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Do publication metrics distort research effort? Bunching evidence from Thailand's 2019 higher-education reforms

by

Nattavudh Powdthavee

June 2026

Discussion Paper

No. 256

Do publication metrics distort research effort? Bunching evidence from Thailand's 2019 higher-education reforms

Nattavudh Powdthavee

Nanyang Technological University and IZA

Abstract

Many universities in middle-income countries lack the peer-review infrastructure to assess research quality directly and instead tie financial rewards to publication in journals classified as Q1 under the SCImago Journal Rank system. By converting continuously varying journal quality into discrete institutional categories, these systems create sharp incentive discontinuities at quartile boundaries. In a preregistered study, we apply a bunching estimator — a method from public finance that detects excess concentration of observations around institutionally salient thresholds — to 149,402 Scopus-indexed publications from Thailand over 2016–2025, exploiting Thailand's 2019 higher-education reform as a source of temporal variation. We find no significant bunching before 2019 but substantial excess concentration immediately above the Q1 boundary afterwards — a pattern not observed in Singapore, whose publication environment is not organised around explicit quartile-based financial rewards. The post-reform excess mass corresponds to roughly 1,575 additional publications over 2020–2025, implying an estimated 39 million THB (approximately US$1.1 million) in cumulative institutional expenditure. These findings indicate that discrete quartile-based reward systems redirect research effort towards threshold optimisation rather than research quality, and that replacing binary quartile rewards with continuous percentile-based incentives would better align institutional evaluation with scientific output.

Keywords: bunching estimation; publication metrics; journal quartile thresholds; higher education reform; Goodhart's law

Corresponding author: Nattavudh Powdthavee, Division of Economics, SHHK Building, Nanyang Technological University, 48 Nanyang Drive, Singapore, 639798. Email: nick.powdthavee@ntu.edu.sg.

1. Introduction

Across much of Asia and the Middle East, universities and ministries have adopted bibliometric evaluation systems that tie academic rewards directly to publication in journals classified as Q1 under the SCImago Journal Rank system. In Thailand, for example, a single Q1 publication can attract up to 500,000 THB (approximately US$15,000) in institutional publication support — more than double the support available for a Q2 publication in the same journal area. By converting continuously varying journal quality into discrete administrative categories, these systems create sharp incentive discontinuities at quartile boundaries that may redirect research effort towards optimising for administratively valuable publication targets rather than research quality itself. In a preregistered study of 149,000 Scopus-indexed publications from Thailand over 2016–2025, we find that Thailand's 2019 higher-education reform generated approximately 1,575 excess publications concentrated immediately above the Q1 boundary over 2020–2025 — roughly one in every six publications observed in that region of the distribution — implying cumulative institutional expenditure of around 39 million THB (approximately US$1.1 million) associated with publication activity that appears to have been strategically reallocated towards the Q1 threshold under the prevailing incentive structure. These findings suggest that the design of research evaluation systems has measurable consequences for how scientific effort is allocated, and that replacing discrete quartile rewards with more continuous percentile-based incentives could better align institutional evaluation with underlying research quality.

The adoption of bibliometric evaluation systems reflects a broader institutional problem confronting many universities and governments, particularly in middle-income countries: how to evaluate research quality at scale in the absence of the costly peer-review infrastructures used in systems such as the United Kingdom's Research Excellence Framework, which rely on extensive disciplinary expertise, administrative coordination, and political legitimacy (Hazelkorn, 2015; Altbach et al., 2009). Bibliometric systems are attractive partly because they transform a difficult evaluative problem into a transparent and administratively tractable metric that can be implemented without large-scale evaluative bureaucracies. Researchers may receive cash bonuses, salary increases, promotion credit, or KPI points for papers published in Scopus-indexed outlets, with rewards often scaled according to SCImago journal quartiles (Hicks, 2012; Franzoni et al., 2011; Quan et al., 2017). Yet the same simplification that makes metric-based systems administratively efficient may also reshape the behaviour they are intended to measure. Once indicators become targets for institutional rewards, organisations and individuals begin adapting strategically to the metrics themselves rather than to the underlying construct those metrics were originally designed to capture (Goodhart, 1984; Strathern, 1997).

Journal quartile systems create a particularly salient form of this dynamic. By converting what is fundamentally a continuous concept of research quality into discrete administrative categories linked to hiring, promotion, funding, and compensation decisions, they create what are effectively institutional notches: rewards change discontinuously at quartile boundaries even though underlying journal quality varies continuously (Espeland & Sauder, 2007; Muller, 2018). Under these conditions, academics need not optimise towards the highest-prestige journals. Instead, they may target the minimum journal quality required to cross an institutionally valuable classification boundary — a strategy that becomes especially attractive because journals near the lower edge of Q1 are often substantially more attainable than elite journals further up the distribution, while still satisfying institutional definitions of internationally competitive research. Publication behaviour in such environments may therefore be shaped not only by the pursuit of research quality itself, but also by attempts to maximise institutional returns relative to publication costs.

Thailand offers a particularly useful setting for examining this possibility. Across many Thai universities, publication metrics derived from Scopus and the SCImago Journal Rank system have become deeply embedded in promotion criteria, KPI systems, publication support schemes, and research evaluation exercises, with rewards varying explicitly by journal quartile in many institutions (Times Higher Education, 2023). The resulting incentive structure — large discrete rewards at the Q1 boundary combined with substantially lower barriers to publication in journals near that boundary than in globally elite outlets — creates precisely the conditions under which localised optimisation around publication thresholds would be expected to emerge.

A growing empirical literature confirms that academics respond strategically to journal evaluation systems. Śpiewanowski and Talavera (2021) show that UK economists became significantly less likely to publish in journals downgraded in the 2015 ABS ranking revision, while publication activity shifted towards upgraded journals. Hudson (2024) finds that journals receiving favourable revisions in the Academic Journal Guide attracted disproportionately large increases in UK-authored business-school publications over 2011–2021. Evidence from China points in the same direction: using a difference-in-differences design, Sun et al. (2024)

show that downgrades in the Chinese Journal Ranking led to substantial declines in publication activity in affected journals. Taken together, these studies establish that publication behaviour responds to institutional classification systems rather than solely to underlying research quality or disciplinary fit.

At the same time, the existing literature relies largely on discrete ranking revisions as its source of identification — an approach well suited to detecting responses to classification changes, but less informative about whether stable evaluation systems generate persistent and cumulatively important distortions in publication behaviour even in the absence of reform. In many countries, quartile-based publication incentives have operated for years under relatively fixed classification structures, allowing academics and institutions to adapt gradually to the incentive environment. Our paper examines whether such adaptation leaves detectable and economically meaningful signatures in the distribution of publications itself.

To do so, we apply the bunching estimator developed by Chetty et al. (2011) — originally used in public finance to detect behavioural responses to tax notches — to Scopus publication data. We exploit Thailand's 2019 higher-education reform as a source of temporal variation and use Singapore, whose publication environment relies substantially less on explicit quartile-based financial rewards, as a comparative benchmark.

The paper makes two contributions relevant to the design of research evaluation systems. First, it provides direct quantitative evidence that discrete quartile-based reward structures generate measurable localised optimisation around publication-classification boundaries — a distortion that becomes embedded in the distribution of scientific output and intensifies over time even without further policy change. More broadly, the findings suggest that discontinuous reward systems may generate allocative distortions because institutional incentives change sharply at classification boundaries while underlying journal quality varies continuously. Second, the paper demonstrates that the scale of this distortion is policy relevant: the estimated excess mass around Thailand's Q1 boundary implies cumulative institutional expenditure of approximately US$1.1 million over five years associated with publication activity strategically concentrated near the threshold. The implications extend beyond Thailand: any university system that ties material rewards to discrete journal-classification boundaries faces the same underlying incentive structure, and potentially the same behavioural response.

