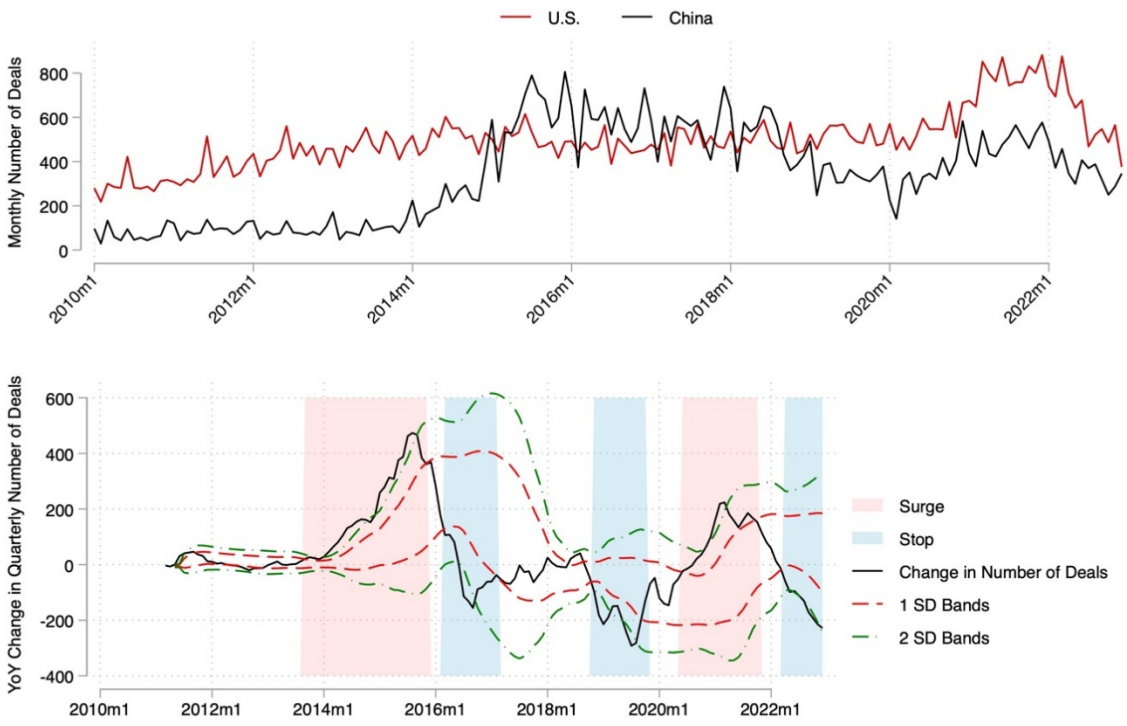

Figure 2: The Ebbs and Flows of Venture Capital Investments in China, Jan 2010 – Dec 2022

Formally, we identify unusually volatile periods by checking the year-on-year growth in monthly number of deals from Jan 2010 to Dec 2022. Let $C_t = \sum_{i=-3}^{0} NUMDEAL_{t+i}$ be the 3-month moving average of the number of deals and compute monthly year-over-year changes in C_t as $\Delta C_t = C_t - C_{t-12}$. Next, we calculate the rolling means and standard deviations of ΔC_t over the previous 1 year (12 months). In the spirit of Forbes and Warnock (2012), we define a "surge" episode in venture investments as the period between when the year-on-year change in the number of venture deals ΔC_t first rises above one standard deviation above the rolling mean, and first reverts to below one standard deviation above the rolling mean. In addition, there has to be at least one period when ΔC_t rises more than two standard deviations above the rolling mean in the surge episode. Likewise, we define a "stop" episode as the period between when ΔC_t first drops below one standard deviation below the rolling mean, and first rises above one standard deviation below the rolling mean. Also, ΔC_t has to drop to more than

two standard deviations below the rolling mean at least once for the episode to be defined as a "stop".

We identify two surge episodes and three stop episodes throughout the period. The year-over-year change in the number of venture investment deals rose sharpy between Sep 2013 and Nov 2015, and over a short period during the pandemic — mainly due to investments in healthcare related industries. One of the stop episodes falls in late 2018, shortly after the trade war started, and another one falls in early 2022, when lockdowns were prevalent in China. Importantly, there is one stop episode between Mar 2016 and Feb 2017, which falls under the sample period that we study.

Besides regulatory change such as the implementation of the Cybersecurity Law, there are three other competing explanations for the weak venture investment activity in China over the period of 2016 and 2017: (1) a slow-down in the economic growth; (2) geopolitical tensions; (3) changes in industry life cycles. If economic slow-down is the main factor dragging venture investments in China, the impact should be distributed across industries. However, Figure 3 left panel shows that the drop is disproportionately larger for internet and industry investments: while the share of monthly number of deals in the internet and software industries remained largely stable before the enactment of CSL, the share dropped sharply after and declined even further after the rollout of CSL, whereas the share of monthly number of deals in other industries rise. Further, when we contrast the monthly number of deals in the internet and software industries of China against that of the US, the decline in the deal number in China tends to be steeper. In Figure 4 right panel, we plot the logged number of deals in internet and software industries in China against its synthetic control group: While the logged number of deals in China tracked that of the control group closely before the CSL enactment, they diverged significantly after. These results serve as a first-pass that the change in regulatory environment likely negatively impacted investments. To alleviate concerns of geopolitical

tension triggered effects, we stop the sample period in June 2018, before the trade war starts. Finally, we discuss the potential impact due to lifecycle changes of internet and software industries in China in Section 5. Table A. in the Appendix provides summary statistics of the overall number of deals and number of deals in different subgroups, as well as the macroeconomic control variables.

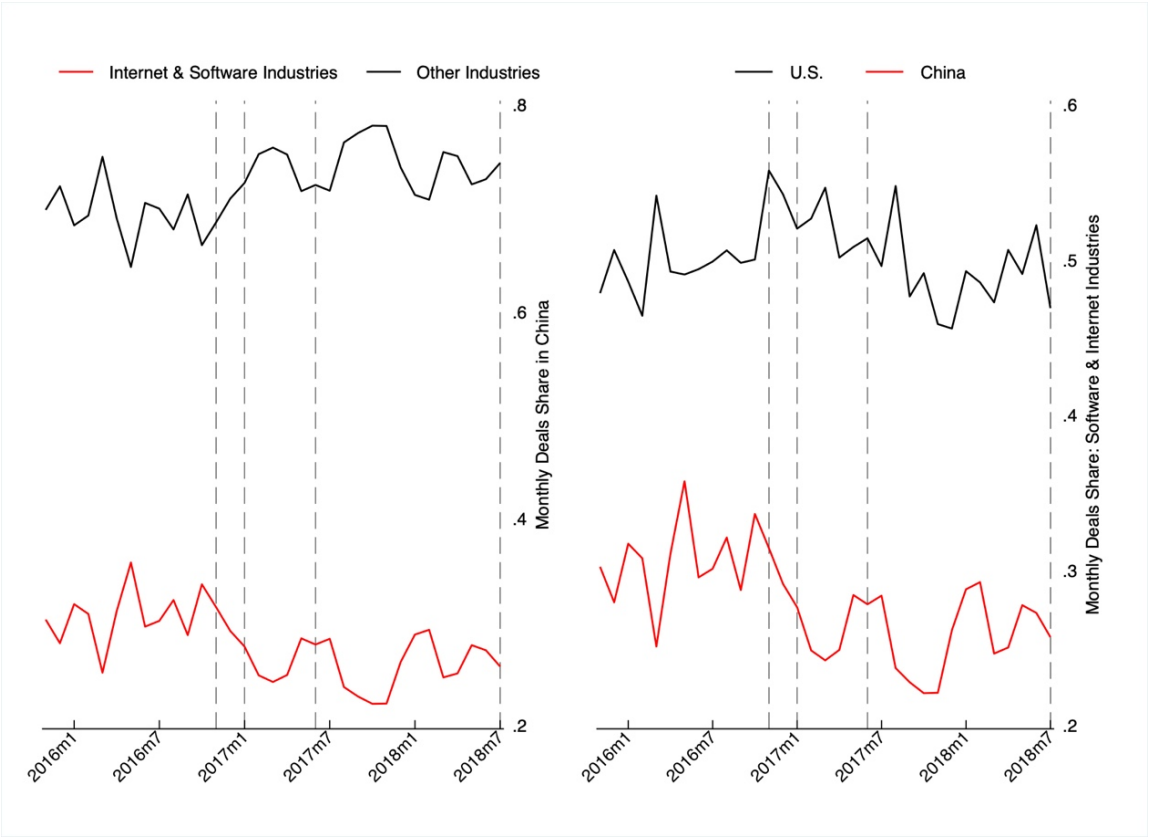

Figure 3: Monthly Deals Share of Internet and Software Industries in China, Nov 2015 – July 2018. Left: Against the deals share of other industries in China. Right: Against the deals share of internet and software industries in US.

