

S.-T. Yau High School Science Award

**Innovation as a Shield? R&D
Investment of Chinese
Semiconductor Firms under the US
CHIPS Act**

Innovation as a Shield? R&D Investment of Chinese
Semiconductor Firms under the US CHIPS Act

Student: Emmy Chen, Enzo Congen Yao, and Jim Guo

School: Fudan International School

School province/state: Shanghai

Country: China

Instructor: Lily Shi

Award category: Economic and Financial Modeling

Submission year: 2026

Innovation as a Shield? R&D Investment of Chinese Semiconductor Firms under the US CHIPS Act

Author: Emmy Chen, Enzo Congen Yao, and Jim Guo

School: Fudan International School

Abstract

Semiconductor firms must allocate scarce funds between research, production and the financial capacity to withstand disruption. We examine whether R&D intensity established before 2022 is associated with subsequent financial performance in Chinese semiconductor firms. The source panel covers 46 companies over 2018–2025; the primary consolidated net-income ROA sample contains 33 firms and 230 observations. A one-standard-deviation difference in transformed baseline research intensity is associated with a 2.445-percentage-point larger post-period change in ROA, with a 95% confidence interval of [1.347, 3.543]. Binary and overlap-weighted comparisons remain inconclusive. The analysis also finds no statistically significant difference between the size-group slopes or between high and low R&D firms' short-term abnormal stock returns. Supplementary ownership pre-trend and fake-2019 placebo tests do not reject their null hypotheses. The evidence is consistent with the emphasis on research capability in China's semiconductor support policies. It informs the evaluation of sustained R&D and complementary resources without establishing an optimal research budget, the causal effect of a particular policy or the superiority of one policy instrument.

Keywords. R&D intensity; semiconductor industry; difference-in-differences; financial performance; return on assets; China

Contents

Abstract	i
1 Industry background and research motivation	1
1.1 The semiconductor industry	1
1.2 Economic importance and the allocation of resources	1
1.3 The changing policy environment	2
1.4 Research motivation	2
2 Research question and hypotheses	3
2.1 Research question	3
2.2 Hypotheses	3
3 Theoretical framework	4
4 Data and measurement	5
4.1 Sources and coverage	5
4.2 Financial outcomes and controls	6
4.3 Baseline exposure and sample construction	8
5 Diagnostic tests	9
5.1 Parallel trends for the research intensity models	9
5.1.1 Purpose and specification	9
5.1.2 Results and interpretation	10
5.2 Placebo test with a fake 2019 policy date	11
5.2.1 Purpose and specification	11
5.2.2 Results and interpretation	12
5.3 Implications for the financial estimates	13
6 DiD models and financial results	13
6.1 Standard binary DiD	14
6.1.1 Model specification	14
6.1.2 Results	14

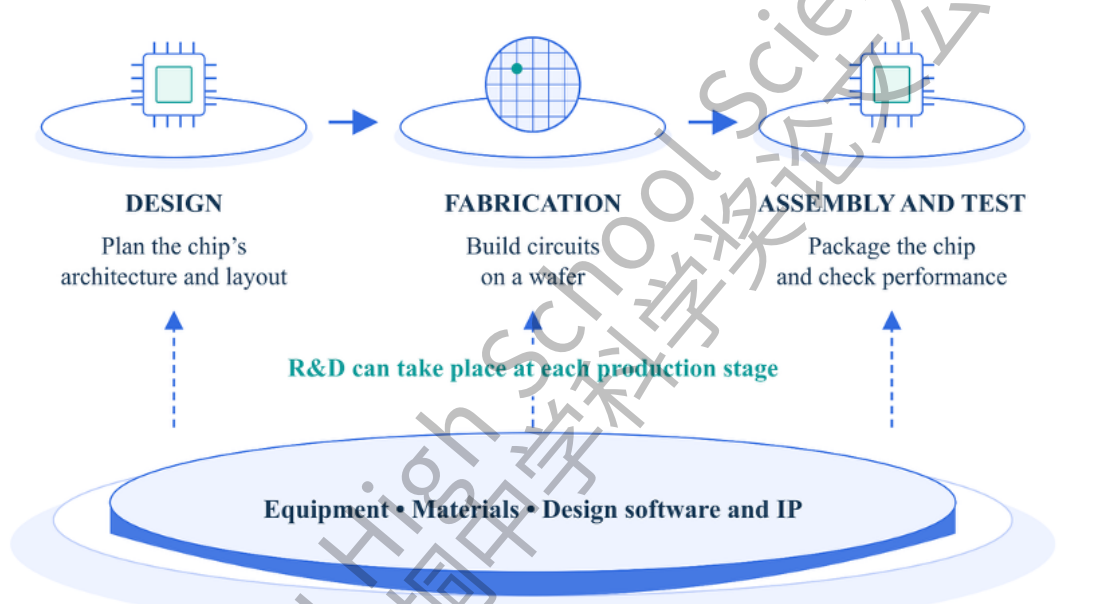
6.2	Continuous exposure DiD	16
6.2.1	Purpose and specification	16
6.2.2	Financial results	17
6.2.3	Interpretation	18
6.3	Overlap weighted binary DiD	18
6.3.1	Purpose and specification	18
6.3.2	Financial results and balance	19
6.3.3	Interpretation	20
6.4	Firm size interaction DiD	21
6.4.1	Purpose and specification	21
6.4.2	Results	21
6.4.3	Interpretation	22
6.5	Sample limits	22
6.6	Comparison across DiD models	23
6.7	Sensitivity to specification choices	24
6.8	Event study results	25
7	Theoretical contributions and policy implications	27
7.1	Theoretical contributions	27
7.2	Implications for government policy	28
7.3	Implications for firm resource allocation	28
8	Limitations and future directions	29
8.1	Policy exposure and causal interpretation	29
8.2	Measurement and sample coverage	29
8.3	Statistical uncertainty	30
9	Main conclusions	30
	References	32
	Acknowledgements	35

1 Industry background and research motivation

1.1 The semiconductor industry

The semiconductor industry has expanded rapidly while remaining organized around specialized firms across countries. Global semiconductor sales reached US\$791.7 billion in 2025, an increase of 25.6% from 2024 (Semiconductor Industry Association [SIA], 2026). Production spans chip design, fabrication, packaging and testing, supported by equipment and materials suppliers. These activities form an interconnected international production chain (OECD, 2025).

Research Illustration A. The semiconductor Production System



1.2 Economic importance and the allocation of resources

Semiconductors are essential inputs into computing, communications, electronics, and motor vehicles. Therefore, their availability matters for economic activity well beyond the industry itself (Haramboure et al., 2023). This importance makes the development of semiconductor firms a concern for both business strategy and public policy.

For individual firms, development requires choices about how to allocate limited resources among research, production capacity, and day-to-day operations. R&D is a long-term commitment, and its commercial returns may take time to materialize (Hall & Lerner, 2009). Examining how prior R&D intensity relates to subsequent financial performance can therefore provide insight into firms' investment decisions and the role of government support for research.

1.3 The changing policy environment

The policy environment changed substantially in 2022. The United States introduced the CHIPS and Science Act, including semiconductor manufacturing incentives and research programs (National Institute of Standards and Technology [NIST], 2022). Separately, the Bureau of Industry and Security introduced controls on advanced computing and semiconductor manufacturing items in October 2022 (BIS, 2022). These developments placed renewed attention on the conditions under which Chinese semiconductor firms operate.

China had already made integrated circuits a priority in its Fourteenth Five-Year Plan, with an emphasis on research, equipment, materials and innovation capacity (State Council, 2021). The evolving international and domestic policy setting provides the context for examining how firms with different prior research commitments performed after 2022.

1.4 Research motivation

Research on absorptive capacity links prior knowledge to a firm's ability to recognize and apply new information (Cohen & Levinthal, 1990). This offers a reason to investigate the financial role of research in a changing semiconductor industry. The question is whether firms that committed a larger share of revenue to R&D before 2022 subsequently experienced different financial changes, and whether that relationship varies by firm size or ownership. Evidence on these relationships can help firms evaluate research within their investment plans and inform the design of government support.

Among the closest studies, Zhu et al. (2017) find a positive relationship between R&D intensity and performance in Chinese electronics manufacturing firms. However, findings within the semiconductor industry are mixed. Shin, Kraemer, and Dedrick (2017) find that higher R&D spending relative to sales is associated with lower net profit margins and returns on assets in their sample. Chen et al. (2019), studying Taiwanese semiconductor firms, find that R&D spending can reduce current performance while bringing benefits in later periods. These studies examine different markets or periods before 2022. They therefore do not directly answer whether Chinese semiconductor firms with higher R&D intensity before 2022 experienced different financial changes afterwards, or whether this relationship varies by firm size or ownership. This study examines that narrower question.

2 Research question and hypotheses

2.1 Research question

Our central research question is: How is pre-2022 R&D intensity associated with Chinese semiconductor firms' subsequent financial performance and short-term stock-market reactions?

We also examine the following sub-question: Does the relationship between R&D intensity and subsequent financial performance differ by firm size?

The analysis treats 2018–2021 as the pre-period and 2022–2025 as the post-period. Financial performance is measured using six outcomes, with consolidated net-income return on average assets (ROA) as the principal profitability measure. Prior R&D intensity is fixed using pre-period information. The question concerns whether subsequent changes differ with that initial research commitment, rather than whether high-R&D firms simply have higher financial levels.

2.2 Hypotheses

Hypothesis 1: Firms with high pre-2022 R&D intensity will exhibit more favorable post-vs-pre changes in long-term financial performance. This is as prior research may help firms faster adapt more quickly to the changes within the industry (Cohen & Levinthal, 1990; Teece et al., 1997).

Hypothesis 2: The relationship between baseline R&D intensity and subsequent financial change differs between large and small firms. Financing constraints can be especially important for small innovative firms (Hall & Lerner, 2009), but possession of resources does not itself demonstrate an ability to reconfigure them (Teece et al., 1997).

Hypothesis 3: Firms with higher pre-2022 R&D intensity will experience a more positive immediate stock-market reaction to the CHIPS Act. Previous research finds that firms with higher R&D intensity can experience larger positive stock-market reactions to technological news (Lee, 2016).