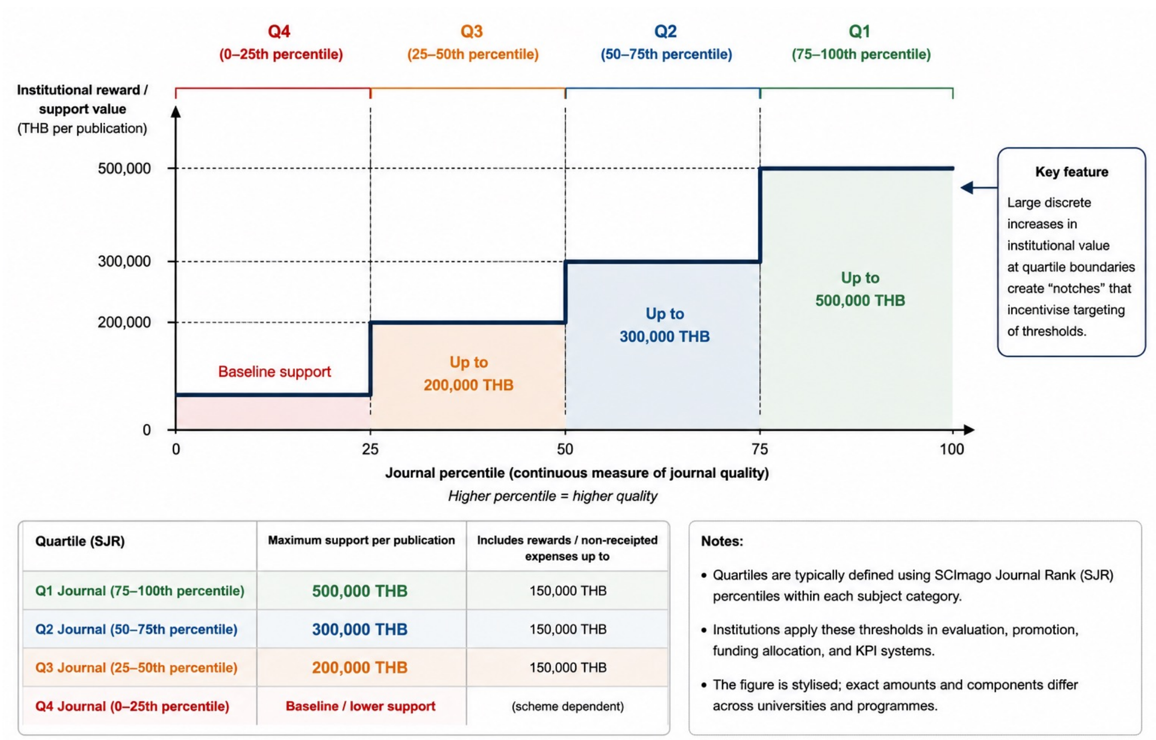
2. Institutional background

2.1 Quartile-based evaluation systems in Thai higher education

Over the past two decades, bibliometric indicators have become increasingly embedded in university evaluation systems across Thailand. Rather than relying primarily on labour-intensive peer review, many universities assess research performance using publication metrics from international indexing databases such as Scopus and the SCImago Journal Rank (SJR) system. In practice, journal quartile classifications are often incorporated into promotion criteria, KPI systems, publication support schemes, and internal research evaluations.

The growing reliance on quartile-based publication metrics coincided with intensified global competition in higher education. International university rankings increasingly incorporate bibliometric indicators and publication visibility into institutional assessments, creating pressure for universities to expand internationally indexed research output (Hazelkorn, 2015). In many rapidly internationalising university systems, quartile-based publication metrics therefore emerged not only as tools for internal evaluation but also as mechanisms to improve institutional visibility in global ranking systems. As these metrics became embedded in promotion criteria, KPI systems, and publication support schemes, journal quartiles evolved from descriptive bibliometric indicators into administratively consequential categories within university governance.

For simplistic administrative purposes, these systems often mechanically assign discrete institutional value to quartile categories rather than treating journal quality as continuous. Figure 1 illustrates a stylised example of how publication-related rewards may vary discontinuously across quartile boundaries under such systems. For example, Chulalongkorn University's publication support scheme allocates substantially different levels of support according to the SJR quartile classification, with support ceilings of 500,000 THB (approximately US$15,000) for Q1 publications, 300,000 THB (approximately US$9,000) for Q2 publications, and 200,000 THB (approximately US$6,000) for Q3 publications. These schemes combine research support, reimbursable expenditures, and publication-related reward components tied to quartile classifications. Similarly, Mahidol University's research administration guidelines explicitly operationalise "Q1" status using the SCImago Journal Rank classification system in publication-related support and evaluation procedures.



Quartile (SJR)	Maximum support per publication	Includes rewards / non-receipted expenses up to
Q1 Journal (75–100th percentile)	500,000 THB	150,000 THB
Q2 Journal (50–75th percentile)	300,000 THB	150,000 THB
Q3 Journal (25–50th percentile)	200,000 THB	150,000 THB
Q4 Journal (0–25th percentile)	Baseline / lower support	(scheme dependent)

Figure 1. Stylised institutional reward structure under quartile-based evaluation systems. *Continuous journal quality is converted into discrete administrative reward tiers, generating institutional "notches" at quartile boundaries.* The figure illustrates how quartile-based evaluation systems may transform a continuous distribution of journal quality into discrete institutional reward categories. The stepwise reward structure is stylised but reflects common features of publication incentive schemes used in Thai universities, where journal quartiles derived from the SCImago Journal Rank (SJR) system are incorporated into research evaluation, promotion, and publication support mechanisms. Reward magnitudes shown in the figure are illustrative and based on publicly available institutional support schedules. **Source:** Adapted from publication support schemes and research evaluation guidelines from Thai universities, including Chulalongkorn University (https://grantgateway.research.chula.ac.th/www/Home/program?id=69267f5a790f9b3f5c000001) and Mahidol University (https://op.mahidol.ac.th/ra/contents/research_regulation/ANNOUNCE_PUB-2568_ENG.pdf).

Under such systems, quartile boundaries create discontinuous incentives: the return to a one-percentile improvement that crosses a Q1/Q2 threshold far exceeds the return to an equivalent improvement within a quartile, despite no discontinuity in underlying journal quality at that point. Hence, quartile classifications function not merely as descriptive rankings but as administratively salient thresholds embedded within university governance systems.

2.2 Thailand's 2019 higher-education reform and the intensification of metric-based evaluation

Thailand's growing reliance on publication-based evaluation systems must also be understood against the backdrop of the broader restructuring of the country's higher education and research sector in the late 2010s. In 2019, Thailand established the Ministry of Higher Education, Science, Research and Innovation (MHESI), consolidating previously separate higher education, science, and national research funding agencies into a unified governance structure. The reform was part of the broader Thailand 4.0 strategy to strengthen research capacity, innovation, and international competitiveness in the higher education sector (NXPO, 2022; MHESI, 2026).

Policy documents associated with the reform repeatedly emphasised internationally visible research output, university rankings, research performance monitoring, and globally competitive scientific production as central objectives of the new governance framework. The reform also coincided with growing institutional pressure on universities to increase internationally indexed publication output and enhance research visibility within global ranking systems. As a result, bibliometric indicators, particularly publication metrics derived from Scopus-indexed journals, became increasingly central to institutional evaluation and performance assessment across many universities.

It is important to note that the reform did not introduce publication incentives from scratch. Incentives linked to publication and bibliometric evaluation systems were already well established in Thai universities before 2019. Instead, the reform seems to have strengthened and intensified existing, metric-focused governance structures across the sector. Before the reform, institutions often prioritised increasing publication output in internationally indexed journals, including a shift from non-indexed or lower-visibility journals to Scopus-indexed outlets. Over time, however, the focus appears to have shifted towards differentiating among indexed journals, especially emphasising Q1 publications as clear indicators of internationally competitive research.

This distinction is important for interpreting the empirical patterns examined later in the paper. If publication incentives primarily encouraged indexed publication output, publication activity might be expected to cluster more broadly around lower inclusion thresholds associated with international indexing. By contrast, if institutional incentives increasingly prioritise differentiation by publication quality within indexed systems, publication activity may become more strongly concentrated around the Q1 boundary. The post-2019 period thus provides a useful setting for examining whether publication distributions became increasingly organised around higher-status publication thresholds under intensified metric-based evaluation pressures.

2.3 Publication thresholds and optimisation under metric governance

Quartile-based publication systems create a mismatch between how journal quality varies and how universities reward publications. In practice, journal quality changes gradually across the publication distribution, yet institutional evaluation systems often convert these continuous differences into discrete categories such as Q1, Q2, or Q3, with materially different consequences attached to crossing these thresholds (Espeland & Stevens, 1998). A paper published just above the Q1 boundary may therefore receive substantially greater institutional value than one published just below it, even when the underlying difference in journal standing is relatively small.

All the while, publishing in higher-ranked journals has become increasingly difficult. Top journals tend to have lower acceptance rates, longer review times, higher methodological expectations, and greater research costs. Importantly, these costs do not rise smoothly across the journal hierarchy. Journals near the lower edge of Q1 are often far more attainable than elite journals at the very top of the distribution, while still meeting institutional definitions of internationally excellent research.

As a result, academics may not necessarily optimise by targeting the highest-prestige journals. Instead, they may aim for the minimum journal quality required to meet institutionally valuable thresholds. When rewards change discretely at quartile boundaries but publication difficulty rises sharply further up the ranking distribution, publication activity may cluster around these thresholds. More broadly, once publication metrics become institutional targets, academics and universities may increasingly adapt their behaviour to the metrics themselves rather than to the underlying construct the metrics were originally intended to capture (Goodhart, 1984; Burrows, 2012; Muller, 2018).

Different incentive systems are therefore likely to shift publication activity across the journal distribution. Systems that primarily aim to increase internationally indexed output may generate concentration near lower indexing thresholds. By contrast, systems that place greater emphasis on publication-quality differentiation within indexed journals may generate stronger concentration at higher-status thresholds, particularly the Q1 boundary (Quan et al., 2017).

We examine this possibility using the bunching framework developed by Chetty et al. (2011), which identifies whether publication activity clusters unusually strongly around institutionally important thresholds relative to an otherwise smooth distribution.