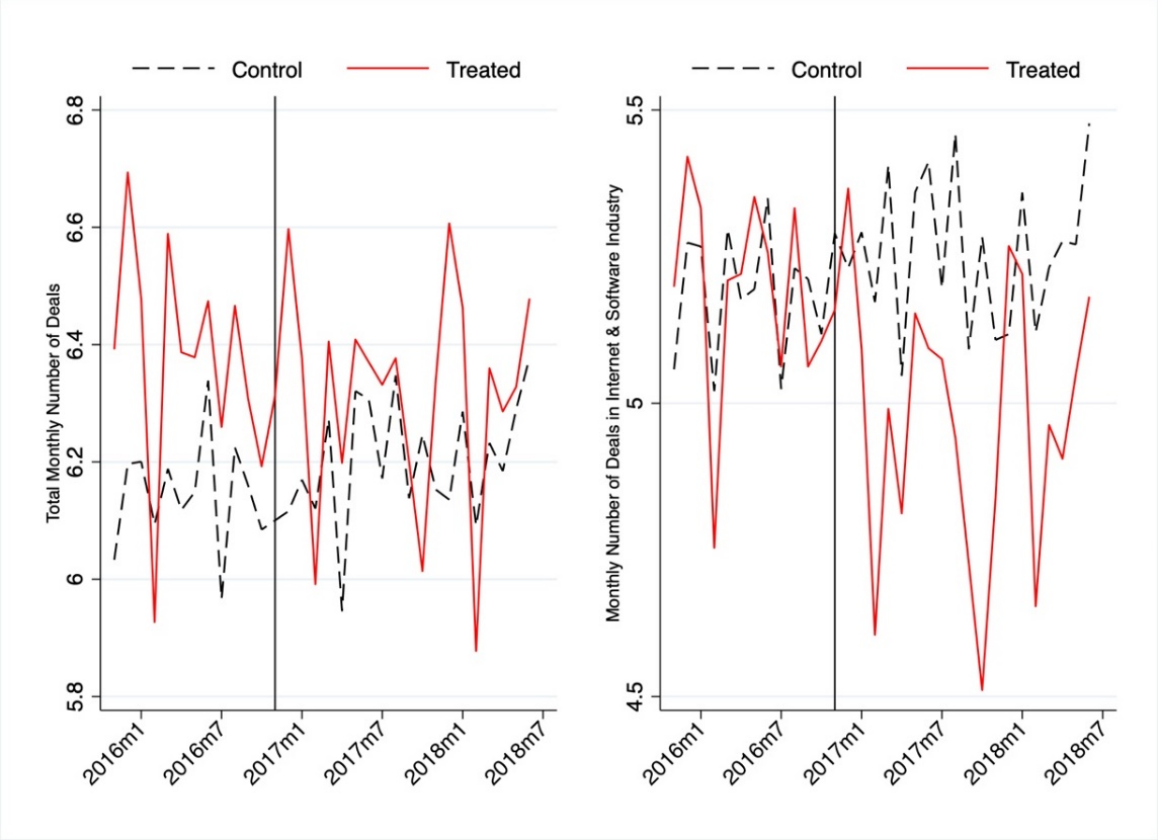

Figure 4: Number of monthly investments in China and synthetic China (in logs), Nov 2015 – Jun 2018. Left: Total number of deals per month (log). Right: Total number of deals in internet and software industry (log). Solid line marks the month when cybersecurity law was passed in China. Number of deals for synthetic China is constructed using synthetic control method.

5. Empirical Strategy

We aim to estimate the effects of the CSL on venture investment activities in China. To do so, we compare the number of venture investment deals in China with those of the rest of the world before and after both the enactment and rollout of the CSL. While the CSL was passed in Nov 2016, it came into effect only in Jun 2017. We hypothesize that the effect of the CSL on venture investment activities would be greater following its enforcement, after which firms must comply with the law, elevating compliance and implementation costs. Apple Inc., for example, announced to set up its first data centre in China, partnering with a local cloud services

company in July 2017[6]. Indeed, Google Trend plot in Appendix A (Figure A2) shows that the interest in the CSL rose sharply after its passage and peaked around the rollout date.

We examine the effect of the CSL using a difference-in-differences (DID) setup. We focus on the monthly number of investments at month-country level both across all categories and within each specific category. Categories can be industries, stages, or origin countries of venture investment deals. The dependent variable could be zero if there are no venture capital deals in that month-country-category.[7]

Our treatment group are the Chinese ventures, and our control group comprises ventures in the other nearly 70 countries. We are aware that there is potential heterogeneity in regulatory regimes and venture activity of the other countries relative to China, and existing literature generally relied on synthetic control when conducting cross-country studies involving China (see Gietel-Basten et al. (2019)). We therefore include a set of macroeconomic and other controls to account for the heterogeneity. Additionally, we check in Section 7 whether our results are robust to using synthetic difference-in-differences, which is superior to synthetic control as it optimally selects both the cross-sectional units and time periods for constructing the weighted average of observations of the control group.

We consider two specifications below:

$$y_{it} = \alpha_i + \alpha_t + \delta X_{it} + \gamma_1 CSL_{it} + \epsilon_{it} \quad (1)$$

$$y_{it} = \alpha_i + \alpha_t + \delta X_{it} + \beta_1 CHN_i \times CSL_{Enact_t} + \beta_2 CHN_i \times CSL_{Rollout_t} + \varepsilon_{it} \quad (2)$$

where i denotes country, t is month indicator, CSL_{it} equals 1 for China if time t is on or after Nov 2016, and 0 otherwise. CHN_i is a dummy that equals 1 if the country is China and 0 otherwise. CSL_{Enact_t} equals to 1 for the period after CSL enactment but before its rollout (i.e., on or after Nov 2016 but before Jun 2017), and is 0 otherwise. Likewise, $CSL_{Rollout_t}$

[6] See for example: https://www.reuters.com/article/us-china-apple-idUSKBN19X0D6.
[7] Countries with all zero observations are dropped in the estimation.

equals 1 if time t is on or after Jun 2017 and 0 otherwise, indexing the period after the CSL came into force. The dependent variable, y_{it}, is the number of venture capital deals in each country-month. Since we use ordinary least squares (OLS) for the baseline estimation, we take the log of 1 plus number of deals as y_{it}. Nevertheless, we later show that the results are robust to Poisson specification. Year-month and country fixed effects are denoted by α_t and α_i, respectively. To account for macroeconomic trends and shocks that could affect the number of deals, we include a set of country-specific macroeconomic controls in X_{it}, including GDP per capita (logged), interest rate and unemployment rate. In addition, to control for other trends or industry lifecycles, we include country-specific linear and quadratic trends when estimating the effect of the CSL on venture investment activities both across categories and within categories such as different industries, stages, and sources of investments. The coefficient γ_1 captures the average effect of the CSL since its enactment, whereas coefficients β_1 and β_2 capture the effects of the CSL's enactment and rollout, respectively. Standard errors are clustered at the country level. Table 2 reports the estimation results.

6. Empirical Analysis

We begin by examining the overall effects of the CSL on the number of deals across all categories for each country each month from before to after the CSL was passed. Column (1) of Table 3 indicates a 12% increase in the total number of deals after the CSL was passed. However, when focusing on the number of deals in the internet and software industries only — the industries that are directly targeted by the CSL — Column (3) suggests an 8% decrease in the number of deals on average after the CSL was passed[8]. Further, the effects of the CSL is

[8] Because the dependent variable is $\log(1 + \#\ of\ deals)$, the actual effect of the CSL on the number of deals would be larger than the estimated coefficients reported in Table 3. Nevertheless, calculations based on the estimated coefficients and taking into account of the log transformation suggest that the marginal effects are very close to the estimated coefficients. This is because the number of deals is very large for China.

estimated to be larger following the rollout of the CSL than post-enactment by before rollout, with an 18% and 9% reduction respectively in the monthly number of deals in the internet and software industries, validating our hypothesis.

The opposite signs in the estimated coefficient of the CSL when aggregating all industry categories versus when separately examining the internet and software industries suggest some potential substitution effects in venture investment activity between the tightly regulated internet and software industries and other industries. Indeed, when we focus on the effects of the CSL on the number of investment deals in non-internet and non-software industries, Column (5) suggests a nearly 20% increase after the CSL enactment and another 19% increase after the rollout of the CSL.