These hypotheses concern financial associations. Demonstrating that innovation causally shields firms from a particular restriction would additionally require direct measures of policy exposure and adaptive capability, together with a credible counterfactual.

The first hypothesis is examined through both a continuous exposure gradient and a high-versus-low contrast. The second requires a direct test of the difference between size groups. In all the models, we verify both the model's assumptions and explain its limitations, outside of examining the financial results. The third hypothesis

is examined using an event study of firms' stock returns around the signing of the CHIPS and Science Act.

3 Theoretical framework

This study draws on the Resource-Based View, absorptive capacity, Dynamic Capabilities Theory and evidence on stock-market reactions to technological news to explain how research commitment established before 2022 may relate to subsequent financial performance, differences between large and small firms, and investor expectations. The central propositions are that earlier research may develop knowledge that helps firms adapt, that firms' size and access to supporting resources may affect their ability to apply this knowledge, and that investors may respond more positively to firms with higher prior R&D intensity.

The Resource-Based View links competitive advantage to valuable resources that competitors cannot readily reproduce or replace (Barney, 1991). In semiconductor firms, sustained research may develop specialised engineering knowledge, process expertise and established research teams. These resources could help firms address technical problems arising from changes in materials, equipment or customer requirements. Higher R&D intensity therefore provides an observable measure of research commitment, whose relationship with subsequent performance requires empirical examination.

Absorptive capacity explains how prior knowledge may assist this adjustment. Existing knowledge helps firms evaluate unfamiliar information and put it to productive use (Cohen & Levinthal, 1990). Applied to the semiconductor industry, this suggests that a firm with relevant research experience may be better equipped to assess an alternative material, modify a production process or incorporate a new technical solution. If such adjustments preserve output, improve efficiency or generate sales, they may subsequently appear in financial performance. These are proposed channels through which prior research could matter; their operation is not directly observed in the financial accounts.

Dynamic Capabilities Theory explains how firms adapt by changing how they use their resources (Teece et al., 1997). Technical knowledge alone may bring few commercial benefits. Firms also need suitable equipment, funding, effective management and customer relationships to turn that knowledge into products or processes. The proposed explanation therefore depends on both a firm's existing research knowledge and its ability to use it. This gives us a reason to compare firms by size. Larger firms may have more resources to support this process, but being larger does not necessarily mean adapting more effectively.

Evidence on stock-market reactions provides a basis for examining investor expect-

tations. Lee (2016) finds that high-R&D firms experienced larger positive abnormal stock returns than low-R&D firms on the day technological information was disclosed. Although this study examines technological disclosures by Korean firms rather than the CHIPS Act, it motivates testing whether prior R&D intensity also shapes investors' response to the policy. Investors may view greater research commitment as evidence that a firm is better equipped to develop alternatives and adapt, leading to a more positive immediate stock-market reaction.

Together, these theories and findings suggest that prior R&D may help firms adapt and improve later financial performance, while firm size and supporting resources may influence their ability to realise these benefits. Investors may also view higher R&D intensity as a source of protection, leading to a more positive immediate stock-market response. These arguments motivate the three hypotheses, which examine subsequent financial changes, differences by firm size and the immediate stock-market response.

4 Data and measurement

4.1 Sources and coverage

The dataset covers 46 companies over eight years, from 2018 to 2025. This gives 368 possible company-year records, with each record representing one company in one year. However, missing data and the model's requirements mean that only some records can be used in the regressions. The dataset therefore does not contain complete annual data for 46 mainland-listed firms throughout the period.

To enter the analysis, firms must have enough data before and after 2022 and meet the model's requirements for comparing baseline R&D intensity. Figure 1 shows how data availability changes across years. Table 1 distinguishes the available records from those used in the regressions.

The data is collected from the firm's official financial reports from the respective years.

Figure 1: Data availability by year

Sample	Firms	Records
Full dataset	46	368
Firms with enough data before and after 2022	37	279
Main financial analysis ¹	34	256
Revenue growth analysis	34	221
Net-income ROA analysis	33	230

Table 1. Data coverage and estimation samples

Missing data are treated as unavailable, and records are excluded from calculations that require those values.

4.2 Financial outcomes and controls

Table 2 defines the six measures of financial performance.

Outcome	Construction	Meaning
Profitability/assets proxy	$(R - C - E) / A$	Constructed residual per unit of year-end assets
R&D-adjusted return	$(R - C - E + D) / A$	Current R&D expense added back once
Gross profit/assets	$(R - C) / A$	Gross profit per unit of assets
Asset turnover	R / A	Revenue per unit of assets

Outcome	Construction	Meaning
Log revenue growth	$\ln R(t) - \ln R(t-1)$	Annual log change; consecutive years
Net-income ROA	$NI / [(A^c(\text{begin}) + A^c(\text{end})) / 2]$	Consolidated NI and average consolidated assets

Table 2. Financial outcomes and interpretation

Note. R = revenue; C = cost of goods sold; E = selling, administrative, R&D and finance expenses, keeping finance expenses positive or negative as reported; D = R&D expense; A = year-end assets; NI = consolidated net income; A^c = consolidated assets. Net income and the assets used to calculate ROA are measured in the same currency. Revenue growth is measured as the change in log revenue. All other outcomes are ratios.

To calculate the profitability/assets proxy, we subtract COGS, selling, administrative, R&D and finance expenses from revenue, keeping finance expenses positive or negative as reported. We then divide the remaining amount by year-end total assets. This is a measure constructed for the analysis, rather than reported net income or a full accounting measure of operating profit. The R&D-adjusted measure adds the current year's R&D expense back once before dividing by assets. This removes that expense from the calculation.

Consolidated net-income ROA divides net income by the average of beginning and ending consolidated assets.

The models control for firm size, measured by log total assets, and debt levels, measured by liabilities divided by assets. Both controls use values from the year being analysed. Firm fixed effects account for company characteristics that stay constant over time. Category-by-year effects account for annual changes shared by firms in the same industry category. Each firm's category is based on its pre-2022 classification.

Firm age and ownership are not included as additional controls without verified data. Ownership information is used to define comparable samples and ownership groups, based on the last available observation before 2022. Size groups use each firm's average log assets before 2022. Firms at or above the eligible sample's median of 3.57045 are classified as large; those below it is classified as small.

Before extreme values are capped separately for each outcome, the difference between the R&D-adjusted return and the profitability/assets proxy is exactly R&D expense divided by year-end assets. The two measures are therefore linked by their formulas. Positive results for both do not provide two independent pieces of evidence that research improves performance. Net-income ROA provides a standard accounting

measure, but it also reflects financing costs, taxes and gains or losses outside normal operations.

For profitability ratios such as ROA, a coefficient of 0.02 means a difference of two percentage points. Revenue growth is measured as the change in log revenue, so its coefficients are expressed in log points.

4.3 Baseline exposure and sample construction

To evaluate pre-2022 research intensity, we calculate each eligible firm's baseline R&D intensity ($\bar{r}_i$) as the mean of its annual R&D-to-revenue ratios during the 2018-2021 pre-policy period:

$$\bar{r}_i = \frac{1}{T_i^{\text{pre}}} \sum_{t \in T_i^{\text{pre}}} \left(\frac{D_{it}}{R_{it}} \right) \quad (1)$$

To enter the sample, firms must have at least two valid pre-period observations and at least one valid post-period observation. We mitigate the impact of the extreme values by clipping inputs and outcomes at the 1st and 99th percentiles of eligible pre-period observations, applying these fixed thresholds uniformly across all years.

Using this baseline identity, we construct two exposure functions:

$$H_i = 1\{\bar{r}_i > \text{median}(\bar{r})\} \quad (2)$$

$$Z_i = \frac{\ln(1 + \bar{r}_i) - \mu_{37}}{\sigma_{37}} \quad (3)$$

Here, H_i is a binary indicator set to 1 for firms strictly above the eligible-sample median baseline intensity (12.388%). Z_i is a standardized continuous exposure, where we first apply a $\ln(1 + r)$ transformation to reduce right skewness and then standardize the measure using the mean (μ_{37}) and standard deviation (σ_{37}) across all 37 eligible firms. These exposures are fixed prior to 2022 to prevent post-policy choices from contaminating the baseline classification. As a concrete example, if a firm reports annual R&D-to-revenue ratios of 10% and 14% in two usable pre-period years, its baseline intensity is calculated as 12% before percentile clipping, representing the average of annual ratios rather than total pre-period R&D spending divided by total revenue.

The initial eligible panel includes 37 firms and 279 firm-year observations. To make fair comparisons, we remove ownership types that do not appear in both the high and low R&D groups. As all three state-owned firms in the initial sample fall into the low-R&D group, they are removed to prevent ownership structure from distorting the

R&D comparison. The adjustment yields a primary estimation sample of 34 private firms, and within this refined group, the panel structure varies slightly by financial variable: Static level outcomes yield 256 firm-year observations, log revenue growth yields 221 observations (as calculating growth requires back-to-back valid years), and net-income ROA covers 230 observations across 33 firms.

5 Diagnostic tests

5.1 Parallel trends for the research intensity models

5.1.1 Purpose and specification

The parallel trends diagnostic evaluates whether exposure-related outcome gaps were changing prior to 2022. A key assumption of the difference-in-differences (DID) framework is that, in the absence of the policy shock, treatment and control groups would have followed parallel outcome trajectories.

To verify this assumption, we estimate dynamic annual interaction models across binary, continuous, and overlap-weighted specifications, using 2021 as the omitted reference year:

$$Y_{it} = \alpha_i + \lambda_{c(i),t} + \sum_{s \neq 2021} \beta_s Q_i \mathbf{1}\{t = s\} + X'_{it} \gamma + \varepsilon_{it} \quad (4)$$

In the equation, Y_{it} denotes the financial outcome for firm i in year t , while α_i captures firm fixed effects. $\lambda_{c(i),t}$ represents industry-year fixed effects and X_{it} includes firm-level controls for log total assets and leverage. The baseline exposure Q_i is defined as either the binary high-R&D indicator (H_i) or the standardized continuous intensity measure (Z_i). The interaction terms allow exposure-related differences to vary dynamically by year relative to the 2021 baseline, whose interaction coefficient is normalized to zero. The error term ε_{it} captures unobserved factors affecting the outcome.