3. Data and empirical strategy

3.1. Data sources and sample construction

The analysis combines publication-level data from Scopus with annual journal-ranking information from the SCImago Journal Rank (SJR) database. Publication records were collected via the Scopus Search API for the period 2016–2025. Following the preregistered sampling strategy, publications were retrieved separately by country, year, and broad subject classification using the Scopus ASJC subject categories. The paper's primary empirical focus is Thailand, although comparable publication data were also collected for Singapore and Malaysia for comparative analyses discussed later in the paper.

For each country-year-subject combination, the Scopus API was queried for journal articles with at least one author affiliated with the relevant country. Retrieved records included publication identifiers, journal titles, Scopus source identifiers, publication year, and subject classifications. Because journals may appear in multiple subject categories and API queries can overlap across categories, publication records were deduplicated using unique Scopus publication identifiers.

The publication records were then merged with annual SCImago Journal Rank (SJR) datasets, downloaded directly from the SCImago website for each year between 2015 and 2025. These datasets provide annual journal quartiles and percentile rankings based on citation performance within subject categories. Journals were matched using Scopus source identifiers and related journal metadata. Using annual SCImago rankings allows the analysis to reflect the contemporaneous quartile classifications observed by universities and academics when publication decisions were made.

The study was preregistered on the Open Science Framework (OSF) before analysis: https://osf.io/qdz5s/overview?view_only=bc253afd31fd47ed86db4343ebea9438. One important deviation from the preregistration concerns the construction of the running variable. The preregistration proposed ranking journals within broad ASJC categories using the study sample itself. However, this procedure produced substantial disagreement with the official SCImago quartile classifications used by universities in practice. Hence, the final analysis uses the official SCImago best-category percentile, which corresponds directly to institutional quartile assignments. This change improves alignment between the empirical design and the actual incentive thresholds faced by academics.

Table 1 presents descriptive statistics for the analytic publication sample. After deduplication and journal-matching procedures, the final dataset comprises publication records from Thailand (N=183,419), Singapore (N=174,679), and Malaysia (N=269,084) for the 2016–2025 period. The vast majority of observations were successfully matched to annual SCImago journal-ranking records. The table also reports the distribution of matched publications across journal quartiles. Consistent with the expansion of internationally indexed publication output during the sample period, Q1 journals account for the largest share of publications in all three countries, although the distribution across quartiles varies considerably across national systems and over time.

Table 1: Descriptive statistics

Country	Raw Records	Unique Publications	Matched to SCImago	Match Rate (%)	Q1 Count	Q1 %	Q2 Count	Q2 %	Q3 Count	Q3 %	Q4 Count	Q4 %
Thailand	186,115	183,419	149,402	80.3	71,736	48.0	39,173	26.2	25,997	17.4	12,496	8.4
Singapore	176,166	174,679	149,457	84.8	120,725	80.8	19,840	13.3	6,825	4.6	2,067	1.4
Malaysia	274,581	269,084	224,860	81.9	86,646	38.5	60,462	26.9	50,002	22.2	27,750	12.3

Note: Q1–Q4 refer to SCImago Journal Rank quartiles. Percentages are computed using matched publications. Source: Scopus API: https://dev.elsevier.com/documentation/ScopusSearchAPI.wadl. The number of publications for Malaysia is slightly underestimated, as we were able to retrieve only 5,000 papers per field per year, whereas some fields, such as computer science, have around 6,000 papers per year. There were no problems collecting Thai and Singaporean data.

3.2. Journal quartiles and running variable

The central running variable in the analysis is the journal percentile ranking used to classify journals into quartiles within the SCImago Journal Rank (SJR) system. SCImago assigns journals to one or more subject categories and reports both percentile rankings and quartile classifications for each category. Universities and research evaluation systems typically refer directly to the official SCImago quartile classification rather than constructing alternative percentile measures from institution-specific publication samples.

A key complication is that many journals belong to multiple subject categories simultaneously. Under the SCImago system, a journal's publicly reported quartile classification corresponds to its best-performing category rather than an average across categories. Consequently, institutional incentives tied to Q1 publication targets are generally linked to the journal's official best-category quartile assignment.

To align the empirical design with the incentive structure faced by academics, the analysis defines the running variable using the official SCImago best-category percentile for each journal-year observation. Quartile thresholds correspond to the standard SCImago percentile cutoffs: Q1 journals occupy the top 25% of journals within a category, Q2 the next 25%, and so forth.

This differs from the procedure originally proposed in the preregistration, which constructed percentile rankings within broad ASJC subject groupings using the study sample itself. In practice, however, this approach produced substantial disagreement with the official SCImago quartile classifications used by universities in evaluation systems and publication incentive schemes. Because the institutional mechanism examined in this paper depends on the thresholds actually observed by academics and universities, the final specification instead uses the official SCImago best-category percentile directly. Figure A1 in the Appendix plots the distribution of the official SCImago best-category percentile running variable across the three country samples and illustrates the institutional quartile cutoffs used throughout the analysis.

3.3 Bunching estimation strategy

The empirical analysis examines whether publication activity clusters disproportionately around institutionally salient journal-quality thresholds. To do so, the paper applies the bunching framework developed by Chetty et al. (2011), which identifies excess concentration of observations around a threshold relative to an estimated smooth counterfactual distribution. The analysis focuses primarily on the Q1/Q2 boundary, corresponding to the 75th percentile cutoff in the SCImago ranking system. Under the institutional interpretation developed in Section 2, disproportionate concentration immediately above this threshold may reflect strategic optimisation around publication targets tied to Q1 journal classifications.

Formally, let c denote the running variable (the official SCImago best-category percentile), and let n_j denote the number of publications in the percentile bin j. The counterfactual distribution is estimated by fitting a pth-order polynomial to the observed publication density outside the excluded region centred on the threshold $c^* = 75$:

$$\hat{n}_j = \sum_{k=0}^{p} \beta_k\, c_j^k + \sum_{i=c_L}^{c_H} \gamma_i\, \mathbf{1}\left[c_j = i\right] + \varepsilon_j$$

where the summation $\sum_{i=c_L}^{c_H}$ excludes bins within the bunching window $[c_L, c_H]$ around the threshold from the polynomial fit, and $\mathbf{1}\left[c_j = i\right]$ are indicators for each excluded bin. The fitted values $\hat{n}_j$ from this regression provide the estimated counterfactual counts in each bin, including within the excluded region.

The bunching coefficient is then defined as the excess mass around the threshold relative to the estimated counterfactual density at the cutoff:

$$b = \frac{B}{\hat{n}_{c^*}}$$

where $B = \sum_{j=c_L}^{c_H}\left(n_j - \hat{n}_j\right)$ is the total excess mass within the bunching window, and $\hat{n}_{c^*}$ is the estimated counterfactual count at the threshold bin. A coefficient of $b = 1$ indicates that the number of publications in the bunching window is twice what would be expected under the smooth counterfactual — that is, 100% excess concentration relative to the baseline. Standard errors are obtained by bootstrapping the full estimation procedure 500 times, resampling publications with replacement within each percentile bin.

Unlike standard regression discontinuity designs, the bunching literature lacks a universally accepted optimal bandwidth or polynomial-order selection procedure. In response to broader concerns about high-order polynomial fitting in discontinuity-based estimation (Gelman & Imbens, 2019), the main specification adopts a fourth-order polynomial ($p = 4$) fitted locally within the 60–90 percentile range around the Q1 threshold ($c_L = 70$, $c_H = 80$). The bunching window excludes observations within five percentile points of the threshold when estimating the counterfactual distribution, thereby preventing the heavily skewed upper tail of the publication distribution from distorting the counterfactual fit. To assess robustness, the analysis evaluates alternative polynomial orders $p \in \{3,4,5,6,7\}$ and three alternative fitting windows (55–95, 60–90, 65–85); results are reported in Figure A2 in the Appendix. The paper also reports supplementary analyses for the Q2/Q3 boundary and exploratory comparisons of Singapore and Malaysia.

3.4 Hypotheses

We pre-registered the following confirmatory hypotheses.

- **H1:** Publication activity in Thailand exhibits excess concentration around the Q1/Q2 boundary.
- **H2:** Q1-boundary bunching in Thailand intensified after the 2019 reform period.
- **H3:** The post-2019 increase in Q1-boundary bunching is larger in Thailand than in Singapore.
- **H4:** Within Thailand, bunching is stronger in disciplinary publication environments characterised by greater metric salience and publication-oriented evaluation pressures.

In addition to the confirmatory analyses, the paper reports three exploratory analyses. First, the paper examines publication concentration within the top 5% of Q1 journals to distinguish threshold-oriented publication behaviour from broader prestige concentration in the upper tail of the journal distribution. Second, the paper evaluates whether similar threshold concentration patterns emerge around the Q2/Q3 boundary. Third, the paper reports comparative evidence for Malaysia, where publication-oriented KPI systems and internationally indexed publication targets have also become increasingly important within university evaluation systems, although without a discrete institutional reform directly comparable to Thailand's 2019 restructuring.

4. Results

4.1. Q1-threshold bunching in Thailand

Figure 2 presents the main pooled bunching analysis for Thailand over the 2016–2025 period. Consistent with H1, publication activity shows a visible excess concentration immediately above the Q1/Q2 boundary, corresponding to the 75th-percentile cutoff in the SCImago ranking system.