Table 2: CSL Impact on the Aggregate Number of Deals, and Number of Deals in Internet and Software Industry and Other Industries: Full Sample

	(1)	(2)	(3)	(4)	(5)
	Total # of Deals		# of Deals in Internet/Software Industries		# of Deals in Other Industries
$Cybersecurity\ Law\ (CSL)$	0.122***	-	-0.078**	-	
	(0.000)	-	(0.036)	-	
$CHN \times CSL\_Enact$	-	0.121***	-	-0.085**	0.197***
	-	(0.001)	-	(0.019)	(0.000)
$CHN \times CSL\_Rollout$	-	0.097**		-0.181***	0.193***
	-	(0.039)		(0.000)	(0.002)
$GDP\ per\ Capita$	-0.517	-0.517	-0.728*	-0.732**	0.042
	(0.200)	(0.207)	(0.065)	(0.064)	(0.917)
$Interest\ rate$	-0.029**	-0.029**	-0.019**	-0.019**	-0.009
	(0.035)	(0.039)	(0.011)	(0.012)	(0.593)
$Unemployment\ rate$	-0.038	-0.038	-0.001	-0.001	-0.081**
	(0.196)	(0.204)	(0.971)	(0.967)	(0.045)
Country FEs	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes
Country-specific linear trend	Yes	Yes	Yes	Yes	Yes
Country-specific quadratic trend	Yes	Yes	Yes	Yes	Yes
Observations	2,208	2,208	2,112	2,112	1,984
Adjusted R^2	0.937	0.937	0.908	0.908	0.923

Notes: The dependent variables in columns (1) – (2) are (log) total number of monthly deals. The dependent variables in column (3) and (4) are (log) monthly number of deals in internet/software industry. The dependent variable in column (5) is the (log) monthly number of deals in other industries. Standard errors are clustered at the country level. Sample period: Nov 2015 – Jun 2018.

Next, we consider the event study specification to examine the dynamic effect of the cybersecurity law. By controlling for fixed differences across countries, over time, and country-specific macroeconomic variables and trends, we assess the evolution of log-transformed

number of deals in the internet and software industries for each quarter after and before the passage of the CSL, following Jia et. al. (2021).

$$y_{it} = \alpha_i + \alpha_t + \delta X_{it} + \sum_{j=1}^{4} \gamma_{-j} D_{t-j} \times CHN_i + \sum_{j=1}^{4} \gamma_j D_{t+j} \times CHN_i + \upsilon_{it} \ , \qquad (3)$$

where y_{it} is the number of deals in the internet and software industries in month t and country i, D_{t-j} is a dummy variable indicating the time j periods (quarters) before the enactment of cybersecurity law, and D_{t+j} indicates the time j periods (quarters) after the enactment of cybersecurity law. The variable CHN_i equals 1 if the venture investment occurred in China, which is the treatment group. Therefore, γ_{-j} and γ_j captures the lead/lag effects of the cybersecurity law enactment. The omitted time period is $t = 0$, the quarter in which the CSL was passed. Therefore, each estimate of γ_{-j} and γ_j yields the change in log-transformed number of deals in China relative to the rest of the countries in the j-th quarter before and after the enactment of the CSL, as measured from the quarter of enactment[9].

The results are reported in Figure 5. While there is no obvious pre-existing differential trend between China and the remaining countries in the number of deals in the internet and software industries prior to the CSL enactment on a quarterly basis, we find a large decrease in the number of deals in China with the quarterly drop being nearly 40% just one quarter after the enactment, which further increased to almost 80%, consistent with our estimate that the effect of the CSL rollout is larger than the effect of the CSL enactment, supporting our earlier hypothesis that the effects take time to fully materialize.

[9] We estimated the lag effect up to 6 quarters after the CSL enactment, and the reduction in the number of deals (log points) persists up to the 6th quarter. Figure 5 shows the lag effects up to 4 quarters, keeping the number of periods before and after the CSL enactment the same. Lag effect up to 6th quarter is available upon request.

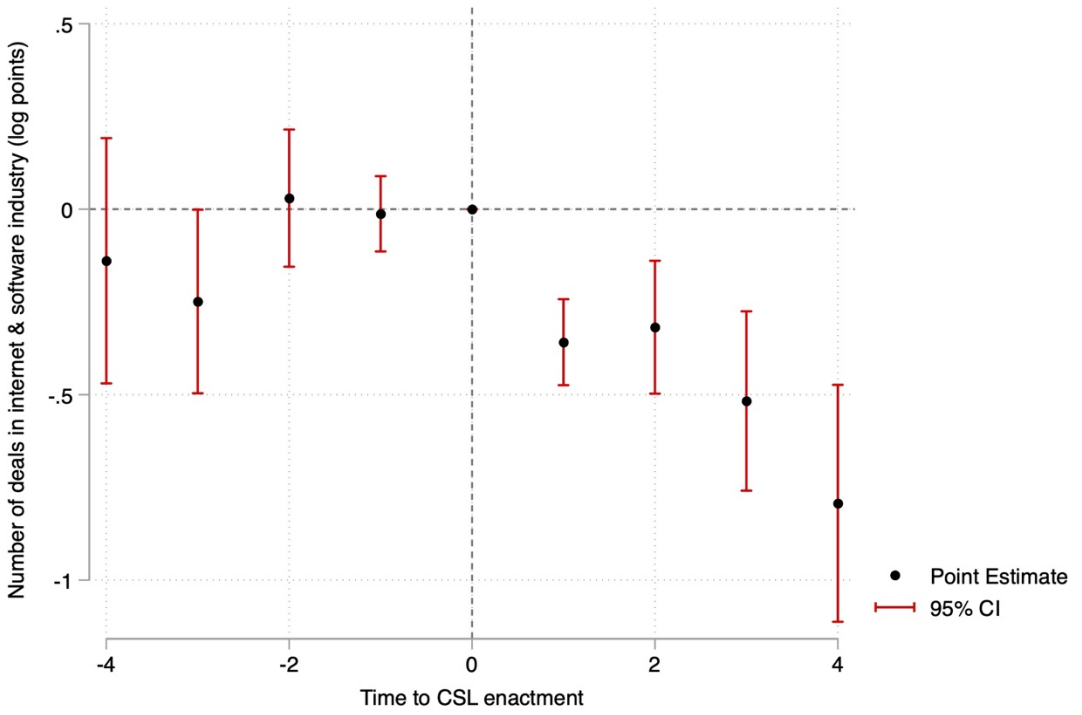

Figure 5: Event study plot of the effect of Cybersecurity Law enactment, at 4 quarters before and 4 quarters after the enactment. Standard errors are clustered at the country level. Full sample of 2,304 observations.

6.2 Heterogeneous Effects

While our main results show a significant positive effect of the Cybersecurity Law on the total number of deals and a significant negative effect on the number of deals on the internet and software industries, it is not clear from the previous specification whether differences exist between types of deals. Therefore, we examine the heterogeneous effects of the CSL across different stages (early, main, or late) as well as on types of investors (foreign, joint, or domestic). We expect early stage deals as well as deals from foreign investors to be most affected, as the impact and uncertainty surrounding new laws is most likely to impact small new firms as well as the uncertainty being larger among foreign investors as they may know less well how the law will be implemented.

We report our results in Table and Table for the total number of deals and the number of deals in internet and software industries, respectively. Columns (1), (2), and (3) report the heterogeneous effects by deal stage. Contrasting Columns (1), (2), and (3) in Table against

those of Table , we find that while the total number of deals increase, especially for main- and late-stage deals, the number of deals in internet and software industries declined uniformly across stages after the rollout of the CSL, and the drop is especially large for early- and late-stage deals, reaching almost 35% and 55%, respectively. These are consistent with our earlier finding of potential substitution between investments in internet and software industries and other industries.

Table 3: CSL Impact on the Aggregate Number of Deals Across Different Subgroups

All industries	(1) Early stage deals	(2) Main stage deals	(3) Late stage deals	(4) From foreign investors	(5) Joint deals	(6) From home investors
$CHN \times CSL\_Enact$	-0.022	0.200***	0.354***	0.005	0.018	0.095***
	(0.565)	(0.000)	(0.000)	(0.898)	(0.647)	(0.007)
$CHN \times CSL\_Rollout$	0.013	0.100	0.064	0.046	-0.145**	0.072
	(0.807)	(0.132)	(0.372)	(0.358)	(0.012)	(0.199)
$GDP\ per\ Capita$	0.228	-0.393	-0.049	-0.352	0.143	-0.316
	(0.594)	(0.259)	(0.855)	(0.373)	(0.682)	(0.388)
$Interest\ rate$	-0.005	-0.003	-0.000	-0.017*	-0.002	-0.012
	(0.633)	(0.795)	(0.957)	(0.075)	(0.798)	(0.116)
$Unemployment\ rate$	0.004	-0.030	-0.050	-0.002	-0.080*	-0.042
	(0.901)	(0.234)	(0.235)	(0.949)	(0.094)	(0.195)
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific linear trend	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific quadratic trend	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,048	1,888	1,376	2,176	1,664	1,984
Adjusted R^2	0.89	0.98	0.83	0.83	0.90	0.93

Notes: The dependent variables in columns (1) – (3) are total number of monthly deals in early stage, main stage, and late stage, respectively. The dependent variables in column (4) - (6) are monthly number of deals from foreign investors only, from both foreign and domestic investors (joint deals), and from domestic investors only. Standard errors are clustered at the country level. Sample period: Nov 2015 – Jun 2018.