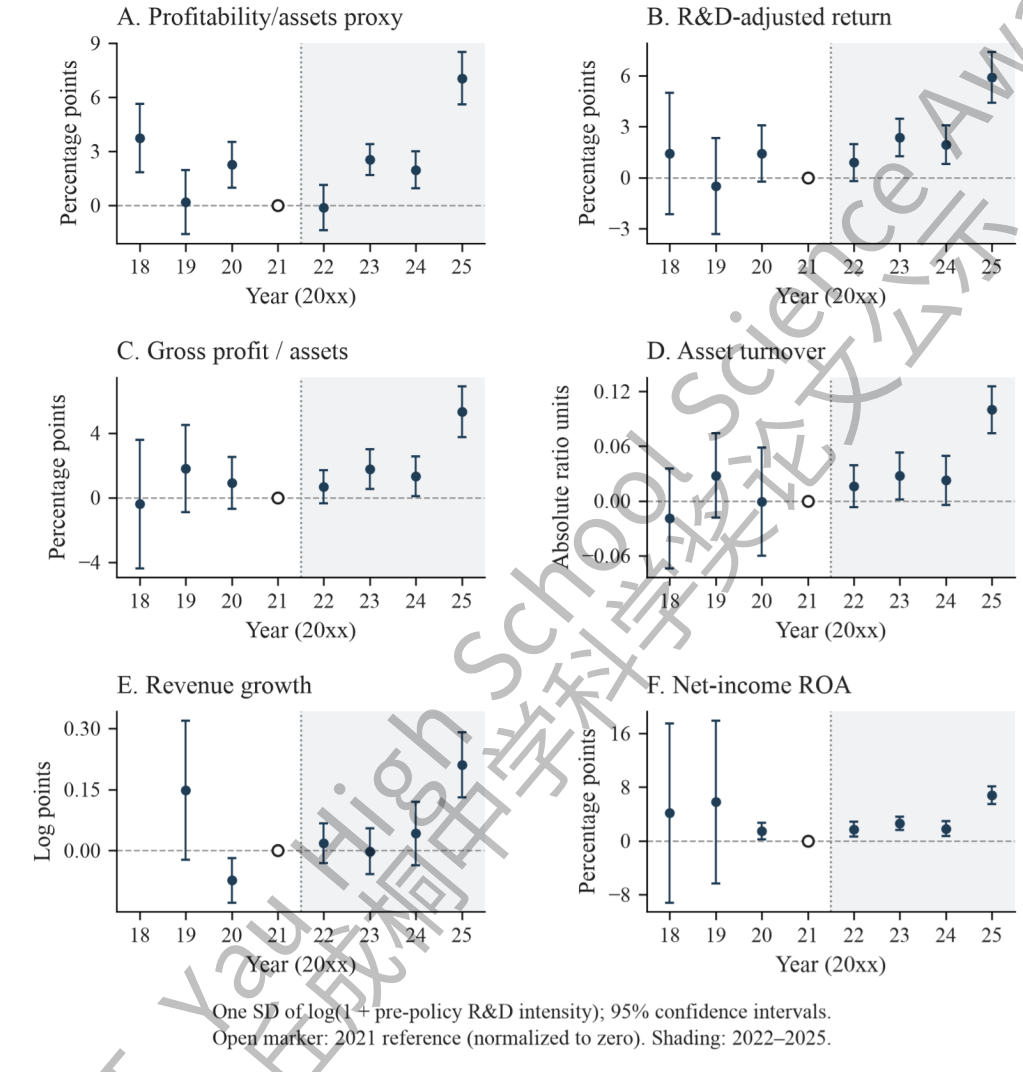
To evaluate pre-policy trend equivalence, we run joint clustered Wald chi-squared tests to observe whether the 2018-2020 interaction coefficients are jointly equal to zero across all six outcomes. Note that log revenue growth excludes a 2018 interaction, as computing growth requires data from the preceding year.

Methodologically, passing a pre-trend test does not guarantee that parallel trends would have held after 2022, since statistical pretests can suffer from limited statistical power and conditioning model choices based on pretests results can distort inference (Roth 2022). Conversely, rejecting the null hypothesis provides evidence of pre-existing trend differences. Therefore, the test should be viewed as an important diagnostic for

the DID design, rather than definitive proof of causal identification.

5.1.2 Results and interpretation

Figure 2: Continuous annual exposure interactions



Outcome	Binary p	Continuous p	Continuous q	Overlap p
Profitability/assets proxy	0.685	< .001	< .001	0.846
R&D-adjusted return	0.649	0.063	0.095	0.685
Gross profit/assets	0.873	0.305	0.305	0.580
Asset turnover	0.607	0.270	0.305	0.532
Log revenue growth	0.838	< .001	< .001	0.524
Net-income ROA	0.737	0.036	0.071	0.464

Table 3. Joint pre-period interaction tests

As illustrated in Figure 2 and reported in Table 3, the joint pre-period tests show clear differences depending on how baseline R&D exposure is measured. Under the continuous specification (Z_i), the parallel trends assumption is rejected for several key financial outcomes prior to the 2022 policy shift. In particular, the continuous specification reveals statistically significant pre-existing differences for both the profitability / assets proxy ($p < 0.001$) and log revenue growth ($p < 0.001$). For net-income ROA, the continuous model also indicates a modest pre-policy gradient, with an unadjusted p-value of 0.036 and an adjusted q-value of 0.071.

On the other hand, specifications that group or weight firms display far more consistent pre-policy trends. As detailed in Table 3, the binary model ($p = 0.737$ for ROA) and the overlap-weighted model ($p = 0.464$ for ROA) fail to reject the null hypothesis of parallel trends at the 5% significance level across all six outcome measures.

While the absence of statistically significant pre-trends in the binary and weighted specifications supports the baseline design, pre-period non-rejection does not fully rule out selection bias or guarantee identical counterfactual paths after 2022. Taken together, these diagnostic results indicate that estimates from continuous R&D specifications should be interpreted as conditional associations rather than strict causal effects, whereas the binary and overlap-weighted models provide a more reliable basis for causal identification.

5.2 Placebo test with a fake 2019 policy date

5.2.1 Purpose and specification

To test baseline timing anomalies, we estimate a placebo model that artificially shifts the policy date to 2019, three years prior to the actual 2022 policy change. If the method detects an apparent effect at that false date, the post-2022 findings may reflect pre-existing trajectory differences rather than the policy shock. The placebo interaction indicator equals one for high-R&D firms in 2019 or later and zero otherwise, capturing the group's relative differential shift in outcomes for the high-R&D group around the artificial break.

The primary placebo specification restricts the panel to years 2018-2021 and uses consolidated net-income ROA as the primary outcome. Restricting the sample to pre-2022 observations ensure the false post-period will not be affected by the actual post-policy period. As a supplementary comparison, we also estimate regression using the 2018-2024 sample and the profitability / assets proxy. Since this specification includes the actual policy period, however, it is only used as a secondary descriptive comparison rather than as a formal pre-policy falsification test.

The econometric model includes firm fixed effects, year fixed effects, and time-

varying controls for firm size (log total assets) and leverage. Standard errors are clustered at the firm level. Stable ownership characteristics are absorbed by firm fixed effects, while calendar age is subsumed by year fixed effects.

For this supplementary exercise, high-R&D status is based on each firm's mean 2018-2021 R&D-to-revenue ratio against the median across available pre-period firm-year ratios (12.6093%), excluding firms without a baseline average. This definition is slightly different from the main model, which applies percentile clipping and uses the median of eligible firm-level averages. Additionally, the placebo employs standard year fixed effects rather than category-year fixed effects. As a result, the test evaluates timing consistency under a simplified setting rather than a falsification holding every feature of the primary specification constant.

5.2.2 Results and interpretation

Version	Years	β in pp	SE in pp	p	N
Pre-policy ROA	2018–2021	2.574	3.698	0.4863	111

Table 4. Fake 2019 policy estimates

As presented in Table 4, the primary pre-policy placebo model over the 2018-2021 period yields an estimated interaction coefficient of 2.574 percentage points, with a firm-clustered standard error of 3.698 percentage points ($p = 0.4863$). Since this estimate is statistically insignificant, it provides no evidence of a differential ROA shift prior to the actual policy change. However, the wide confidence interval indicates statistical imprecision, meaning non-rejection alone does not fully rule out underlying pre-period differences.

The auxiliary 2018-2024 profitability proxy regression produces a coefficient of -2.344 percentage points ($p = 0.4423$). Because this specification spans the actual post-policy period and employs different sampling and variable construction rules, it does not serve as a direct falsification test or an independent confirmation of the primary pre-policy result.

Methodological limitations of the placebo test further constrain our interpretation. The sample contains only a single year prior to the artificial 2019 intervention, with just 18 firms contributing usable 2018 data. Furthermore, because high R&D status is assigned using mean intensity over 2018-2021, the treatment classification incorporates post-2019 data rather than reflecting a true pre-intervention baseline. Consequently, while the non-significant placebo result does not establish a causal effect for the 2022 policy, it confirms that the timing falsification exercise detects no artificial break in

2019.