H1: Thailand Q1/Q2 bunching, pooled across all years

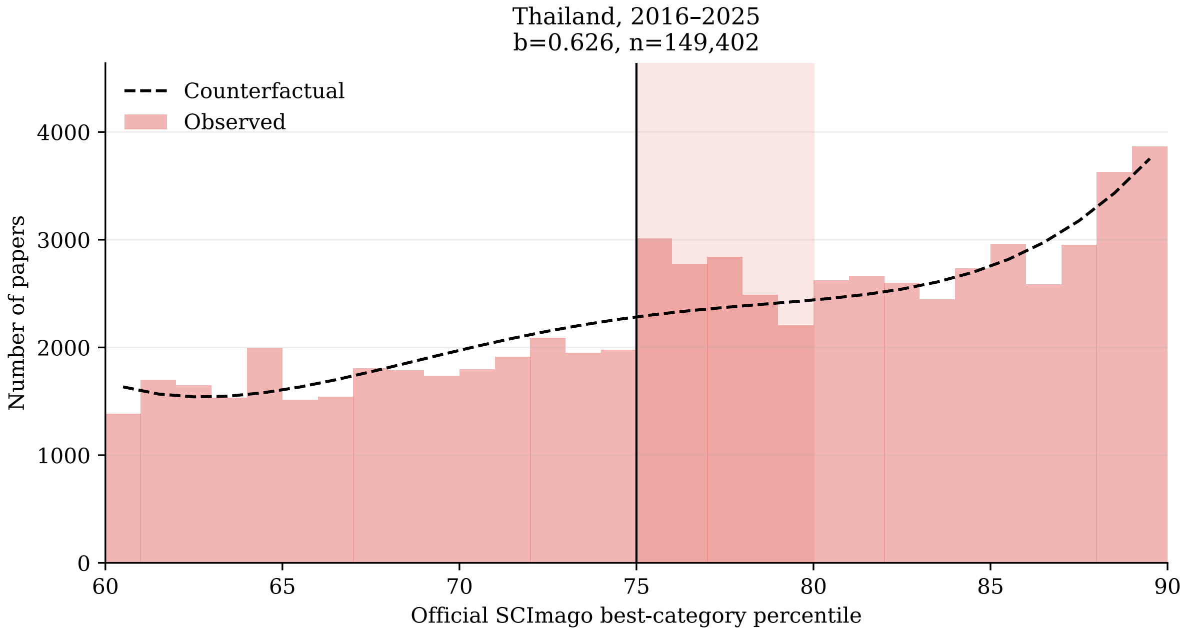


Figure 2. Q1/Q2 bunching in Thailand, pooled across 2016-2025. The figure plots the distribution of publications across official SCImago best-category percentiles for Thailand over the 2016–2025 period. The vertical line indicates the Q1/Q2 cutoff at the 75th percentile. Bars represent observed publication counts, while the dashed line shows the estimated smooth counterfactual distribution obtained from the main bunching specification using a fourth-order polynomial fitted locally within the 60–90 percentile range, excluding observations within five percentile points of the threshold during estimation.

Using the main specification — a fourth-order polynomial fitted locally within the 60–90 percentile range — the estimated bunching coefficient is b = 0.626 (SE = 0.103, z = 6.09, 95% CI [0.424, 0.828]). In practical terms, this means that the number of publications appearing immediately above the Q1 threshold is approximately 62.6% higher than would be expected under a smooth counterfactual distribution without threshold concentration.

The estimated excess mass corresponds to approximately 1,483 additional publications concentrated within five percentile points above the Q1 cutoff, relative to the estimated counterfactual distribution. This represents roughly 11% of all publications in the narrow 75–80 percentile interval and approximately 2.1% of all Q1 publications in the Thai sample. Put differently, if publication activity were distributed smoothly in the absence of strong threshold salience, roughly one out of every nine publications currently observed immediately above the Q1 boundary would instead be expected to fall elsewhere in the journal-quality distribution.

More importantly, the observed pattern reflects a local excess concentration near the Q1 boundary rather than a smooth increase in publication activity across progressively higher-ranked journals. If the results merely reflected a broad preference for publishing in more prestigious journals, publication density would be expected to rise gradually and continuously across the upper tail of the distribution. Instead, the publication distribution exhibits a distinct local spike immediately above the 75th percentile cutoff, while the counterfactual distribution tracks the observed density relatively closely outside the excluded bunching region.

It is also crucial to note that journals immediately on either side of the Q1 threshold are often similar in underlying quality, visibility, and citation performance. Small differences in percentile ranking can nevertheless place journals in different quartile categories, with potentially important institutional consequences. Hence, the observed discontinuity appears concentrated around the institutional classification boundary itself rather than reflecting large underlying differences in journal quality.

In other words, the discontinuity appears concentrated specifically around the institutional Q1 threshold rather than across the entire prestige hierarchy. This pattern is therefore more consistent with threshold-oriented publication behaviour tied to quartile classification than with general prestige concentration alone.

4.2 Intensification of Q1-threshold bunching after 2019

Figure 3 compares Thailand's publication distribution before and after the 2019 reform period. The results reveal a marked change in publication concentration around the Q1 boundary between the two periods.

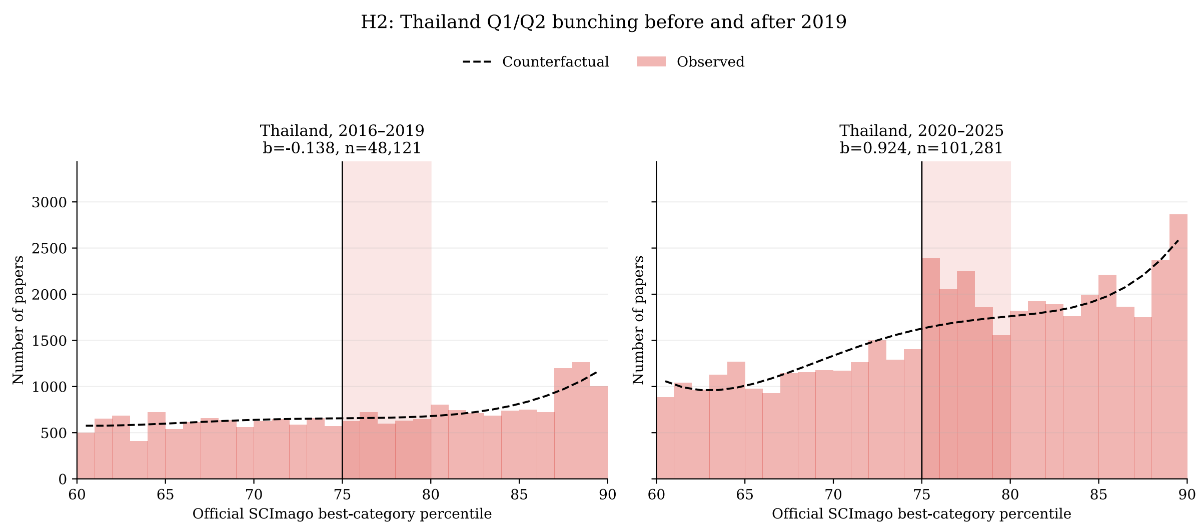


Figure 3. Q1/Q2 bunching in Thailand before and after 2019. The figure compares the distribution of publications across official SCImago best-category percentiles in Thailand before (2016–2019) and after (2020–2025) the 2019 reform period. The vertical line indicates the Q1/Q2 cutoff at the 75th percentile. Bars represent observed publication counts, while the dashed line shows the estimated smooth counterfactual distribution obtained from the main bunching specification using a fourth-order polynomial fitted locally within the 60–90 percentile range, excluding observations within five percentile points of the threshold during estimation.

During the pre-reform period (2016–2019), the estimated bunching coefficient is small and statistically indistinguishable from zero (b = -0.138, SE = 0.176, z = -0.78, 95% CI [-0.483, 0.207]). The publication distribution during this period appears relatively smooth around the Q1 cutoff, with little evidence of disproportionate concentration immediately above the threshold.

By contrast, the post-reform period (2020–2025) exhibits substantial and statistically significant bunching around the Q1 boundary. The estimated bunching coefficient increases to b = 0.924 (SE = 0.125, z = 7.41, 95% CI [0.679, 1.169]), implying that publication activity immediately above the Q1 cutoff is approximately 92.4% higher than would be expected under the estimated smooth counterfactual distribution without threshold concentration. This appears consistent with H2.

The estimated excess mass in the post-2019 period corresponds to approximately 1,575 additional publications, concentrated within five percentile points above the Q1 threshold relative to the estimated counterfactual distribution. This represents approximately 15.6% of all publications in the narrow 75–80 percentile interval and roughly 3.2% of all Q1 publications in Thailand during the post-2019 period. Put differently, in the absence of a strong threshold concentration, roughly one out of every six publications currently observed immediately above the Q1 boundary would instead be expected to fall elsewhere in the journal-quality distribution.