Columns (4), (5), and (6) in both Table and Table report the heterogeneous effects of the CSL for different types of investors. For the total number of deals, the effects of the CSL's enactment are insignificant, both economically and statistically, for investments involving foreign investors (Columns 4 and 5 in Table), but significantly positive for domestic investors (Column 6). Meanwhile, the effect of the rollout of the CSL was significantly negative for joint deals, decreasing the number of deals by about 15% on average. These results suggest potential substitution of investments from foreign investors with investments from domestic investors. Focusing on the internet and software industries, Table Column (4) and (5) indicate that both

the enactment and the rollout of the CSL have significant negative effects for both foreign and joint deals, reducing the number of venture deals in both categories by about 16% and 32% after enactment, and 41% and 61% after rollout, respectively. Column (6) suggests that there is no significant effect for venture deals in the internet and software industries by domestic investors. These results mirror findings by Jia et al. (2020), who also find that foreign deals are more negatively affected by the GDPR than those from domestic investors at -22.2% versus -12.1%.

Table 4: CSL Impact on the Number of Deals in Internet and Software Industries Across Different Subgroups

Deals in internet & software industries	(1) Early stage deals	(2) Main stage deals	(3) Late stage deals	(4) From foreign investors	(5) Joint deals	(6) From home investors
$CHN \times CSL\_Enact$	-0.253***	0.001	0.302***	-0.161***	-0.320***	-0.025
	0.000	(0.975)	(0.000)	(0.000)	(0.000)	(0.480)
$CHN \times CSL\_Rollout$	-0.345***	-0.191***	-0.549***	-0.414***	-0.610***	-0.061
	0.000	0.001	0.000	0.000	0.000	(0.296)
$GDP\ per\ Capita$	0.204	-0.017	0.052	-0.567	0.254	-0.271
	(0.626)	(0.969)	(0.880)	(0.146)	(0.414)	(0.334)
$Interest\ rate$	0.000	-0.006	0.013	-0.020***	0.012*	-0.009*
	(0.972)	(0.347)	(0.612)	(0.006)	(0.063)	(0.095)
$Unemployment\ rate$	0.012	0.002	0.021	0.053	-0.078	-0.012
	(0.658)	(0.909)	(0.554)	(0.261)	(0.153)	(0.652)
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific linear trend	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific quadratic trend	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,952	1,792	992	2,080	1,632	1,920
R^2	0.85	0.88	0.77	0.75	0.86	0.91

Notes: The dependent variables in columns (1) – (3) are number of monthly deals in internet and software industries that are in early stage, main stage, and late stage, respectively. The dependent variables in column (4) - (5) are monthly number of deals in internet and software industries from foreign investors only and from both foreign and domestic investors (joint deals). Standard errors are clustered at the country level. Sample period: Nov 2015 – Jun 2018.

7. Robustness Tests

7.1 Synthetic Difference-in-Differences Estimates

Arguably, potential heterogeneity may exist in regulatory regimes and venture activity of the other countries relative to China, questioning the choice of the control group used in the main analysis. To address this, we check the robustness of our main results by resorting to the synthetic difference-in-differences (SDID) methodology (see Appendix B for a detailed

description of SDID). The advantages of SDID are twofold: First, both sample periods and countries are optimally weighted to construct the control group; Second, the restriction on parallel pre-trends can be relaxed (Arkhangelsky et al. (2021)).

By estimating the change in the number of venture deals in China after the CSL enactment over the extended sample period between Jan 2010 and Dec 2022, for example, we obtain the group of countries and the time periods optimally selected by the SDID algorithm for constructing the control group. These are shown in Figure 6.

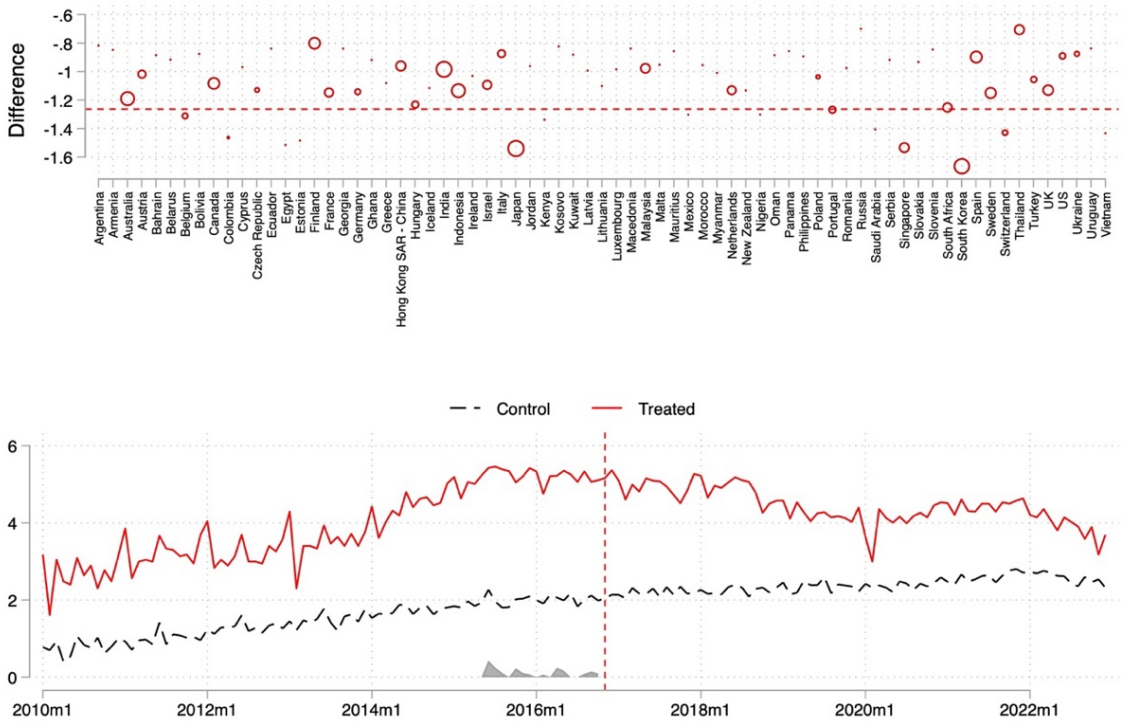

Figure 6: Difference in the means of number of deals after and before cybersecurity law was passed between the treated (China) and the control group of countries (dashed line, top), and the trends in the number of venture investment deals of the treated unit and the control (bottom).

Figure 6 upper panel shows the difference in the mean number of deals post- and pre-enactment of the CSL, with the size of the bubble indicating the relative weight of each country in the construction of the synthetic control. As most countries are included when constructing the control group, our earlier DID approach, where all countries except China form the control group, is justified. The lower panel shows the trends in the number of deals between China in

red and the synthetic control group in black. The shaded areas in grey highlight the relative weight of each time period in constructing the control unit. The SDID algorithm optimally selected periods from mid-2015 to just before the CSL was enacted in November 2016 in constructing the control group, lending support to our previous choice of sample period that contains months between November 2015 and June 2018, which covers one year before the enactment of CSL and one year after the rollout of CSL.

Next, we check for robustness of our main results by re-estimating Equation (1) using synthetic DID for the same sample period of Nov 2015 to Jun 2018 as our main analysis.[10] Table 5 reports the results, showing that while the enactment of the CSL had no significant impact on the total number of deals or the number of deals in non-internet and non-software industries, it reduced the number of deals in the internet and software industries by almost 36%, confirming the significant negative impact of the CSL enactment on the number of deals in internet and software industries.