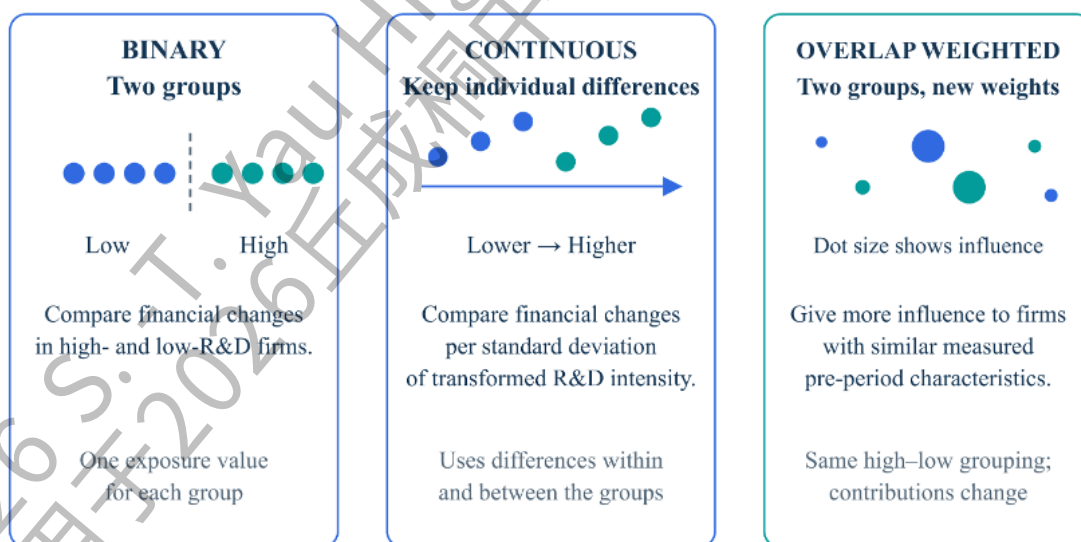
5.3 Implications for the financial estimates

The supplementary ownership and timing tests detect no significant fake-2019 ROA effect. The main continuous-exposure tests nevertheless identify earlier differential changes. The financial models that follow should therefore be interpreted as conditional associations, with caution applied to outcomes that show pre-period differences. Ultimately, a positive post-period coefficient cannot settle the causal question left open by these baseline diagnostics.

6 DiD models and financial results

The models ask three related questions. Standard binary difference-in-differences (DiD) compares changes in financial outcomes between high- and low-R&D firms. Continuous exposure DiD asks whether these changes vary with firms' prior R&D intensity. Overlap-weighted binary DiD also compares high- and low-R&D firms, but gives more weight to firms with similar measured characteristics across the two groups. The size interaction tests whether the relationship between prior R&D intensity and financial changes differs between large and small firms. Ownership is examined separately because the available sample limits this comparison.

Research Illustration B. How the three DiD comparisons differ



The main models compare financial outcomes in 2018–2021 with those in 2022–2025. The tables report estimates, firm-clustered standard errors (SE), 95% confidence intervals (CI), raw p-values, and adjusted q-values. Firm-clustered SE account for the fact that observations from the same firm may be related. The q-values adjust for

testing six outcomes within each model specification (Benjamini & Hochberg, 1995).

6.1 Standard binary DiD

6.1.1 Model specification

The standard binary difference-in-differences (DiD) model divides firms into two groups based on their R&D intensity before the policy. It then compares how each group's performance changed from before 2022 to 2022 onwards. This shows whether performance changed more in the high-R&D group than in the low-R&D group.

R&D intensity is the share of revenue a firm spends on research and development. We calculate each firm's average R&D intensity over 2018–2021, then find the median—the middle value across firms. Firms above the median join the high-R&D group, coded as 1. Firms at or below it join the low-R&D group, coded as 0. Each firm stays in its original group throughout the study, even if its R&D spending changes after 2021.

The model is:

$$Y_{it} = \alpha_i + \lambda_{c(i),t} + \beta(H_i \times Post_t) + \gamma_1 Size_{it} + \gamma_2 Leverage_{it} + \varepsilon_{it}$$

Here, Y_{it} is the performance outcome for firm i in year t . $Post_t$ equals 1 for 2022–2025 and 0 for 2018–2021. The interaction $H_i \times Post_t$ therefore equals 1 only for high-R&D firms in the post-policy period.

Firm fixed effects, α_i , account for differences between firms that remain stable over time. Category-by-year fixed effects, $\lambda_{c(i),t}$, account for annual changes shared by firms in the same semiconductor category. Each firm's category is fixed using its last observed pre-policy classification. The model also controls for firm size, measured as the natural logarithm of total assets, and leverage, measured as debt divided by total assets. The error term, ε_{it} , captures variation left unexplained by the model.

The main coefficient, β , measures the high-R&D group's additional post-policy change relative to the low-R&D group, after these adjustments. For example, if ROA rose by three percentage points in the high-R&D group and one percentage point in the low-R&D group, the unadjusted DiD would be two percentage points.

The model uses equal weights for observations. Standard errors are clustered by firm to allow a firm's outcomes to be related across years. A causal interpretation requires the two groups to have followed comparable trends without the policy, with no other changes affecting them differently. Because both groups may be affected by the policy, β measures their relative change rather than the policy's total effect.

6.1.2 Results

Outcome	DiD coefficient	p-value
Operating return proxy	0.02436	0.303
R&D-adjusted return	0.01930	0.467
Gross profit/ assets	0.01440	0.631
Asset turnover	0.06059	0.365
Revenue growth	0.09476	0.174
Net-income ROA	0.02034	0.361

Table 5. Baseline DiD results

Table presents the baseline Difference-in-Differences (DiD) results examining whether firms with higher pre-policy R&D intensity experienced different changes in performance following the implementation of the US CHIPS Act. The DiD coefficient captures the difference in the post-policy change between firms classified as high-R&D and those classified as low-R&D. A positive and statistically significant coefficient would provide evidence consistent with the hypothesis that higher R&D investment helped firms perform better following the policy shock.

The results do not provide statistically significant evidence of such an effect. For the main operating return proxy, the estimated DiD coefficient is 0.02436, with a p-value of 0.303. Although the coefficient is positive, its statistical insignificance indicates that the observed difference between the high-R&D and low-R&D groups cannot be distinguished from zero at conventional significance levels. Therefore, the baseline result does not support the hypothesis that high-R&D firms experienced significantly superior operating performance after the CHIPS Act.

The result is similar when alternative measures of firm performance are considered. The DiD coefficient for the R&D-adjusted return measure is 0.01930 ($p = 0.467$), while the coefficient for gross profit relative to total assets is 0.01440 ($p = 0.631$). The specification using net-income ROA, which is the primary accounting performance measure defined in the research design, produces a coefficient of 0.02034 with a p-value of 0.361. Thus, the estimated effect remains positive across these profitability-related measures, but none of the coefficients is statistically significant.

The additional operating indicators also do not provide significant evidence of a differential post-policy effect. The estimated coefficient for asset turnover is 0.06059 ($p = 0.365$), while the coefficient for revenue growth is 0.09476 ($p = 0.174$). These results suggest that the absence of a statistically significant treatment effect is not limited to a particular profitability measure. Across the alternative outcome variables examined, the estimated DiD coefficients are positive but consistently fail to reach conventional

levels of statistical significance.

Overall, the baseline DiD results do not support H1, which predicts that Chinese semiconductor firms with higher R&D investment would exhibit significantly superior performance following the CHIPS Act shock. While the positive signs of the estimated coefficients are directionally consistent with the proposed role of R&D as a potential protective mechanism, the relatively large p-values indicate that the analysis does not establish a statistically significant performance advantage for high-R&D firms. Accordingly, the baseline evidence suggests that higher pre-policy R&D intensity alone was not sufficient to generate a statistically detectable improvement in firm performance during the observed post-policy period.

6.2 Continuous exposure DiD

6.2.1 Purpose and specification

The continuous model tests whether firms with higher research intensity before 2022 had different financial changes from 2022 onward. Standard binary DiD assigns all firms in the high-R&D group one exposure value and all firms in the low-R&D group another. The continuous model keeps the differences between individual firms, including those within each group. It assumes a straight-line relationship: each equal increase in the transformed research-intensity measure is linked to the same difference in financial change (Altman & Royston, 2006; Callaway et al., 2024).

We first transform each firm's baseline R&D ratio using $\log(1 + \text{R\&D intensity})$. This reduces the gaps between unusually large ratios. We then standardize these transformed values across the 37 eligible firms: we subtract their average and divide by their standard deviation, a measure of how spread out they are. The resulting score shows each firm's position relative to the average. A score of 0 means average, 1 means one standard deviation above average, and -1 means one standard deviation below average.

Equation (5) tests whether financial changes after 2022 vary with firms' baseline research intensity. It accounts for stable differences between firms, annual conditions within each production-chain category, and current firm size and leverage. In this model, Q is the standardised research-intensity score Z .

$$Y_{it} = \alpha_i + \lambda_{c(i),t} + \beta(Q_i P_t) + X'_{it} \gamma + \varepsilon_{it} \quad (5)$$

Y represents one of the six financial outcomes. The firm effect α gives each firm its own baseline outcome level, accounting for differences between firms that remain stable over time. The category-by-year effect λ accounts for annual conditions shared by firms in the same production-chain category. P equals 1 from 2022 onwards and 0

before then. Q is each firm's fixed baseline exposure, Z , while X contains current log assets and leverage.

The key term is $Q \times P$. Before 2022, it equals zero. From 2022 onwards, it equals the firm's baseline exposure. Its coefficient β therefore shows how much the estimated pre-to-post financial change differs for firms one standard deviation apart in transformed baseline research intensity, after the model's adjustments.

The model does not need separate terms for fixed exposure or the common post-2022 shift. Firm effects already account for fixed differences in exposure, while category-by-year effects account for the common shift over time. The interaction captures whether financial changes differ with exposure.

These adjustments help account for other influences on financial performance, but they cannot remove all possible explanations. Changes in management quality, access to funding, or product demand may affect firms differently and still influence the results. A causal interpretation also requires firms with different R&D intensities to have followed comparable financial trends without the changes being studied (Roth et al., 2023). We therefore interpret the estimates as associations, rather than direct proof that R&D or a particular policy caused better performance.

6.2.2 Financial results

Table 6 reports the continuous model's results. All six estimates are positive and remain statistically significant after adjusting for the six outcome tests within this model ($q < .05$). For ROA, the coefficient is 0.024446, or about 2.445 percentage points. This means that a firm with transformed baseline R&D intensity one standard deviation higher is estimated to have a 2.445-percentage-point greater change in ROA from before to after 2022, after the model's adjustments. The 95% confidence interval for this difference is 1.347 to 3.543 percentage points.