The difference between the two periods is itself statistically large. The estimated post-pre change in the bunching coefficient is 1.062 (SE = 0.216, z = 4.92, 95% CI [0.639, 1.485]). This indicates that the local concentration of publications around the Q1 threshold increased substantially after the reform period.

As with the pooled sample, the post-2019 pattern appears highly localised around the Q1 boundary rather than showing a smooth increase across the broader upper tail of the journal distribution. Journals immediately on either side of the Q1 cutoff are often similar in underlying quality and visibility, yet crossing the quartile boundary may entail substantially different institutional consequences. The results are therefore more consistent with the growing salience of quartile classification itself than with a general increase in preference for publishing in higher-ranked journals.

4.3 Difference-in-differences comparison: Thailand versus Singapore

Figure 4 compares changes in Q1-threshold bunching in Thailand and Singapore before and after 2019. Here, we see that the results reveal markedly different publication patterns between the two countries. As shown previously, Thailand exhibits little evidence of bunching before 2019 (b = -0.138, SE = 0.176) but substantial positive bunching after 2019 (b = 0.924, SE = 0.125). The estimated post-pre change in Thailand is therefore large and statistically significant (Δb = 1.062, SE = 0.216, z = 4.92, 95% CI [0.639, 1.485]).

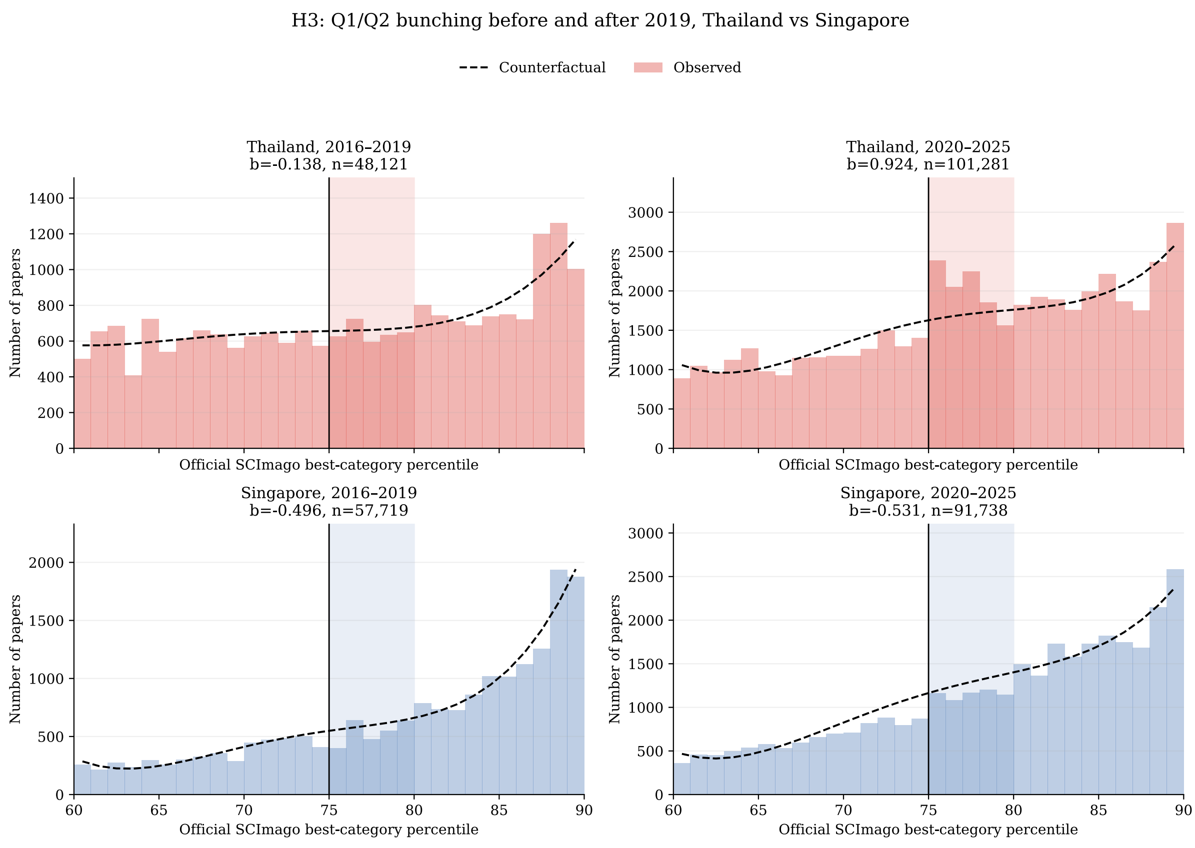


Figure 4. Q1/Q2 bunching before and after 2019: Thailand versus Singapore. The figure compares the distribution of publications across official SCImago best-category percentiles in Thailand and Singapore before (2016–2019) and after (2020–2025) the 2019 reform period. The vertical line indicates the Q1/Q2 cutoff at the 75th percentile. Bars represent observed publication counts, while the dashed line shows the estimated smooth counterfactual distribution obtained from the main bunching specification using a fourth-order polynomial fitted locally within the 60–90 percentile range, excluding observations within five percentile points of the threshold during estimation.

Singapore, by contrast, exhibits no comparable increase in bunching across the two periods. The estimated bunching coefficients remain negative both before 2019 (b = -0.496, SE = 0.174, 95% CI [-0.837, -0.155]) and after 2019 (b = -0.531, SE = 0.108, 95% CI [-0.743, -0.320]). The estimated post-pre change is correspondingly close to zero (Δb = -0.035, SE = 0.205, z = -0.17, 95% CI [-0.437, 0.367]).

Most importantly, the difference between the Thai and Singaporean post-pre changes is substantial and statistically significant. The estimated difference-in-differences coefficient is 1.097 (SE = 0.298, z = 3.69, 95% CI [0.513, 1.681); see Figure 5. This indicates that the increase in local publication concentration around the Q1 threshold after 2019 was significantly larger in Thailand than in Singapore, consistent with H3.

The visual patterns in Figure 4 further illustrate the institutional distinction between the two systems. In Thailand, publication density shows a clear local spike immediately above the Q1 boundary after 2019. In Singapore, by contrast, publication activity rises relatively smoothly across the upper tail of the journal distribution both before and after 2019, with no evidence of disproportionate local concentration around the Q1 cutoff. The Thai discontinuity thus provides further support for the interpretation that publication behaviour after 2019 became increasingly shaped by quartile classification rather than by a general preference for more prestigious journals.

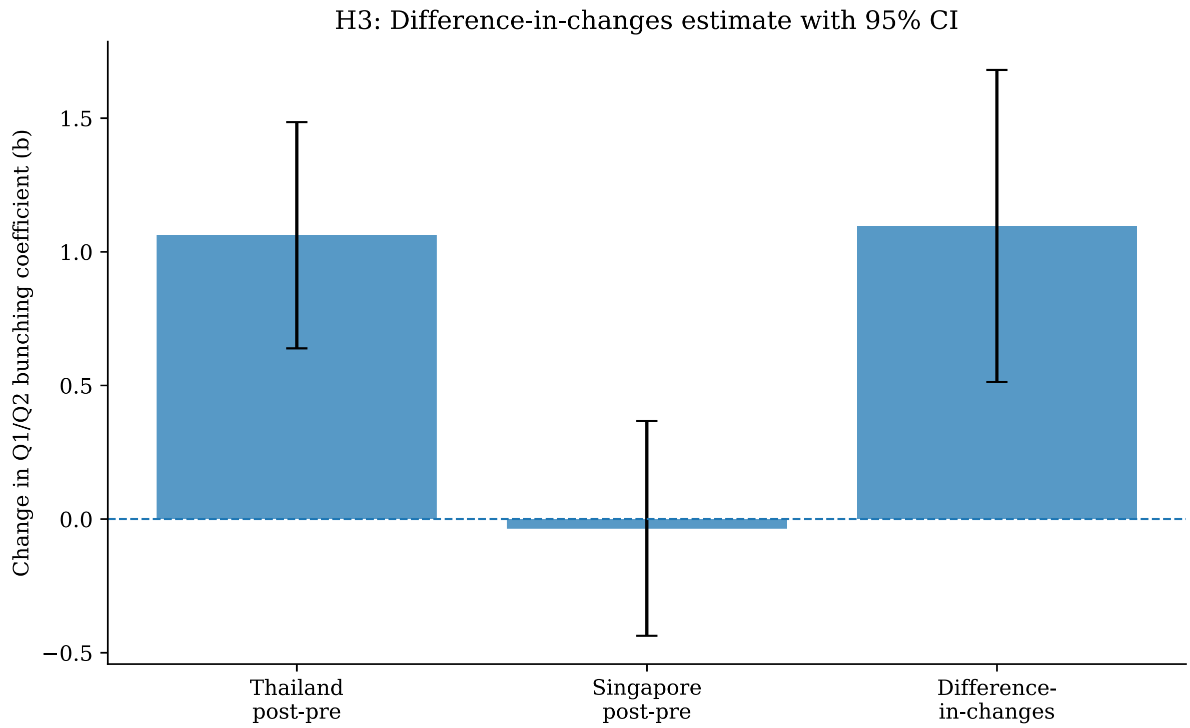


Figure 5. Difference-in-differences estimate: Thailand versus Singapore, post-2019. The figure plots the estimated difference-in-differences coefficient comparing the post-2019 change in Q1-threshold bunching in

Thailand with that in Singapore. The point estimate and 95% confidence interval are obtained from the main bunching specification by fitting a fourth-order polynomial locally within the 60–90 percentile range. A positive coefficient indicates that the increase in local publication concentration around the Q1 boundary after 2019 was larger in Thailand than in Singapore.