Table 5: Robustness Check Using SDID

	(1)	(2)	(3)
	Total # of Deals	# of Deals in Internet/Software Industries	# of Deals in Other Industries
CSL	-0.196	-0.357**	-0.072
	(0.531)	(0.026)	(0.734)
Macroeconomic Controls	Yes	Yes	Yes
Country FEs	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes
Observations	2304	2304	2304

Notes: Sample period 2015m11 – 2018m6. Unlike the main analysis, we did not drop countries with all zero observations, since SDID optimally assigns weights to countries in constructing the control group. Both the treatment and the control units are adjusted for the macroeconomic covariates based on "optimized" procedure. Linear and quadratic trends are not included to avoid multicollinearity with country and time fixed effects, which may cause the results to be sensitive (Clarke et al. (2023)). However, the estimates are similar if trend variables are included.

We next repeat the estimation of heterogeneous effects using SDID, as reported in Table 6 and Table 7, for total number of deals and the number of deals in internet and software industries, respectively. The coefficients in Column (1) and (4) in both tables confirm the

[10] We did not re-estimate Equation (2) using SDID because the current algorithm only allows for one treatment variable.

significant negative effect of the CSL on early-stage deals and deals from foreign investors, especially for the internet and software industries.

Table 6: Robustness check Using SDID for Heterogeneous Effects

All deals	(1) Early stage deals	(2) Main stage deals	(3) Late stage deals	(4) From foreign investors	(5) Joint deals	(6) From home investors
CSL	-0.444*	-0.037	0.04	-0.290**	0.072	-0.161
	(0.099)	(0.751)	(0.773)	(0.050)	(0.676)	(0.544)
Macroeconomic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,304	2,304	2,304	2,304	2,304	2,304

Notes: Sample period 2015m11 – 2018m6. Unlike the main analysis, we did not drop countries with all zero observations, since SDID optimally assigns weights to countries in constructing the control group. Both the treatment and the control units are adjusted for the macroeconomic covariates based on "optimized" procedure. Linear and quadratic trends are not included to avoid multicollinearity with country and time fixed effects, which may cause the results to be sensitive (Clarke et al. (2023)). However, the estimates are similar if trend variables are included.

Table 7: Robustness Check Using SDID for Heterogeneous Effects for Deals in Internet & Software Industries

Deals in internet & software industries	(1) Early stage deals	(2) Main stage deals	(3) Late stage deals	(4) From foreign investors	(5) Joint deals	(6) From home investors
CSL	-0.651**	-0.183	0.169***	-0.332**	-0.024	-0.257***
	(0.012)	(0.139)	(0.009)	(0.027)	(0.857)	(0.028)
Macroeconomic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,304	2,304	2,304	2,304	2,304	2,304

Notes: Sample period 2015m11 – 2018m6. Unlike the main analysis, we did not drop countries with all zero observations, since SDID optimally assigns weights to countries in constructing the control group. Both the treatment and the control units are adjusted for the macroeconomic covariates based on "optimized" procedure. Linear and quadratic trends are not included to avoid multicollinearity with country and time fixed effects, which may cause the results to be sensitive (Clarke et al. (2023)). However, the estimates are similar if trend variables are included.

Finally, we construct event study type of plot using the SDID estimates, following Clarke et al. (2023). Figure 7 upper panel shows that while the average number of deals (log points) in the internet and software industries in China declined significantly and persistently in post-CSL enactment periods compared to the control group, the bottom panel indicates little significant change in the average number of deals (log points) in the other industries in China after CSL enactment relative to the control group.

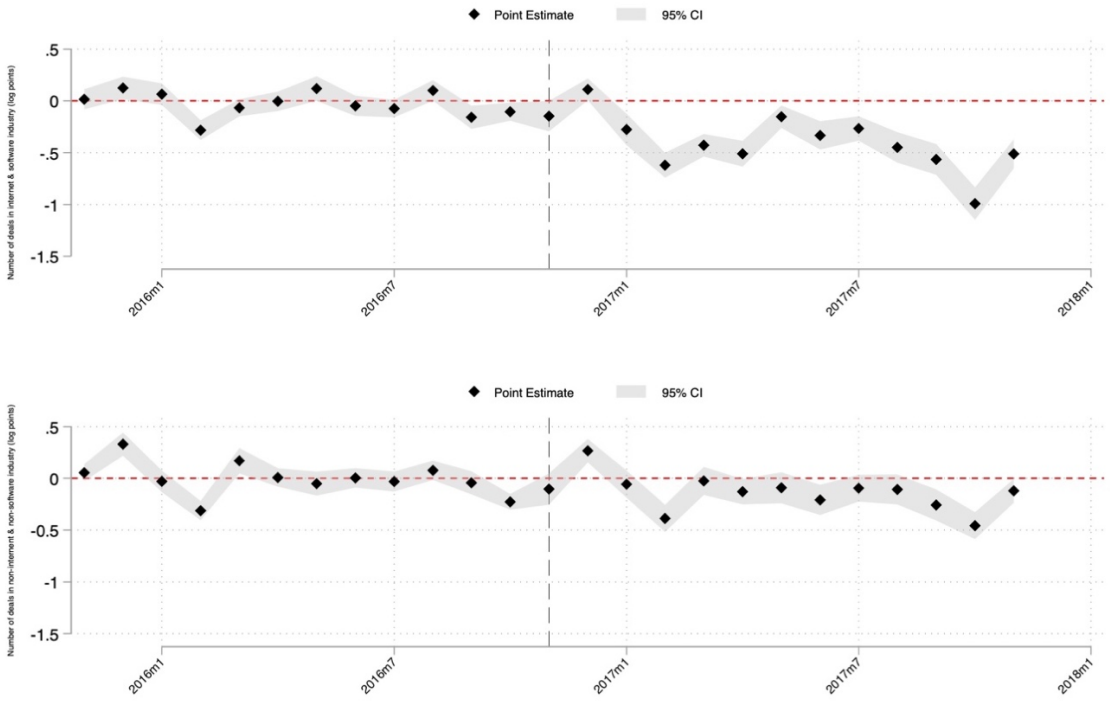

Figure 7. Event study plot based on synthetic difference-in-difference estimates. Top: monthly number of deals in the internet and software industry. Bottom: monthly number of deals in the non-internet and non-software industry. Sample period: Nov 2015 – Jun 2018.

7.2 Poisson Regression Estimates

As "log-like" transformations of outcome variables that can equal to zero—such as the number of venture deals considered in the current study—could bias the estimated effects (Chen and Roth, 2024), it warrants a further check of the robustness of our main empirical results to Poisson specification. To this end, we re-estimate the coefficients presented in Table 3, 4, and 5 using Poisson regression, and the results are shown in Table 8 – 10 below.

Compared to the main results reported in Table 3, estimated coefficients of the Poisson specification in Table 8 yield very similar results. The marginal effect of the rollout of the CSL on the number of deals in the internet and software industries is about -10%, larger than the effect of the enactment, which is around -9%. Further, the estimated marginal effects are positive for the number of deals in the other industries, again, suggesting potential substitution effects. Table A.2 presents estimated results when country-specific trends are omitted. The results are largely similar, but the impact of CSL on non-internet and non-software industries are very much muted.

Column 4 and 5 in both Table 9 and 10 again confirms that the CSL enactment and rollout reduces venture investment activities mainly for investments involving foreign investors. Focusing on the internet and software industries, the estimated effects of the CSL enactment and rollout are negative across stages of investments, but loses significance for early-stage deals, in contrast to our main results. Table A.3 presents estimates of Table 10 but without country-specific trends. Again, deals with foreign investors are negatively impacted.

Figure 8 shows event study coefficients. Again, we find (1) no pre-existing differential trend between the treatment and the control group for deals in both the internet and software industries (top panel) and the other industries (bottom panel), and (2) the estimated coefficients in the internet and software industries decline significantly immediately following the CSL enactment, whereas there is no significant change for the other industries.

Table 8: Robustness Check with Poisson Specification

	(1)	(2)	(3)	(4)	(5)
	Total # of Deals		# of Deals in Internet/Software Industries		# of Deals in Other Industries
Cybersecurity Law (CSL)	0.082***	-	-0.090***	-	-
	(0.000)	-	(0.008)	-	-
$CHN \times CSL\_Enact$	-	0.083***	-	-0.094***	0.195***
	-	0.000	-	(0.004)	0.000
$CHN \times CSL\_Rollout$	-	0.087***		-0.107***	0.174***
	-	(0.006)		(0.006)	0.000
GDP per Capita	-0.043	-0.045	-0.125	-0.119	-0.058
	(0.885)	(0.879)	(0.733)	(0.747)	(0.867)
Interest rate	-0.033**	-0.034**	-0.061***	-0.060***	-0.025
	(0.025)	(0.028)	(0.006)	(0.006)	(0.265)
Unemployment rate	-0.219***	-0.219***	-0.140**	-0.140**	-0.296***
	(0.000)	(0.000)	(0.031)	(0.032)	(0.000)
Marginal Effect (CSL)	8.55%***	-	-8.61%***	-	-
ME ($CHN \times CSL\_Enact$)	-	8.65%***	-	-8.97%***	21.53%***
ME ($CHN \times CSL\_Rollout$)	-	9.09%***	-	-10.15%***	19.01%***
Country FEs	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes
Country-specific linear trend	Yes	Yes	Yes	Yes	Yes
Country-specific quadratic trend	No	No	No	No	No
Observations	2,208	2,208	2,112	2,112	1,984

Notes: The dependent variables in columns (1) – (3) are total number of monthly deals. The dependent variables in column (4) and (5) are monthly number of deals in internet/software industry. The dependent variable in column (6) is the monthly number of deals in other industries. Standard errors are clustered at the country level. Sample period: Nov 2015 – Jun 2018.