Outcome	β (SE)	95% CI	p	q	N
Profitability/assets proxy	0.0149 (0.0052)	[0.005, 0.025]	0.005	0.007	256
R&D-adjusted return	0.0227 (0.0075)	[0.008, 0.037]	0.003	0.006	256
Gross profit/assets	0.0172 (0.0081)	[0.001, 0.033]	0.035	0.035	256
Asset turnover	0.0398 (0.0128)	[0.015, 0.065]	0.002	0.006	256
Log revenue growth	0.0485 (0.0212)	[0.007, 0.090]	0.024	0.029	221

Outcome	β (SE)	95% CI	p	q	N
Net-income ROA	0.0244 (0.0056)	[0.013, 0.035]	< .001	< .001	230

Table 6. Continuous estimates

6.2.3 Interpretation

The positive estimates for asset turnover and revenue growth show that the pattern extends beyond profitability. However, the six outcomes use some of the same financial figures, so they do not provide six independent pieces of evidence as they contain overlap. The checks in Section 5.1 also show that, for a few outcomes, firms with different R&D intensities were already following different trends before 2022.

The continuous model therefore shows an association between higher baseline R&D intensity and more positive financial changes after 2022. It does not directly compare the high- and low-R&D groups as binary DiD does. The next model returns to that group comparison and gives more weight to firms with similar measured characteristics across the two groups.

6.3 Overlap weighted binary DiD

6.3.1 Purpose and specification

The overlap-weighted model compares financial changes in high- and low-R&D firms, giving more weight to firms with similar measured characteristics before 2022. Firms that are poor comparisons for the other group receive less weight. The model keeps the same high-versus-low grouping as standard binary DiD; it changes how much each firm contributes to the estimate.

We first estimate each firm's propensity score, e . This is its predicted probability of belonging to the high-R&D group, based on its measured pre-period characteristics, B (Li et al., 2018). Equation (6) then assigns a weight of $1 - e$ to high-R&D firms and e to low-R&D firms.

$$\hat{e}_i = \Pr(H_i = 1 \mid B_i), \quad w_i = H_i(1 - \hat{e}_i) + (1 - H_i)\hat{e}_i \quad (6)$$

For example, a high-R&D firm with $e = 0.9$ receives a weight of 0.1. Its characteristics strongly predict high-R&D membership, so it contributes less to the comparison. A high-R&D firm with $e = 0.5$ receives a larger weight of 0.5. Low-R&D firms receive weight e : a firm with $e = 0.1$ receives weight 0.1, while one with $e = 0.5$ receives weight 0.5. These examples illustrate the calculation; they are not actual sample observations.

To estimate the scores, we use pre-period firm size, leverage, gross profit divided by assets, and asset turnover. We also include pre-period trends in gross profit/assets and asset turnover. Ownership is excluded because it is the same across all firms in the primary sample.

The weighted financial model uses Equation (5), with Q replaced by H : 1 for high-R&D firms and 0 for low-R&D firms. It applies the weights from Equation (6) and still accounts for firm effects, category-by-year effects, and current size and leverage. The coefficient β therefore measures the weighted difference between the two groups' pre-to-post financial changes.

6.3.2 Financial results and balance

Table 7 reports the overlap-weighted results. All six estimates are positive, consistent with more favourable financial changes among high-R&D firms. However, none is statistically significant based on either its p-value or its adjusted q-value, and all 95% confidence intervals include zero. The estimates therefore point towards an advantage, but do not provide clear evidence of one.

For ROA, the estimated difference is 1.444 percentage points in favour of high-R&D firms. Its 95% confidence interval ranges from -3.231 to 6.119 percentage points, with $p = .543$ and $q = .979$. This wide range allows for both less and more favourable changes among high-R&D firms. The result remains uncertain; it also does not establish that the two groups responded equally.

Outcome	β (SE)	95% CI	p	q	N
Profitability/assets proxy	0.0133 (0.0257)	[-0.037, 0.064]	0.604	0.979	256
R&D-adjusted return	0.0081 (0.0274)	[-0.046, 0.062]	0.767	0.979	256
Gross profit/assets	0.0007 (0.0315)	[-0.061, 0.063]	0.983	0.983	256
Asset turnover	0.0153 (0.0656)	[-0.114, 0.145]	0.815	0.979	256
Log revenue growth	0.0934 (0.0646)	[-0.034, 0.221]	0.150	0.902	221
Net-income ROA	0.0144 (0.0237)	[-0.032, 0.061]	0.543	0.979	230

Table 7. Overlap weighted estimates

We assess the weighting by checking propensity-score ranges, differences in average

pre-period characteristics, and effective sample size. Effective sample size describes how concentrated the weights are. Within each group, it equals the squared sum of weights divided by the sum of squared weights. Smaller values mean that the comparison relies more heavily on some firms than others. It is not an actual firm count or a complete measure of how precise the financial estimates are.

The estimated propensity scores range from .01372 to .95516. After weighting, the differences between the groups' averages are effectively zero for the characteristics included in the full-sample weighting model. This shows improved balance in those measured averages, which overlap weighting is designed to achieve (Li et al., 2018).

The effective sample sizes are 9.32 for low-R&D firms and 13.12 for high-R&D firms, compared with actual counts of 16 and 18. Weighting therefore makes the groups more comparable on the included averages, while placing more influence on a smaller set of firms.

Measure	Result
Fitted propensity range	0.01372 to 0.95516
Low-R&D firms and effective firms	16 and 9.32
High-R&D firms and effective firms	18 and 13.12
Largest absolute weighted mean difference	Below 0.000001 SD
Covariates used	Six pre-period means or trends

Table 8. Full primary-sample weighting diagnostics

Table 8 shows that weighting makes the groups' averages almost identical for the six included pre-period characteristics. However, the lower effective sample sizes show that some firms contribute more than others. This balance improves comparability on the measured averages.

6.3.3 Interpretation

The balance checks in Table 8 cover the full primary sample. However, some firms lack data for particular outcomes, especially ROA, and cannot be included in those analyses. Excluding these firms or their yearly observations can change the balance between the groups. For example, if smaller firms in one group have missing ROA data, the groups' weighted average sizes may no longer match in the ROA analysis.

We keep each remaining firm's original weight rather than estimating new weights for each outcome. This keeps the weighting approach consistent, but means that the balance reported in Table 8 may not hold for every outcome. Even where measured averages match, firms may still differ in unmeasured factors, such as management quality.

Weighting does not make group membership random or remove these unmeasured differences.

The weighted financial estimates are positive, but their wide confidence intervals leave the high-R&D advantage uncertain.

6.4 Firm size interaction DiD

6.4.1 Purpose and specification

The size interaction model tests Hypothesis 2: whether the relationship between research intensity and post-period changes in outcomes differs between large and small firms. It extends the continuous DiD model by adding a three-way interaction between continuous exposure, the post-period indicator and a large-firm indicator.

$$Y_{it} = \alpha_i + \lambda_{c(i),t,L_i} + \beta Z_i P_t + \delta Z_i P_t L_i + X'_{it} \gamma + L_i X'_{it} \eta + \varepsilon_{it} \quad (7)$$

In Equation (7), L equals 1 for large firms and 0 for small firms. For small firms, β measures how post-period financial changes vary with baseline research intensity. The coefficient δ measures how much this relationship differs for large firms, whose slope is therefore $\beta + \delta$. The model also allows annual conditions within each industry category, and the relationships between the controls and the outcome, to differ by firm size. We test $\delta = 0$ to assess whether the two slopes differ.

A statistically significant result for one group and a non-significant result for the other does not necessarily mean the groups differ. One estimate may simply be less precise. We therefore test the difference between the slopes directly and report its confidence interval, rather than comparing the two groups' significance labels (Gelman & Stern, 2006).

6.4.2 Results

For ROA, a one-standard-deviation increase in baseline research intensity is associated with a 4.513-percentage-point larger post-period change for small firms and a 2.717-percentage-point larger change for large firms. The estimated large-minus-small difference is -1.796 percentage points, with a 95% confidence interval of $[-12.225, 8.633]$ and $p = .734$. This wide interval allows for either group to have a substantially larger slope.

Outcome	Small slope (SE)	Large slope (SE)	Large – small [95% CI]	Diff. p	Diff. q
Profitability/asset proxy	0.0217 (0.0423)	0.0240 (0.0073)	0.0023 [−0.0834, 0.0880]	0.958	0.958
R&D-adjusted return	−0.0103 (0.0613)	0.0366 (0.0097)	0.0469 [−0.0770, 0.1708]	0.456	0.881
Gross profit/assets	−0.0229 (0.0750)	0.0334 (0.0097)	0.0563 [−0.0946, 0.2071]	0.462	0.881
Asset turnover	−0.0321 (0.1080)	0.0658 (0.0131)	0.0979 [−0.1192, 0.3150]	0.374	0.881
Log revenue growth	0.0337 (0.1367)	0.0893 (0.0346)	0.0556 [−0.2257, 0.3369]	0.696	0.881
Net-income	0.0451	0.0272	−0.0180	0.734	0.881
ROA	(0.0517)	(0.0069)	[−0.1222, 0.0863]		

Table 9. Firm-size slopes and differences: private-firm sample

6.4.3 Interpretation

For the first four outcomes, the sample includes 18 small firms with 131 observations and 16 large firms with 125 observations. For ROA, it includes 17 small firms with 110 observations and 16 large firms with 120 observations. Each observation represents one firm in one year.

The large-firm estimates show a consistent positive relationship between baseline research intensity and later financial changes across all six outcomes. These estimates are also more precise than those for small firms. This pattern is consistent with the idea that research capability may help firms adapt, although it does not establish that larger firms benefit more. The direct tests find no statistically significant differences between the two size groups, leaving Hypothesis 2 unresolved. The wide confidence intervals allow for meaningful differences that this sample cannot estimate precisely.

6.5 Sample limits

The sample varies by outcome because some firms lack the required data. The first four outcomes use 34 firms and 256 firm-year observations. Revenue growth uses 34 firms and 221 observations because it requires data from consecutive years. ROA uses 33 firms and 230 observations with suitable net-income and asset data.