4.4 Heterogeneity across disciplinary publication environments

Figure 6 examines heterogeneity in Q1-threshold bunching across broad disciplinary publication environments within Thailand. Both field groupings exhibit positive excess concentration around the Q1 boundary, although the estimated magnitude differs across groups.

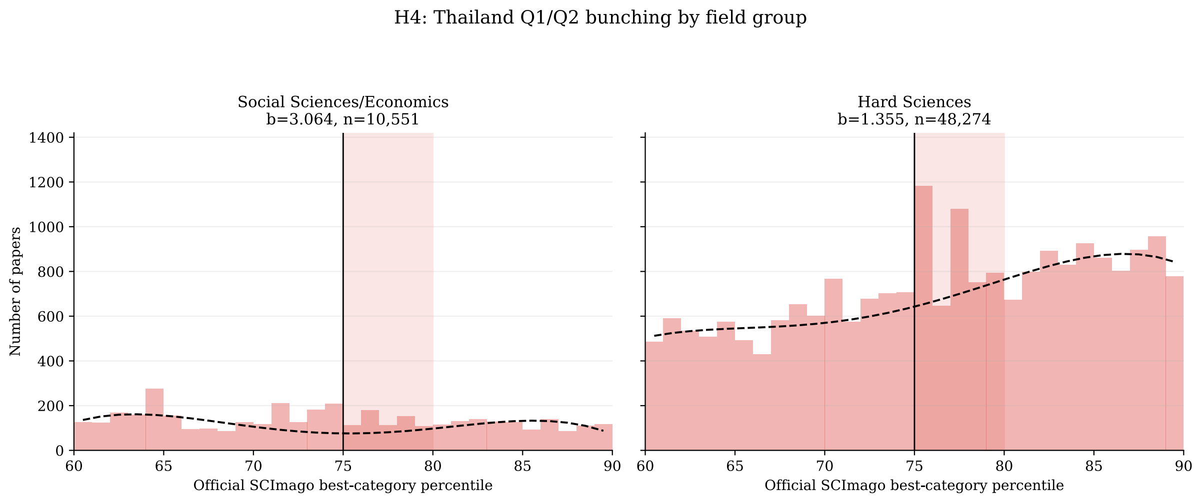


Figure 6. Q1/Q2 bunching by disciplinary field group in Thailand. The figure compares Q1/Q2 bunching patterns across two broad disciplinary field groups in Thailand over the 2016–2025 period: Social Sciences/Economics and Hard Sciences. The vertical line indicates the Q1/Q2 cutoff at the 75th percentile in the official SCImago best-category percentile distribution. Bars represent observed publication counts, while the dashed line shows the estimated smooth counterfactual distribution obtained from the main bunching specification using a fourth-order polynomial fitted locally within the 60–90 percentile range, excluding observations within five percentile points of the threshold during estimation.

For the Social Sciences/Economics grouping, the estimated bunching coefficient is b = 3.064 (SE = 1.046, z = 2.93, 95% CI [1.014, 5.114]). The estimated excess mass corresponds to approximately 253 additional publications concentrated immediately above the Q1 threshold relative to the estimated counterfactual distribution. However, the estimate is substantially noisier than the corresponding estimate for the Hard Sciences due to the smaller sample size and lower underlying publication density near the threshold. Although the results suggest a local concentration around the Q1 boundary, the estimated magnitude should be interpreted with caution.

The Hard Sciences grouping also exhibits substantial positive bunching around the Q1 threshold. The estimated coefficient is b = 1.355 (SE = 0.222, z = 6.10, 95% CI [0.920, 1.790]), corresponding to approximately 950 excess publications concentrated within the threshold region relative to the estimated counterfactual distribution. Visually, the publication distribution in the Hard Sciences exhibits a clearer and more stable local spike immediately above the Q1 boundary.

H4 predicted that bunching would be stronger in the Social Sciences/Economics fields than in the Hard Sciences. The point estimate for the between-group difference is positive and in the predicted direction (b_diff = 1.709, SE = 1.069, z = 1.60, 95% CI [−0.386, 3.804]), but does not reach conventional levels of statistical significance. There are two distinct reasons why H4 cannot be accepted on the current evidence. First, the Social Sciences/Economics estimate carries a standard error nearly five times larger than its Hard Sciences counterpart, a direct consequence of the smaller publication base and sparser density near the threshold. This asymmetry directly propagates into the between-group comparison, inflating its standard error and widening the confidence interval to nearly 4 units. Second, and relatedly, the test of H4 is severely underpowered in this grouping: the sample size is insufficient to reliably detect between-group differences even if they exist in the population. The failure to reject the null should therefore not be interpreted as evidence that bunching intensities are similar across fields — only that the Social Sciences/Economics data do not provide enough information to resolve the comparison. A replication with a larger Social Sciences/Economics sample, or a longer observation window that accumulates more publications near the threshold, would be needed to test H4 conclusively.

Taken together, the results establish that threshold-oriented publication behaviour is present in both disciplinary domains. The question of whether it is more pronounced in fields where individual papers and journal placements carry greater career weight — as H4 predicted — remains open.

4.5 Exploratory analyses

4.5.1 Concentration within the top 5% of Q1 journals

Figure 7 compares the share of Q1 publications in journals within the top 5% of the SCImago percentile distribution across Thailand, Singapore, and Malaysia before and after 2019. The patterns differ markedly from the main Q1-threshold bunching results. Singapore shows substantially greater concentration in the extreme upper tail of the journal distribution than

Thailand does in both periods, with a considerably larger share of Q1 publications in top-5% journals, consistent with increased bunching of published papers immediately above the Q1/Q2 boundary post-2019. Malaysia occupies an intermediate position between the two countries.

It is worth noting that these upper-tail prestige patterns contrast with the earlier bunching results around the Q1 threshold. Whereas Thailand exhibited the strongest post-2019 increase in local concentration immediately above the Q1 boundary, Singapore appears substantially more concentrated in the extreme upper tail of the publication distribution. This distinction suggests that threshold-oriented publication behaviour and broader prestige concentration are analytically distinct publication patterns.

Figure 7's results are consistent with the hypothesis that Thailand's publication environment became increasingly shaped by incentives tied to quartile classification thresholds, whereas Singapore's system appears more consistent with continuous prestige competition across the upper tail of the journal hierarchy. In other words, despite the absence of clear financial incentives per publication, Singapore appears to show greater concentration in globally elite journals, without a corresponding local concentration immediately above the Q1 boundary.

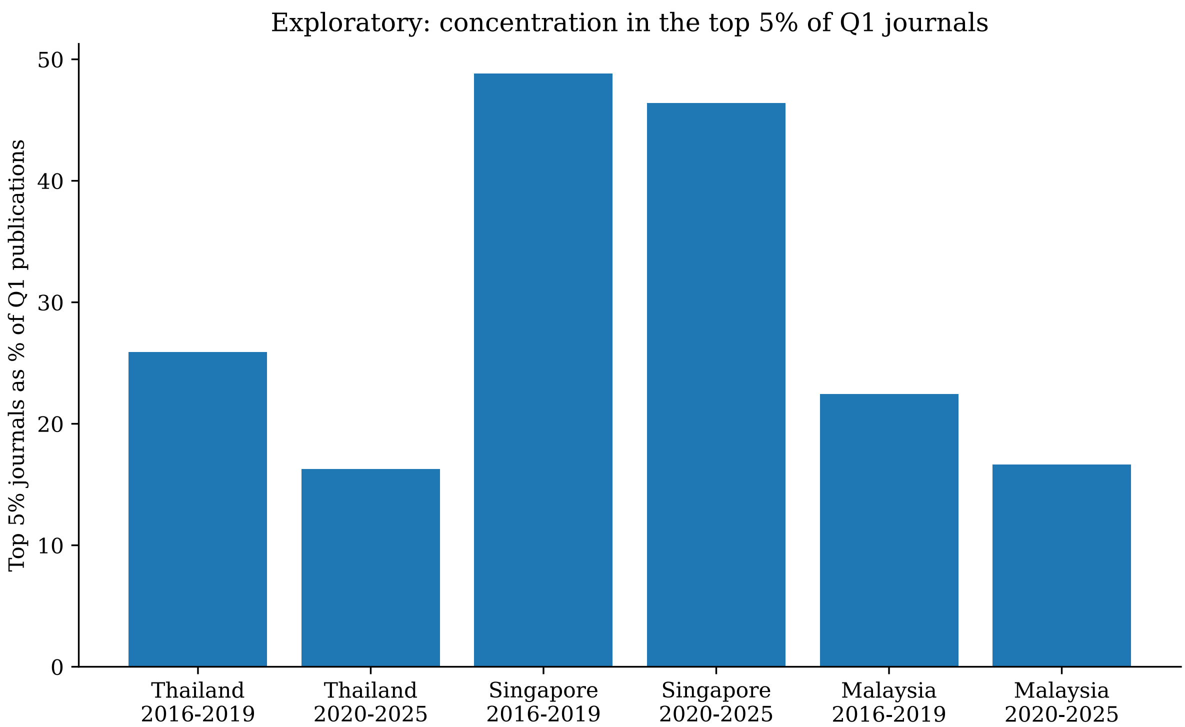


Figure 7. Concentration within the top 5% of Q1 journals across Thailand, Singapore, and Malaysia. The figure reports the share of Q1 publications appearing in journals located within the top 5% of the official SCImago best-category percentile distribution across Thailand, Singapore, and Malaysia before (2016–2019) and after

(2020–2025) 2019. Higher values indicate greater concentration of publication activity within the extreme upper tail of the journal distribution.