Table 9: Robustness Check with Poisson Specification for Heterogeneous Effects

All industries	(1) Early stage deals	(2) Main stage deals	(3) Late stage deals	(4) From foreign investors	(5) Joint deals	(6) From home investors
$CHN \times CSL\_Enact$	0.048	0.143***	-0.002	-0.157***	-0.160***	0.128***
	(0.342)	(0.001)	(0.986)	(0.003)	(0.005)	0.000
$CHN \times CSL\_Rollout$	0.09	0.073	-0.089	-0.024	-0.349***	0.145***
	(0.266)	(0.222)	(0.531)	(0.783)	0.000	(0.005)
$GDP\ per\ Capita$	-0.003	1.059**	-0.401	-0.072	-0.112	0.038
	(0.993)	(0.049)	(0.746)	(0.883)	(0.839)	(0.937)
$Interest\ rate$	-0.056**	0.002	-0.027	-0.061**	0.052**	-0.031
	(0.029)	(0.919)	(0.703)	(0.018)	(0.041)	(0.254)
$Unemployment\ rate$	-0.190*	-0.179**	-0.222	-0.07	-0.265***	-0.272***
	(0.094)	(0.019)	(0.221)	(0.271)	(0.003)	(0.001)
ME ($CHN \times CSL\_Enact$)	4.92%	15.37%***	-0.20%	-14.53%***	-14.79%***	13.66%***
ME ($CHN \times CSL\_Rollout$)	9.42%	7.57%	-8.52%	-2.37%	-29.46%***	15.60%***
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific linear trend	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific quadratic trend	No	No	No	No	No	No
Observations	2048	1888	1376	2176	1664	1984

Notes: The dependent variables in columns (1) – (3) are total number of monthly deals in early stage, main stage, and late stage, respectively. The dependent variables in column (4) - (5) are monthly number of deals from foreign investors only and from both foreign and domestic investors (joint deals). Standard errors are clustered at the country level. Sample period: Nov 2015 – Jun 2018.

Table 10: Robustness Check with Poisson Specification for Heterogeneous Effects for Internet & Software Industries

Deals in internet & software industries	(1) Early stage deals	(2) Main stage deals	(3) Late stage deals	(4) From foreign investors	(5) Joint deals	(6) From home investors
$CHN \times CSL\_Enact$	-0.12	-0.083**	-0.455*	-0.284***	-0.602***	0.022
	(0.140)	(0.041)	(0.099)	(0.001)	0.000	(0.550)
$CHN \times CSL\_Rollout$	-0.101	-0.209***	-1.190***	-0.450***	-0.825***	0.038
	(0.434)	(0.002)	0.000	(0.002)	0.000	(0.525)
$GDP\ per\ Capita$	0.042	0.286	0.681	-0.723	-0.135	0.143
	(0.932)	(0.675)	(0.710)	(0.271)	(0.882)	(0.765)
$Interest\ rate$	-0.118*	-0.059	0.181	-0.108***	0.150***	-0.104***
	(0.064)	(0.115)	(0.355)	(0.002)	0.000	0.000
$Unemployment\ rate$	-0.094	-0.034	0.329	0.132	-0.348**	-0.214**
	(0.492)	(0.451)	(0.113)	(0.360)	(0.026)	(0.025)
ME ($CHN \times CSL\_Enact$)	-11.31	-7.96**	-36.56*	-24.72***	-45.23***	2.22
ME ($CHN \times CSL\_Rollout$)	-9.61	-18.86***	-69.58***	-36.24***	-56.18***	3.87
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific linear trend	Yes	No+	Yes	Yes	Yes	Yes
Country-specific quadratic trend	No	No	No	No	No	No
Observations	1952	1792	992	2080	1632	1920

Notes: The dependent variables in columns (1) – (3) are number of monthly deals in internet and software industries that are in early stage, main stage, and late stage, respectively. The dependent variables in column (4) - (6) are monthly number of deals in internet and software industries from foreign investors only, from both foreign and domestic investors (joint deals), and from home investors only. Standard errors are clustered at the country level. Sample period: Nov 2015 – Jun 2018. +: No quadratic trend was included in column (2) due to nonconverging issues.

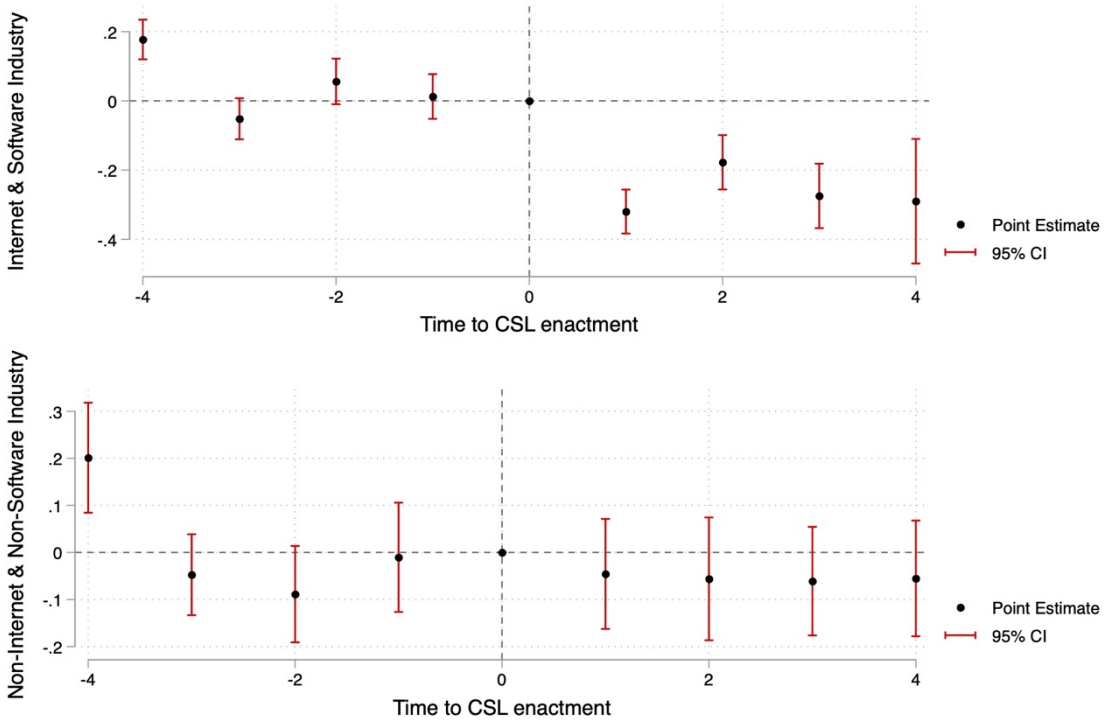

Figure 8: Event study plot of the effect of Cybersecurity Law enactment, at 4 quarters before and 4 quarters after the enactment. Standard errors are clustered at the country level. Top: internet and software industry. Bottom: non-internet and non-software industry. Different from the results in Table 8, country-specific trends are not included in the estimation. Sample period: Nov 2015 – Jun 2018. The lag effect up to 6 quarters after the CSL enactment is available upon request.

8. Conclusion

We presented analyses of the effects of the Cybersecurity Law (CSL) on venture investments in China. We broke down the effects based on the ventures' propensities to be affected by the CSL, by industries, stages of investments, and types of investors. Our results indicate negative, significant, and persistent effects on the number of venture deals in internet and software industries after the CSL enactment. Further, the effects are larger after the enforcement of the CSL than after the enactment. On the contrary, the effects of the CSL on the number of venture deals in other industries are largely positive and significant, suggesting potential substitution of investments in the internet and software industries with investments in other industries.

Within the internet and software industries, the reduction in the number of deals are large and significant for investments by foreign investors, and the reduction is greater after the rollout of the CSL than the enactment. There's broad reduction in the number of deals across stages,

but our main results suggest that early-stage deals are especially prone to both enactment and rollout of the CSL.