These data requirements limit the sample's coverage. The findings describe the privately controlled firms included in the analysis and may not represent the wider

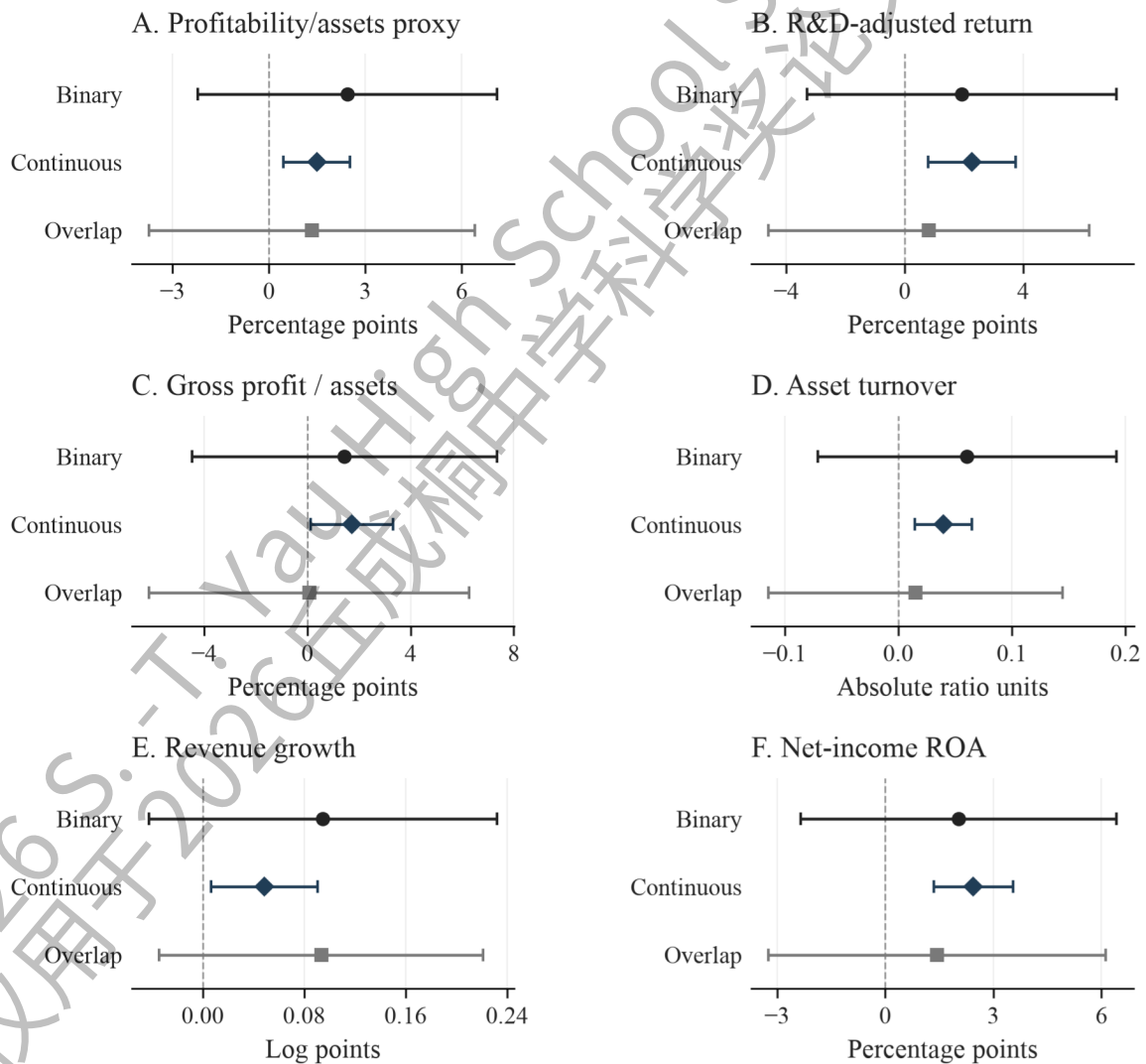
semiconductor industry.

6.6 Comparison across DiD models

Figure 3 compares the three main financial models. For ROA, the binary estimate is 2.034 percentage points, with a 95% confidence interval of $[-2.348, 6.416]$. The continuous estimate is 2.445 percentage points per standard deviation of transformed baseline research intensity, while the overlap-weighted estimate is 1.444 percentage points.

All three estimates are positive, but they measure different comparisons. Binary and overlap-weighted DiD compare high- and low-R&D firms. The continuous model measures how financial changes vary with research intensity across individual firms.

Figure 3: Main estimates and their uncertainty



Note. Dots show estimates and bars show 95% confidence intervals

6.7 Sensitivity to specification choices

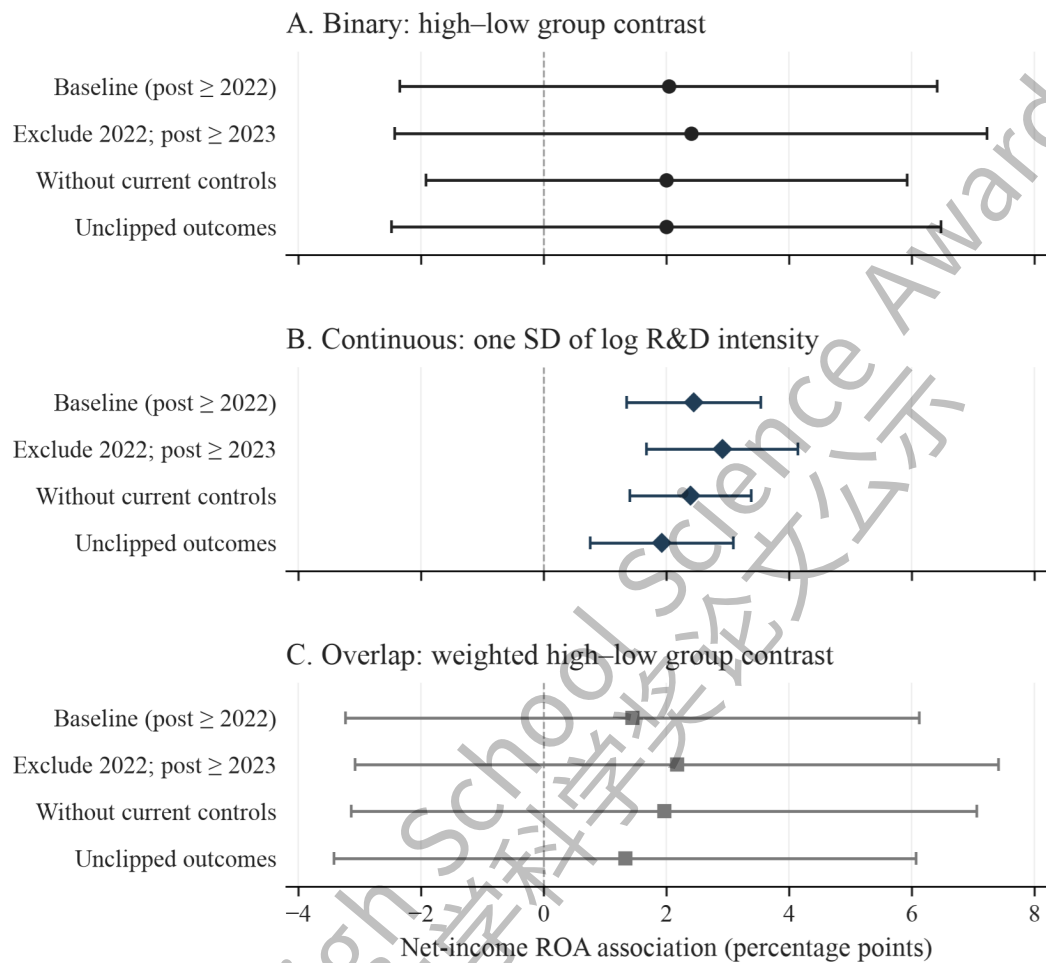
We check whether the results change under three alternative specifications. First, we exclude 2022 and start the post-period in 2023 to reduce dependence on the transition year. This also changes the observations included. Second, we remove current size and leverage controls, since these may respond to the same conditions as financial performance. Third, we use outcomes without capping extreme values, while keeping the exposure and control definitions unchanged.

The continuous ROA estimate remains positive across the main model and all three alternatives, ranging from 1.922 to 2.910 percentage points. Its confidence intervals remain above zero. By contrast, the binary and overlap-weighted intervals include zero in every specification. These checks show that the positive continuous association persists under the choices tested.

Specification	Binary β [CI]	Continuous β [CI]	Overlap β [CI]
Main 2022	2.034 [-2.348, 6.416]	2.445 [1.347, 3.543]	1.444 [-3.231, 6.119]
Exclude 2022	2.400 [-2.431, 7.230]	2.910 [1.679, 4.140]	2.169 [-3.073, 7.412]
No current controls	1.999 [-1.920, 5.919]	2.393 [1.406, 3.381]	1.962 [-3.138, 7.061]
Unclipped outcomes	1.999 [-2.479, 6.476]	1.922 [0.753, 3.091]	1.327 [-3.415, 6.069]

Table 10. Net-income ROA sensitivity

Note. Estimates and 95% confidence intervals are in ROA percentage points.

Figure 4: Net income ROA sensitivity

Note. Coefficients and 95% intervals are ROA percentage points.

We use these checks to see whether the findings depend heavily on particular modelling choices. Excluding 2022 tests whether including the transition year changes the results. Removing current size and leverage controls checks whether adjusting for these factors affects the estimated relationship, since they may also change after 2022. Leaving outcomes unclipped tests whether the results depend on capping extreme values.

Together, these checks show which findings remain stable when we change how the analysis is carried out. Similar results across the alternatives give greater confidence that the findings do not depend on a single modelling choice.