4.5.2 The Q2/Q3 threshold

One question of interest is whether there is also bunching at the Q2/Q3 threshold, given the financial incentive to publish in Q2 journals at many Thai universities. Figure 8 reports an additional bunching analysis around the Q2/Q3 boundary corresponding to the 50th percentile cutoff in the SCImago system. The results differ noticeably from the corresponding patterns observed around the Q1 boundary.

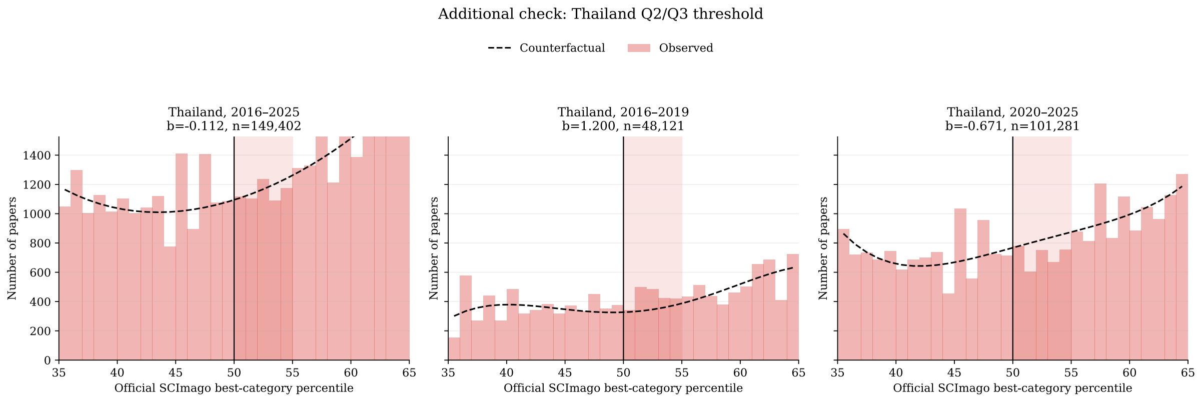


Figure 8. Additional check: Q2/Q3 bunching in Thailand. The figure presents bunching analyses around the Q2/Q3 boundary, corresponding to the 50th-percentile cutoff in the official SCImago best-category percentile distribution for Thailand. The vertical line marks the Q2/Q3 cutoff. Bars show observed publication counts, while the dashed line shows the estimated smooth counterfactual distribution from the main bunching specification, fitted with a fourth-order polynomial locally around the threshold.

For the pooled 2016–2025 sample, the estimated bunching coefficient around the Q2/Q3 threshold is close to zero (b = -0.112, SE = 0.130, z = -0.86). However, the underlying pre- and post-2019 patterns differ substantially. During the pre-2019 period, the estimated coefficient is positive and statistically significant (b = 1.200, SE = 0.294, z = 4.08), whereas the post-2019 period shows significant negative bunching around the Q2/Q3 boundary (b = -0.671, SE = 0.141, z = -4.76).

Visually, the distribution of publications around the Q2/Q3 boundary appears considerably less sharply concentrated than the corresponding distribution around the Q1 threshold. One possible interpretation is that publication concentration has shifted increasingly towards the Q1 margin since 2019, reducing the relative salience of lower-quartile boundaries within the publication system.

These exploratory patterns are broadly consistent with the interpretation that institutional incentives became increasingly concentrated around Q1 classification rather than around quartile thresholds more generally. Nevertheless, the instability of the Q2/Q3 estimates across periods warrants a more careful interpretation of the results.

4.5.3 Exploratory comparison: Malaysia

Figure 9 presents exploratory estimates of Q1/Q2 bunching in Malaysia before and after 2019. The Malaysian results show a pattern qualitatively similar to those in Thailand, although the institutional interpretation is less straightforward given the absence of a discrete higher-education restructuring comparable to Thailand's 2019 reform.

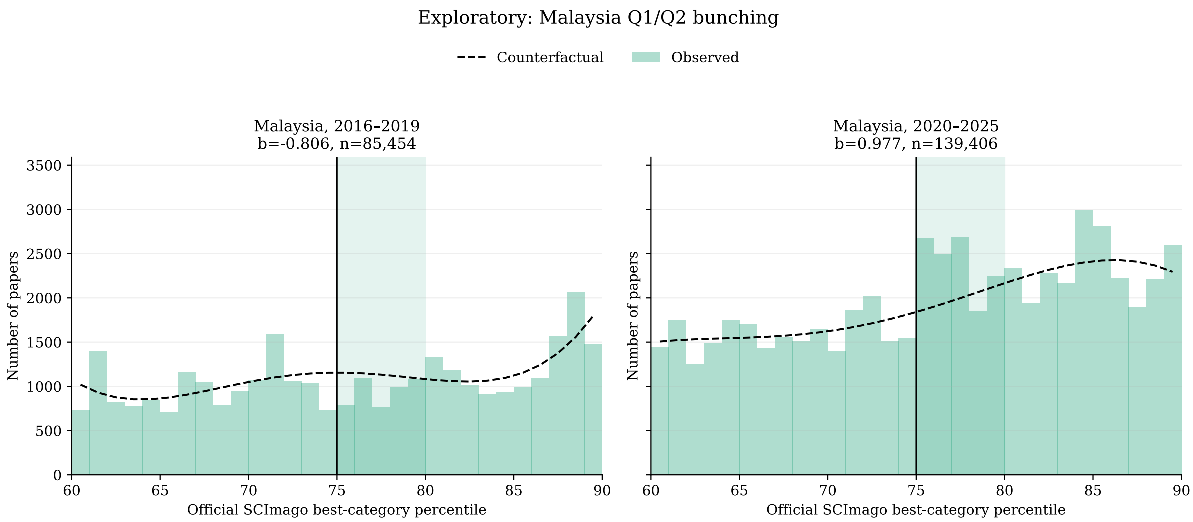


Figure 9. Exploratory Q1/Q2 bunching comparison for Malaysia before and after 2019. The figure compares the distribution of publications across official SCImago best-category percentiles in Malaysia before (2016–2019) and after (2020–2025) 2019. The vertical line indicates the Q1/Q2 cutoff at the 75th percentile. Bars represent observed publication counts, while the dashed line shows the estimated smooth counterfactual distribution obtained from the main bunching specification using a fourth-order polynomial fitted locally within the 60–90 percentile range, excluding observations within five percentile points of the threshold during estimation.

Before 2019, Malaysia exhibited substantial negative estimated bunching around the Q1 threshold (b = -0.806, SE = 0.113, z = -7.14, 95% CI [-1.027, -0.585]). By contrast, the post-2019 period exhibited substantial positive bunching around the Q1 boundary (b = 0.977, SE = 0.119, z = 8.22, 95% CI [0.744, 1.210]), with visible local concentration emerging immediately above the cutoff.

The Malaysian results are informative because they suggest that threshold-oriented publication behaviour may emerge even when publication incentives operate primarily through KPI systems, promotion criteria, and institutional ranking pressures rather than through highly explicit threshold-based reward schedules. However, unlike Thailand, Malaysia did not experience a similarly discrete post-2019 restructuring of the higher-education system, so the observed changes may reflect the gradual evolution of longer-running KPI systems and publication incentives rather than a single identifiable institutional shift.

4.6 Robustness checks

Figures A2 and A3 in the Appendix present two robustness checks. First, Figure A2 assesses the sensitivity of the Thailand–Singapore difference-in-differences estimates to alternative polynomial orders and fitting windows. The estimated post-2019 increase in Thailand's Q1-threshold bunching relative to Singapore remains consistently positive across specifications, including substantially narrower and wider fitting windows. Although the magnitude of the estimates varies somewhat across specifications, the core qualitative pattern remains stable. Importantly, the main specification lies near the centre of the distribution of estimated effects rather than representing an extreme specification choice. Overall, these patterns suggest that the main results are unlikely to be driven mechanically by a particular polynomial order or bandwidth selection.