One caveat, however, is that the reduction in venture investments does not necessarily map one-to-one to welfare reduction. It could be that following data regulations such as the CSL, prevented investments that could potentially be harmful from broader perspectives. As currently no data exists that measures the impact of CSL on consumer rights or the intended national interest outcomes, we can't estimate an economy-wide effect of the CSL. Further, our estimates are for the short-run effects of the CSL, and we leave the analysis of longer-run effects of such data regulations for future studies.

Overall, our findings indicate that data regulations could carry negative economic implications, aligning with earlier studies on the European Union's General Data Protection Regulation, which further highlight the need for policies that carefully balance the trade-offs between regulatory objectives and economic growth.

References

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., & Wager, S. (2021). Synthetic Difference-in-Differences. *American Economic Review*, *111*(12), 4088–4118. https://doi.org/10.1257/aer.20190159

Bessen, J. E., Impink, S. M., Reichensperger, L., & Seamans, R. (2020). GDPR and the Importance of Data to AI Startups. *NYU Stern School of Business*.

Blind, K., Niebel, C. M., & Rammer, C. (2022). The Impact of the EU General Data Protection Regulation on Innovation in Firms. *ZEW Discussion Papers*, *22–047*. https://doi.org/10.2139/ssrn.4257740

Chander, A., Abraham, M., Chandy, S., Fang, Y., Park, D., & Yu, I. (2021). Achieving Privacy: Costs of Compliance and Enforcement of Data Protection Regulation. *World Bank Group, Policy Research Working Paper 9594*. https://doi.org/10.1596/1813-9450-9594

Chen, C., Frey, C. B., & Presidente, G. (2022). *Privacy regulation and firm performance: Estimating the GDPR effect globally*. The Oxford Martin Working Paper Series on Technological and Economic Change.

Chen, J., & Roth, J. (2024). Logs with Zeros? Some Problems and Solutions. *The Quarterly Journal of Economics*, 139 (2), 891–936. https://doi.org/10.1093/qje/qjad054

Creemers, R. (2022). China's emerging data protection framework. *Journal of Cybersecurity*, *8*(1), tyac011.

Forbes, K. J., & Warnock, F. E. (2012). Capital flow waves: Surges, stops, flight, and retrenchment. *Journal of International Economics*, *88*(2), 235–251. https://doi.org/10.1016/j.jinteco.2012.03.006

Geradin, D., Karanikioti, T., & Katsifis, D. (2021). GDPR Myopia: How a well-intended regulation ended up favouring large online platforms-the case of ad tech. *European Competition Journal*, *17*(1), 47–92.

Gietel-Basten, S., Han, X., & Cheng, Y. (2019). Assessing the impact of the "one-child policy" in China: A synthetic control approach. *PLOS ONE*, *14*(11), e0220170. https://doi.org/10.1371/journal.pone.0220170

Jia, J., Jin, G. Z., & Wagman, L. (2020). GDPR and the Localness of Venture Investment. *Available at SSRN 3436535*.

Jia, J., Jin, G. Z., & Wagman, L. (2021). The short-run effects of the general data protection regulation on technology venture investment. *Marketing Science*, *40*(4), 661–684.

Johnson, G. A., & Shriver, S. K. (2020). Privacy & market concentration: Intended & unintended consequences of the GDPR. *Marketing Science Institute Working Paper Series*, *Report No. 20-111*.

Koski, H., & Valmari, N. (2020). *Short-term Impacts of the GDPR on Firm Performance*. ETLA Working Papers.

Liu, L. (2021). The rise of data politics: Digital China and the world. *Studies in Comparative International Development*, *56*, 45–67.

Martin, N., Matt, C., Niebel, C., & Blind, K. (2019). How Data Protection Regulation Affects Startup Innovation. *Information Systems Frontiers*, *21*(6), 1307–1324. https://doi.org/10.1007/s10796-019-09974-2

Peukert, C., Bechtold, S., Batikas, M., & Kretschmer, T. (2020). European privacy law and global markets for data. *Center for Law & Economics Working Paper Series*, *1*.

Peukert, C., Bechtold, S., Batikas, M., & Kretschmer, T. (2022). Regulatory spillovers and data governance: Evidence from the GDPR. *Marketing Science*, *41*(4), 746–768.

Qi, A., Shao, G., & Zheng, W. (2018). Assessing China's cybersecurity law. *Computer Law & Security Review*, *34*(6), 1342–1354.

Xie, T., Liu, J., Sengstschmid, U., & Ge, Y. (2023). *Navigating Cross-Border Data Transfer Policies: The Case of China* (SSRN Scholarly Paper 4408947). https://doi.org/10.2139/ssrn.4408947

Appendix A. Supplementary Figures

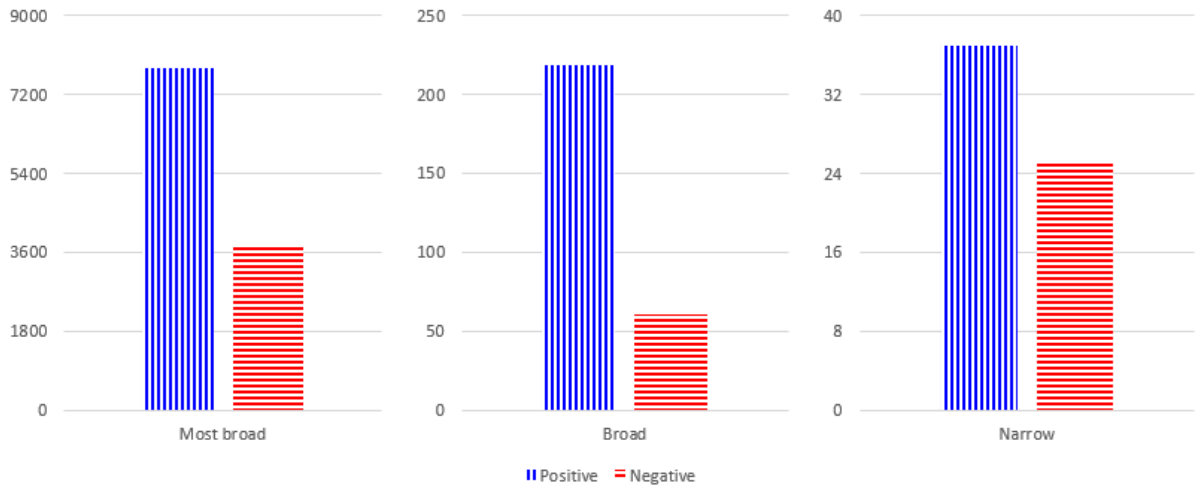

Figure A.1: Factiva Search Results on market sentiments surrounding venture capital environment in China by broadness of search, 1 November 2015 - 31 October 2016. Keywords used for positive and negative sentiments respectively: Most broad: China and venture capital and (increas* or improv* or positive or up or rise* or grow*); China and venture capital and (decreas* or worse* or negative or down or drop* or shrink*). Broad: China/F50/ and venture capital/F50/ and (increas* or improv* or positive or up or rise* or grow*); China/F50/ and venture capital/F50/ and (decreas* or worse* or negative or down or drop* or shrink*). Narrow: (venture capital in China or China's venture capital) and (increas* or improv* or positive or up or rise* or grow*); (venture capital in China or China's venture capital) and (decreas* or worse* or negative or down or drop* or shrink*). For both most broad and broad searches, sources were limited to Business sources, Dow Jones sources, General Interest sources, Major News and Business sources, News Digest sources, Newspapers: All, Banking/Credit Top Sources, Financial Services Top Sources, Investing/Securities Top Sources

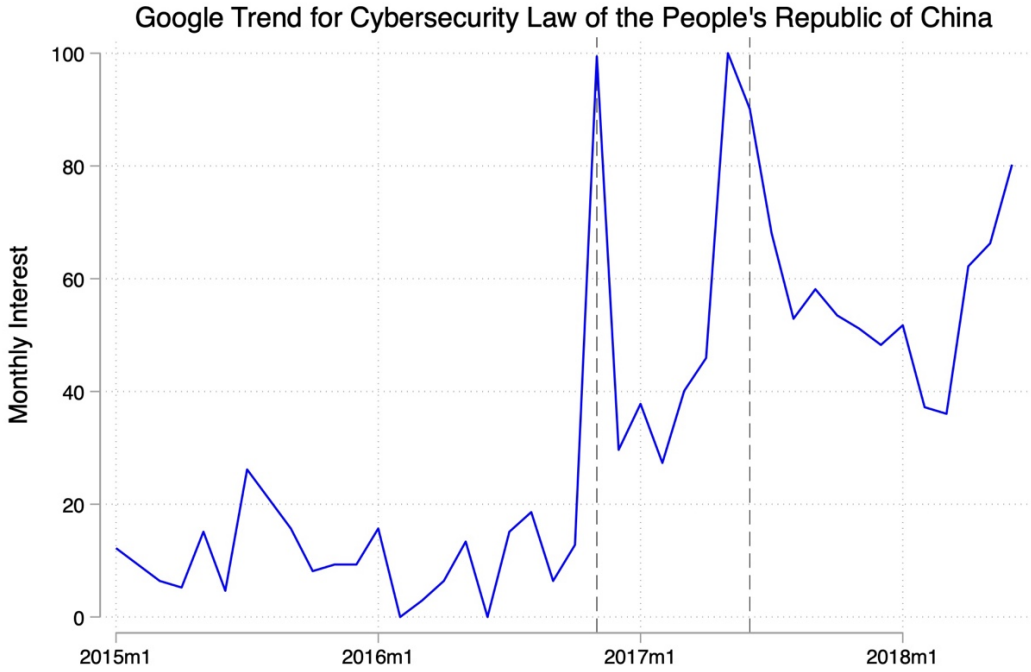

Figure A.2 Monthly interest for topic "Cybersecurity Law of the People's Republic of China" according to Google Trend.