6.8 Event study results

	9 Aug 2022	10 Aug 2022
Event study method	Primary	Timing sensitivity
Event window (trading days)	$[-3, +3]$	$[-3, +3]$
Firms — high R&D / low R&D	36 — 16 / 20	36 — 16 / 20
High-R&D mean CAR	5.48%	2.95%
Low-R&D mean CAR	6.93%	5.07%
Mean CAR difference (high minus low)	-1.45 pp	-2.12 pp
Standard error of difference	3.26 pp	2.79 pp
95% confidence interval of difference	$[-8.10, 5.20]$ pp	$[-7.79, 3.55]$ pp
Exploratory Welch test p value	0.6599	0.4524
Positive difference significant at 5%	No	No

Table 11. Event study results

The event study examines the short-term stock market reaction to the signing of the US CHIPS Act on August 9, 2022. The event window covers three trading days before and after the announcement, or $[-3, +3]$. Abnormal returns are estimated using a market model fitted over trading days -120 to -21 relative to the event date. The event-study sample contains 36 firms, of which 16 are high-R&D firms, and 20 are low-R&D firms.

Results show that both groups experienced positive average cumulative abnormal returns (CAR) during the event window. The mean CAR was 5.48% for the high R&D firms and 6.93% for the low-R&D group. Therefore, the high-R&D group had a lower average CAR than the low-R&D group, with a difference of -1.45 percentage points.

However, the difference is not statistically significant. Its standard error is 3.26 percentage points, and the 95% confidence interval from -8.10 to 5.20 percentage points. The exploratory Welch test yields a p-value of 0.6599. As a result, the results provide no statistically significant evidence that the market response to the CHIPS Act announcement differed according to firms' pre-policy R&D intensity.

Robustness checks confirm that these findings are not sensitive to event-date specifications. Shifting the target date to August 10, 2022, yields a mean CAR of 2.95% for high R&D firms and 5.07% for low R&D firms. This alternative specification confirms that shifting the event date does not materially change the empirical takeaway.

We also verify whether the result is sensitive to the choice of the event date by shifting the date from August 9 to August 10, 2022. With this alternative event date, the mean CAR is 2.95% for high-R&D firms and 5.07% for low-R&D firms, producing a difference of -2.12 percentage points. The corresponding 95% confidence interval

ranges from -7.79 to 3.55 percentage points, with a Welch test p-value of 0.4524. The result therefore remains statistically insignificant, and changing the event date does not materially alter the conclusion.

The event-study results do not support Hypothesis 3. Although both groups have positive mean cumulative abnormal returns, the high-R&D group has a lower point estimate. However, the confidence interval for the difference includes both negative and positive values. The results therefore provide no statistically significant evidence that high-R&D firms experienced a more positive market response; they do not establish that the groups responded equally.

7 Theoretical contributions and policy implications

7.1 Theoretical contributions

Our findings connect prior research commitment with later financial performance, but do not show how this relationship arises. The positive continuous association is consistent with absorptive capacity theory, which suggests that existing knowledge helps firms understand and use new information (Cohen & Levinthal, 1990). Research experience may therefore help firms adapt when conditions change, although confirming this explanation would require evidence of how they applied their knowledge. The event study examines whether this possible advantage also appears in investors' immediate responses to policy news. We find no statistically significant stock-market advantage for high-R&D firms around the CHIPS Act announcement. Together, these findings suggest that the relationship between research commitment and later financial performance should be examined separately from its recognition by investors. They do not establish that investors ignored research capability or failed to anticipate its value.

The size comparison adds a further question: what helps firms turn research commitment into better performance? We find no statistically significant difference in the R&D–performance relationship between large and small firms, leaving the role of supporting resources unresolved. Dynamic Capabilities Theory suggests that performance depends on how firms use and adapt their resources (Teece et al., 1997). Future research should therefore examine access to funding, equipment and management practices directly, rather than use firm size to represent them. Our study connects research commitment with financial outcomes while identifying two questions that remain open: how firms put their knowledge to use, and under what conditions investors recognise its value.

7.2 Implications for government policy

The continuous model finds that firms with higher pre-2022 R&D intensity experienced more favourable financial changes after 2022. This suggests that evaluations of research-support programmes could track firms' research commitment alongside later financial performance. However, the binary and overlap-weighted models do not establish a clear advantage for the high-R&D group. Our results therefore provide no basis for using the study's high–low dividing point as a funding threshold. Policymakers could assess R&D intensity alongside evidence of technical progress and commercial use, rather than treat crossing a spending threshold as proof that support has succeeded. Since our models examine firms' research intensity, they do not establish that a subsidy would produce the same financial relationship.

The size model also gives no clear basis for favouring large or small firms when allocating research support. We do not find a statistically significant difference between their R&D–performance relationships. A more defensible approach would be to assess the constraints facing each project, such as access to funding, equipment or specialist expertise. These factors could help explain why research translates into performance more successfully in some firms. They remain possible explanations, however, because our models do not measure them directly.

Finally, the event study finds no statistically significant immediate stock-market advantage for high-R&D firms around the CHIPS Act announcement. Together with the positive continuous financial association, this suggests that programme evaluations should examine later operating results as well as short-term market reactions. An immediate share-price response alone would provide limited evidence of whether supported research eventually helps a firm adapt and improve its performance.

7.3 Implications for firm resource allocation

Firms exposed to geopolitical tensions should consider giving greater priority to research that reduces dependence on vulnerable foreign technologies. [Flynn et al. \(2025\)](#) find that exposure to foreign political risk directs innovation towards affected sectors and that this innovation reduces reliance on risky import sources. For semiconductor firms, this suggests allocating resources to projects that develop alternative components or adapt production processes to available inputs. The value of these projects may include both future sales and a reduced risk of production disruption.

Our continuous model provides evidence consistent with this argument: firms with higher pre-2022 R&D intensity experienced more favorable financial changes after 2022. Because our measure captures research commitment before the policy shift, the finding supports considering research capability as preparation for disruption. Related evidence

comes from [Cao et al. \(2024\)](#), who find that US restrictions reduced Chinese firms' patent output, but firms with larger existing patent stocks suffered smaller declines. Together, these findings strengthen the case for building research capability before access to foreign technology becomes restricted.

Managers could therefore give additional weight to research projects that address their firm's most exposed technological dependencies. For example, a project that allows production to continue using alternative inputs may deserve greater priority when access to an existing input is uncertain. This is a practical implication of the combined evidence, rather than a mechanism tested by our model.

8 Limitations and future directions

8.1 Policy exposure and causal interpretation

Our study cannot isolate the effect of a specific policy because prior R&D intensity measures research commitment, rather than direct exposure to restrictions or support. Firms with similar R&D intensity may depend on different foreign technologies, equipment or customers and therefore face different risks. Future research could measure these dependencies before a policy change and link them to the policy's timing and coverage. This would make the comparison more closely reflect which firms faced disruption. Tracking later changes in suppliers or product designs could also show how firms adapted, rather than infer adaptation from financial results alone.

Earlier financial trends create a second limitation. In the continuous model, some outcomes were already changing differently across R&D levels before 2022. Part of the later relationship may therefore reflect trends that began before the policy shift. The binary and overlap-weighted models do not detect significant earlier trend differences, but this does not prove that firms would have followed comparable paths without the policy change. Future research could use a longer pre-policy period and test how the estimates change when some continuation of earlier trends is allowed. We therefore interpret the continuous results as associations, rather than direct evidence that research spending caused greater resilience to policy restrictions.

8.2 Measurement and sample coverage

R&D intensity measures research spending relative to revenue but does not directly show the quality or practical value of that research. Two firms with similar R&D intensity may differ in staff expertise, technical progress and the success of their products. The ratio can also rise because revenue falls, even when research spending remains unchanged. Future research could examine spending and revenue separately, alongside measures such as research staff, patent quality and sales from new products.

These measures would help distinguish the resources devoted to research from the results it produces.

The sample also limits how widely the findings apply. Our main financial models focus on publicly-listed firms that meet the study's data and comparison requirements, so the results may not extend to the wider semiconductor industry. Missing financial observations also mean that some outcomes are estimated using fewer firms or years than others. Future work could expand coverage and compare the characteristics of included and excluded firms.

8.3 Statistical uncertainty

The limited number of firms makes some estimates imprecise. The binary, overlap-weighted and firm-size comparisons have confidence intervals that include both positive and negative differences. These results therefore leave the differences unresolved; they do not establish that research intensity or firm size has no role in financial performance. Overlap weighting also concentrates influence on a smaller number of firms, which can reduce precision. Future research could use methods designed for small numbers of firms to check the confidence intervals and repeat the analysis while leaving out one firm at a time. This would help assess whether the findings depend heavily on particular firms.

The event study faces a related concern because firms' stock returns may move together in response to shared industry news. The current comparison does not fully account for this dependence, which may affect the estimated uncertainty around the high-low R&D difference. Future work could use methods that allow returns across firms to be correlated. It could also examine earlier policy announcements, since investors may have reacted before the selected event date. These checks would help assess whether the inconclusive result reflects a limited market difference, imprecise estimates or a response that occurred outside the chosen window.

9 Main conclusions

This study examines whether research commitment before 2022 is associated with later financial performance among Chinese semiconductor firms. The continuous model finds a positive relationship across all six financial measures. Firms with higher prior R&D intensity experienced more favourable financial changes after 2022, suggesting that research history is relevant to understanding performance during a period of policy uncertainty. However, the binary and overlap-weighted comparisons remain inconclusive, so the evidence does not establish a clear financial advantage from belonging to the high-R&D group.

The additional models help define the limits of this finding. We do not establish that the R&D–performance relationship differs between large and small firms, or that high-R&D firms received a more favourable immediate stock-market response around the CHIPS Act announcement. The results therefore offer stronger evidence of a continuous financial association than of differences by firm size or immediate investor response. Earlier financial trends and the absence of direct measures of policy exposure also prevent us from concluding that research spending caused firms to withstand restrictions more successfully.

The findings are consistent with the theoretical view that accumulated knowledge may help firms respond to changing conditions, although the process linking research to adaptation remains unobserved. For firms facing geopolitical risks, the evidence strengthens the case for considering sustained, targeted research when allocating resources, particularly where projects could reduce vulnerable technological dependencies. It does not identify an optimal budget or guarantee returns from additional spending. The practical question is therefore how firms can turn research commitment into capabilities that address specific disruptions and support financial performance.