Table A.1: Summary Statistics

	Total	Mean	S.D.	10%	90%
		Panel A: Whole sample			
Number of deals	18403	575.1	103.3	408	726
Amount raised (USD million)	230205.1	7193.9	4286.6	3600	11990.5
GDP (1,000 USD million)	-	3007.9	263.7	2757.7	3474.5
Interest rate	-	3.8	0.8	2.8	4.7
Unemployment rate	-	4.5	0.1	4.3	4.6
Population (million)	-	1388.9	6.3	1383.8	1398.4
		Panel B: Subgroup by industry			
Internet & Software					
Number of deals	5140	161	35	112	206
Value per deal	-	29.1	170.9	0.46	47.3
Others					
Number of deals	13263	414	75	318	519
Value per deal	-	38.6	273.2	0.6	51.5
		Panel C: Subgroup by funding stage			
Early stage					
Number of deals	5910	185	50	125	237
Value per deal	-	3.4	22.7	0.19	3.1
Main stage					
Number of deals	8084	253	46	193	291
Value per deal	-	39.4	294.2	2.25	58.2
Late stage					
Number of deals	358	11	4	6	16
Value per deal	-	223.8	412.1	7.9	500
Other stage					
Number of deals	4051	127	31	87	162
Value per deal	-	38.8	240.5	1	45
		Panel D: Subgroup by source country			
Outside Mainland China					
Number of deals	831	26	8	16	36
Value per deal	-	64.4	286.9	0.6	100
Joint Deals					
Number of deals	1506	47	15	30	70
Value per deal	-	125.9	592.2	3.1	200

Notes: Summary statistics of total number of deals and amount raised by Chinese VC firms between Nov 2015 and Jun 2018, mean values of macroeconomic control variables, and number of deals and mean value per deal for different subgroups, as well as standard deviations and the 10th and 90th percentiles. All values are in USD million.

Table A.2: CSL Impact on the Aggregate Number of Deals, and Number of Deals in Internet and Software Industry and Other Industries

	(1)	(2)	(3)	(4)	(5)
	Total # of Deals		# of Deals in Internet/Software Industries		# of Deals in Other Industries
Cybersecurity Law (CSL)	-0.053	-	-0.209***	-	-
	(0.176)	-	(0.000)	-	-
CHN × CSL_Enact	-	-0.024	-	-0.178***	0.072**
	-	(0.351)	-	(0.000)	(0.038)
CHN × CSL_Rollout	-	-0.106**		-0.254***	-0.047
	-	(0.050)		(0.000)	(0.453)
GDP per Capita	-0.865**	-0.640	-0.768*	-0.605	-0.713
	(0.042)	(0.138)	(0.071)	(0.187)	(0.138)
Interest rate	-0.044**	-0.035	-0.050*	-0.045	-0.031
	(0.049)	(0.116)	(0.087)	(0.118)	(0.190)
Unemployment rate	-0.039	-0.032	-0.046	-0.041	-0.023
	(0.306)	(0.382)	(0.214)	(0.266)	(0.584)
Marginal Effect (*CSL*)	-5.16%	-	-18.86%***	-	-
ME (*CHN × CSL_Enact*)	-	-2.37%	-	-16.31%***	7.47%**
ME (*CHN × CSL_Rollout*)	-	-10.06%**	-	-22.4%***	-4.59%
Country FEs	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes
Observations	2,208	2,208	2,112	2,112	1,984

Notes: The dependent variables in columns (1) – (3) are total number of monthly deals. The dependent variables in column (4) and (5) are monthly number of deals in internet/software industry. The dependent variable in column (6) is the monthly number of deals in other industries. Standard errors are clustered at the country level. Sample period: Nov 2015 – Jun 2018.

Table A.3: CSL Impact on the Number of Deals in Internet and Software Industries Across Different Subgroups

Deals in internet & software industries	(1) Early stage deals	(2) Main stage deals	(3) Late stage deals	(4) From foreign investors	(5) Joint deals	(6) From home investors
$CHN \times CSL\_Enact$	-0.429***	-0.083**	0.083	-0.253***	-0.075	-0.164***
	(0.000)	(0.041)	(0.455)	(0.000)	(0.327)	(0.000)
$CHN \times CSL\_Rollout$	-0.697***	-0.209***	-0.342***	-0.363***	0.132	-0.291***
	(0.000)	(0.002)	(0.020)	(0.000)	(0.288)	(0.000)
$GDP\ per\ Capita$	0.293	0.286	1.722	-0.933*	-0.311	-0.533
	(0.734)	(0.675)	(0.120)	(0.080)	(0.612)	(0.439)
$Interest\ rate$	-0.011	-0.059	0.044	-0.035	-0.008	-0.072*
	(0.811)	(0.115)	(0.430)	(0.276)	(0.859)	(0.069)
$Unemployment\ rate$	-0.085	-0.034	0.167*	-0.061	-0.124*	-0.001
	(0.301)	(0.451)	(0.073)	(0.143)	(0.078)	(0.992)
ME ($CHN \times CSL\_Enact$)	-34.88%***	-7.96**	8.65	-22.35***	-7.23	-15.13***
ME ($CHN \times CSL\_Rollout$)	-50.19%***	-18.86***	-28.97***	-30.44***	14.11	-25.25***
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1952	1792	992	2080	1632	1920

Notes: The dependent variables in columns (1) – (3) are number of monthly deals in internet and software industries that are in early stage, main stage, and late stage, respectively. The dependent variables in column (4) - (6) are monthly number of deals in internet and software industries from foreign investors only, from both foreign and domestic investors (joint deals), and from home investors only. Standard errors are clustered at the country level. Sample period: Nov 2015 – Jun 2018.

Appendix B. Synthetic Difference-in-Differences

The synthetic difference-in-differences (SDID) is introduced by Arkhangelsky et al. (2021) and is commonly employed for evaluating effects of policy changes. SDID combines attributes from both the difference-in-difference (DID) and synthetic control (SC) methods. It not only accommodates the assumption of correlated parallel trends found in DID, which is valuable when randomized trials are unfeasible, but also constructs a 'synthetic' control group. This synthetic control group is created by amalgamating multiple untreated units in a manner that closely mirrors the characteristics of the treated units, akin to the process in the SC method.

Consider a balanced panel comprising N units and T time periods. Denote the outcome variable of unit i at period t as Y_{it}, and the binary indicator for treatment as $W_{it} \in \{0,1\}$. Assume N_{co} units in the control group, and $N_{tr} = N - N_{co}$ units in the treatment group, which are subject to the treatment after time T_{pre}. Given optimally selected weights for cross-section units, $\widehat{\omega_i}$, and time periods, $\widehat{\lambda_t}$, the average treatment effect on the treated (ATT), τ, is estimated by minimizing the following

$$\left(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = \underset{\tau, \mu, \alpha, \beta}{\arg min} \left\{\sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2 \widehat{\omega_i} \widehat{\lambda_t}\right\}.$$

where α_i accounts for unit fixed effects and β_t accounts for time fixed effects.

Cross-sectional weights, ω_i, are optimally selected to ensure parallel trend between the control and treated units in the pre-treatment periods. Time weights, λ_t, are chosen to minimize the difference between the pre-treatment period (time-) weighted average (λ_t being the weights) outcome and the post-treatment period simple (time-) average of each cross-section unit in the control group up to a constant. Essentially, this means more weight will be drawn from pre-treatment periods which are more similar to post-treatment periods.