References

Altman, D. G., & Royston, P. (2006). The cost of dichotomising continuous variables. *BMJ*, 332(7549), 1080. <https://doi.org/10.1136/bmj.332.7549.1080>

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99–120. <https://doi.org/10.1177/014920639101700108>

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society: Series B (Methodological)*, 57(1), 289–300. <https://doi.org/10.1111/j.2517-6161.1995.tb02031.x>

Bureau of Industry and Security. (2022, October 7). *Commerce implements new export controls on advanced computing and semiconductor manufacturing items to the People's Republic of China (PRC)* [Press release]. U.S. Department of Commerce. <https://www.bis.gov/node/20292>

Callaway, B., Goodman-Bacon, A., & Sant'Anna, P. H. C. (2024). *Difference-in-differences with a continuous treatment* (NBER Working Paper No. 32117). National Bureau of Economic Research. <https://doi.org/10.3386/w32117>

Cao, Y., de Nicola, F., Mattoo, A., & Timmis, J. (2024). *Technological decoupling? The impact on innovation of US restrictions on Chinese firms* (Policy Research Working Paper No. 10950). World Bank. <https://documents1.worldbank.org/curated/en/099350410152412143/pdf/IDU-7954e88e-293d-4ad0-aa77-956865a270c9.pdf>

Chen, T.-c., Guo, D.-Q., Chen, H.-M., & Wei, T.-t. (2019). Effects of R&D intensity on firm performance in Taiwan's semiconductor industry. *Economic Research-Ekonomska Istraživanja*, 32(1), 2377–2392. <https://doi.org/10.1080/1331677X.2019.1642776>

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35(1), 128–152. <https://doi.org/10.2307/2393553>

Flynn, J. P., Levy, A. B., Moscona, J., & Wo, M. (2025). *Foreign political risk and technological change* (NBER Working Paper No. 33964). National Bureau of Economic Research. <https://doi.org/10.3386/w33964>

Gelman, A., & Stern, H. (2006). The difference between “significant” and “not significant” is not itself statistically significant. *The American Statistician*, 60(4), 328–331. <https://doi.org/10.1198/000313006X152649>

Hall, B. H., & Lerner, J. (2009). *The financing of R&D and innovation* (NBER Working Paper No. 15325). National Bureau of Economic Research. <https://doi.org/10.3386/w15325>

Haramboure, A., Lalanne, G., Schwellnus, C., & Guilhoto, J. (2023). *Vulnerabilities in the semiconductor supply chain* (OECD Science, Technology and Industry Working Papers No. 2023/05). OECD Publishing. <https://doi.org/10.1787/6bed616f-en>

Lee, P. (2016). Stock market reaction of disclosure of technological information and R&D intensity. *Journal of the Korea Society of Computer and Information*, 21(11), 151–158. <https://doi.org/10.9708/jksoci.2016.21.11.151>

Li, F., Morgan, K. L., & Zaslavsky, A. M. (2018). Balancing covariates via propensity score weighting. *Journal of the American Statistical Association*, 113(521), 390–400. <https://doi.org/10.1080/01621459.2016.1260466>

National Institute of Standards and Technology. (2022, September 7). *Biden administration releases implementation strategy for \$50 billion CHIPS for America program*. <https://www.nist.gov/news-events/news/2022/09/biden-administration-releases-implementation-strategy-50-billion-chips>

Organisation for Economic Co-operation and Development. (2025). *Mapping the semiconductor value chain: Working towards identifying dependencies and vulnerabilities* (OECD Science, Technology and Industry Policy Papers No. 182). OECD Publishing. <https://doi.org/10.1787/4154cdbf-en>

Roth, J. (2022). Pretest with caution: Event-study estimates after testing for parallel trends. *American Economic Review: Insights*, 4(3), 305–322. <https://doi.org/10.1257/aeri.20210236>

Roth, J., Sant’Anna, P. H. C., Bilinski, A., & Poe, J. (2023). What’s trending in difference-in-differences? A synthesis of the recent econometrics literature. *Journal of Econometrics*, 235(2), 2218–2244. <https://doi.org/10.1016/j.jeconom.2023.03.008>

Semiconductor Industry Association. (2026, February 6). *Global annual semiconductor sales increase 25.6% to \$791.7 billion in 2025*. <https://www.semiconductors.org/global-annual-semiconductor-sales-increase-25-6-to-791-7-billion-in-2025/>

Shin, N., Kraemer, K. L., & Dedrick, J. (2017). R&D and firm performance in the semiconductor industry. *Industry and Innovation*, 24(3), 280–297. <https://doi.org/10.1080/13662716.2016.1224708>

State Council of the People’s Republic of China. (2021). *Outline of the 14th Five-Year Plan (2021–2025) for national economic and social development and vision 2035 of the People’s Republic of China*. https://wb.fujian.gov.cn/English/usefulinformation/NewInitiatives/202108/t20210809_5666236.htm

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7), 509–533. [https://doi.org/10.1002/\(SICI\)1097-0266\(199708\)18:7<509::AID-SMJ882>3.0.CO;2-Z](https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z)

Zhu, G.-l., Zhang, Y., Chen, K.-h., & Yu, J. (2017). The impact of R&D intensity on firm performance in an emerging market: Evidence from China's electronics manufacturing firms. *Asian Journal of Technology Innovation*, 25(1), 41–60. <https://doi.org/10.1080/19761597.2017.1302492>

2026 S.-T. Yau High School Science Award
仅用于2026丘成桐中学科学奖论文公示

Acknowledgements

This research project was jointly completed by Emmy Chen, Enzo Congen Yao, and Jim Guo under the supervision of Ms. Lily Shi. The topic, “Innovation as a Shield? R&D Investment of Chinese Semiconductor Firms under the US CHIPS Act,” was developed through discussions among the three members based on our shared interest in the effects of the CHIPS Act on Chinese semiconductor firms and technological competition.

We sincerely thank our supervising teacher, Ms. Lily Shi, a teacher in the Mathematics Department at our school and our IB Mathematics: Analysis and Approaches HL teacher, for her guidance and technical assistance. She supervised the project as part of her regular educational responsibilities and received no payment or other compensation. Her main contribution was helping us resolve technical difficulties, particularly in quantitative modelling. For example, when our event study initially failed to run correctly, she helped us identify possible implementation problems and troubleshoot the model. The research question, analytical framework, methodological choices, empirical analysis, and interpretation were developed and conducted by the three students.

Division of Research Work and Responsibilities

Emmy Chen served as the team leader and coordinated the overall research process. During the initial stage, when all three members were relatively unfamiliar with financial and econometric modelling, Emmy organized and led weekly study sessions in which we independently learned different quantitative methods and then presented and taught them to one another. Once the writing and empirical research process began, she continued to coordinate the team through weekly meetings, helping organize tasks, track progress, and consolidate the members’ respective contributions. Additionally, Emmy focused particularly on the Two-Way Fixed Effects Difference-in-Differences (TWFE DiD) and event study methods, while also contributing substantially to coding, empirical analysis, and interpretation. She also handled the complete LaTeX typesetting, document structure, and formatting of the paper.

Enzo Congen Yao was responsible for the Instrumental Variable (IV) and mediation-effect methods and was leading extracting financial information from company reports and cross-checking it against the Wind database.

Jim Guo focused on parallel-trends testing, placebo testing, and Propensity Score Matching Difference-in-Differences (PSM-DID), while contributing substantially to coding and empirical analysis.

After studying and presenting the different methods to one another, the three

members jointly assessed their suitability and established the final analytical framework, which incorporated TWFE DiD, parallel-trends assessment, placebo testing, event study analysis, and the IV approach. An ownership-related hypothesis was also considered but removed because sufficient data were unavailable for reliable analysis.

Data Collection, Analysis, and Writing

All three members contributed to locating and collecting annual reports, financial statements, and other publicly available company information. Enzo coordinated the extraction of financial variables and their cross-checking against Wind, while all members reviewed the data and resolved discrepancies. Emmy and Jim led the coding and empirical calculations, with all three members participating in the interpretation and evaluation of the results.

The main challenges included learning unfamiliar econometric methods, translating mathematical specifications into code, identifying data inconsistencies, and troubleshooting models that initially failed. We addressed these issues through independent study, team discussions, repeated code testing, data cross-checking, and consultation with Ms. Lily when necessary. Records of our meetings and methodological learning are included in the supplementary materials.

For the first draft, each member wrote sections related to the methods they had studied most closely. Enzo contributed strongly to the written development and organization of the research, while Emmy and Jim contributed strongly to coding and quantitative implementation. The three members then integrated their respective contributions through several rounds of joint revision, with Emmy coordinating the consolidation of the sections and the final presentation of the report. She finalized the LaTeX typesetting, formatting, document structure, and overall presentation.

Use of Artificial Intelligence

We used GLM 5.2, ChatGPT 5.6 Sol, and DeepSeek V4 as supplementary tools throughout the research process. AI was used intermittently rather than continuously, primarily when a specific need arose. For example, when code produced an error or did not run as intended, we consulted AI tools to help identify possible causes, suggest debugging approaches, or clarify how a mathematical specification could be implemented in code.

Because we were initially relatively inexperienced with financial and econometric modelling, AI was also used during the methodological learning stage. We used it to help explain the concepts, assumptions, and implementation of different models, after which team members independently studied the methods further and presented what they had learned to one another. AI was also used intermittently for industry, policy,

and background research related to the semiconductor sector, the CHIPS Act, and the broader context of the study.

Thus, AI use varied according to the stage of the research and arose mainly in response to specific questions or problems, rather than according to a fixed schedule or frequency. Its principal uses included methodological learning, background research, small programming tasks, debugging, and troubleshooting.

AI did not determine our research question, theoretical framework, overall model selection, empirical conclusions, or interpretation of the results. The research logic and methodological decisions were developed by the three students. Any AI-generated explanations, code, or suggestions were reviewed, tested, and, where necessary, modified by us before being incorporated into the research process.

During AI-assisted work involving research models and code, we used available privacy or temporary “ghost” modes where applicable. Relevant AI-assisted conversations and records are retained in the supplementary materials (“Other Materials”) for transparency.