Second, Appendix Figure A3 compares year-by-year bunching estimates using the same-year SCImago rankings and a lagged *t*-1 ranking specification. This robustness check is motivated by the fact that publication decisions are typically made well before papers formally appear in publication databases, often during earlier submission and revision stages when authors observe journal rankings from previous years rather than contemporaneous rankings. The post-2019 increase in bunching remains qualitatively similar under the lagged specification, suggesting that the main results are unlikely to be driven mechanically by contemporaneous changes in journal quartile assignments. At the same time, the similarity between the same-year and lagged estimates is not entirely surprising because journal rankings themselves tend to evolve gradually over time, with relatively limited year-to-year movement around quartile boundaries for most journals.

5. Discussions

This paper examines whether publication-oriented evaluation systems generate strategic concentration around institutionally salient journal-quality thresholds. Using ten years (2016–2025) of publication data from Thailand linked to official SCImago percentile rankings, the analysis finds substantial post-2019 excess concentration immediately above the Q1/Q2 boundary. Following the intensification of metric-based evaluation systems associated with Thailand's 2019 higher-education reforms, publication activity became increasingly clustered around the institutional threshold defining Q1 journal status.

The observed discontinuities are highly localised around the Q1 boundary, rather than reflecting smooth increases in publication activity across progressively higher-ranked journals. Journals immediately on either side of the threshold are often similar in underlying quality and visibility, yet crossing the quartile boundary may entail substantially different institutional consequences under the post-2019 incentive architecture. The findings should therefore not be interpreted as implying that journals immediately above the Q1 threshold are of low quality. Rather, they suggest that discrete classification boundaries generate disproportionate behavioural responses even when underlying journal quality changes relatively smoothly across the threshold, a pattern consistent with the broader literature on notch-based incentive responses (Chetty et al., 2011).

The findings contribute to the literature on how evaluation systems shape research behaviour and the organisation of science. Economists of science have long recognised that reward structures influence not only the volume but also the direction of research effort (Stephan, 2012; Franzoni & Sauermann, 2014). The concern that metric-based systems may distort rather than merely measure quality has been articulated theoretically through Goodhart's Law (Goodhart, 1984; Strathern, 1997) and has been empirically demonstrated across education and professional evaluation systems (Espeland & Sauder, 2007; Hicks et al., 2015; Muller, 2018). Recent empirical work documents strategic responses to revisions to journal rankings (Śpiewanowski & Talavera, 2021; Hudson, 2024; Sun et al., 2024). The present findings extend this literature in a distinct direction: strategic concentration may arise not only in response to ranking changes but also as a persistent equilibrium feature of stable institutional thresholds once those thresholds become sufficiently salient within promotion, retention, and funding systems. This distinction matters because it implies that bunching may intensify over time even without further metric reforms.

The exploratory comparison with Singapore highlights an important dynamic in how publication systems evolve. Singapore shows relatively little evidence of local bunching around the Q1 boundary, despite substantially greater concentration within the global top 5% of journals. Thailand, by contrast, shows both local threshold concentration and increasing density towards the upper tail of the Q1 distribution. One interpretation, consistent with a saturation account, is that coarse thresholds lose their disciplining power as competition crowds the category: once Q1 status becomes broadly attainable, institutional attention shifts towards finer distinctions within Q1 itself, including top-decile journals and globally elite outlets. An alternative account is that Singapore's researcher pool already operates in an environment where grant competition, international collaboration, and individual prestige create more continuous publication incentives, thereby reducing the salience of quartile boundaries irrespective of category crowding.

These interpretations carry different implications. The saturation account predicts that Thailand may gradually converge toward Singapore's pattern as Q1 competition intensifies. The selection-based account instead suggests that without changes in underlying researcher capacity, hiring standards, and institutional selectivity, the transition may be slower or incomplete. Distinguishing between these mechanisms would improve understanding of how academic labour markets and evaluation systems co-evolve over time.

The exploratory Malaysian results are also consistent with the interpretation that metric-based publication systems generate threshold-oriented bunching more broadly across the region. Unlike Thailand, Malaysia did not undergo a single discrete reform in 2019; instead, publication incentives have been embedded in the MyRA institutional rating system and the Malaysia Education Blueprint 2015–2025 for well over a decade (Ministry of Education Malaysia, 2015). The post-2019 emergence of bunching in Malaysia may therefore reflect the gradual intensification of longer-running KPI systems rather than a single identifiable policy shift. This distinction is informative: it suggests that the bunching mechanism identified in Thailand is not unique to a particular reform design but may emerge wherever quartile-based incentives become sufficiently salient within university governance — whether introduced sharply or accumulated gradually.

The policy implications of our findings are not that publication metrics should be abandoned. Internationally comparable publication systems remain important for research visibility, benchmarking, and global academic integration. The more precise implication is that systems that rely heavily on discrete thresholds — such as binary Q1/Q2 classifications embedded in institutional performance agreements — may create stronger incentives for local optimisation around institutional categories than systems based on more continuous or multidimensional forms of evaluation. One possible reform direction would be to replace or supplement binary quartile rewards with sliding incentive scales based on continuous percentile rank, thereby reducing the sharp payoff discontinuity at the Q1 boundary while preserving metric-based accountability.

At the institutional level, the findings point toward a broader reallocation of resources away from *ex post* publication rewards and toward upstream investments in research capacity itself. Reducing teaching and administrative burdens for research-active faculty, expanding research assistance, strengthening international collaboration structures, and improving research infrastructure all target the conditions under which high-quality research is produced rather than merely rewarding outputs after publication.

At the same time, stronger competition for higher-ranked journals may also generate positive selection effects, improve international visibility, and increase integration into global research networks. The findings should therefore not be interpreted as implying that all forms of publication-oriented competition are welfare-reducing. The paper's more specific concern is that coarse threshold-based systems may redirect effort towards optimisation around institutional categories rather than towards underlying research quality itself.

To illustrate the scale of the underlying incentives, we apply stylised publication-support values and first-author eligibility restrictions to the estimated post-2019 excess mass around the Q1 threshold. Under the conservative assumptions described in Appendix B, the implied institutional expenditure associated with excess bunching-related publications over 2020–2025 is approximately 39 million THB (roughly US$1.1 million). This figure should be interpreted as an order-of-magnitude illustration of resource reallocation rather than a fiscal estimate. Nevertheless, it suggests that even localised bunching around a single classification boundary may entail nontrivial cumulative institutional expenditure.

Several limitations should be acknowledged. First, the paper identifies publication concentration around institutional thresholds but cannot directly observe the underlying decision-making processes — including author submission behaviour, editorial selection, or institutional pressure — that generate these patterns. Second, the Thailand–Singapore comparison remains observational and cannot definitively establish the mechanisms underlying the observed differences. Third, bunching estimates become less stable in smaller publication environments, so the exploratory heterogeneity analyses should be interpreted cautiously. Finally, the paper focuses on publication distributions rather than downstream outcomes such as citation impact, innovation quality, or long-run research productivity. Whether threshold-oriented bunching ultimately affects research quality remains an important question for future work.

More generally, our findings suggest that publication systems shape the distribution of research effort as much as they measure it. As universities increasingly rely on metric-based governance systems to allocate prestige, funding, and career advancement, understanding how researchers adapt strategically to those systems becomes increasingly important for designing higher-education policies that strengthen research quality rather than the optimisation of its proxies.

Data and code availability

Python codes and information about how to obtain the data are available at https://github.com/npowdthavee/strategicbunching.

Declaration of generative AI and AI-assisted technologies in the writing process

The author used Claude (Anthropic) and ChatGPT (OpenAI) to assist with manuscript drafting and editing, as well as to develop Python code for data analysis and figure generation. All scientific decisions, including study design, pre-registration, data collection, statistical analysis, interpretation of results, and final editorial judgment over all manuscript content, were made by the author. The author takes full responsibility for the integrity and accuracy of the work reported.

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https://www.timeshighereducation.com/news/buy-papers-or-lose-your-job-dilemma-facing-thai-academics. [Last accessed: 18/05/2026].

Appendix A. Descriptive statistics and robustness checks

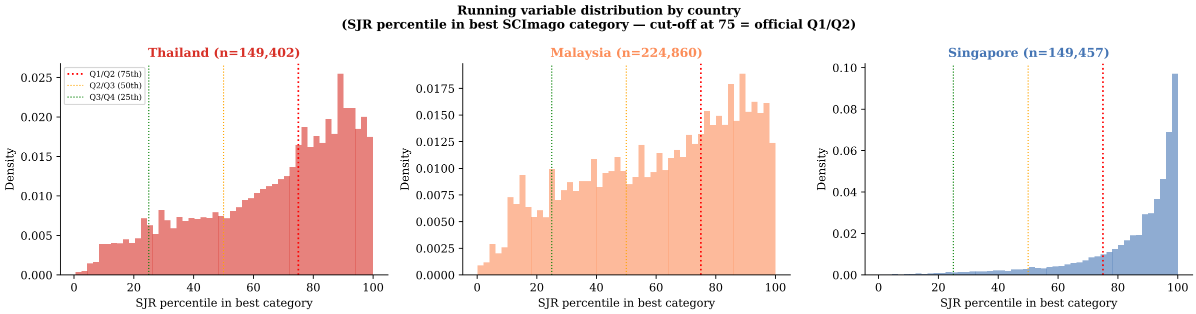

Figure A1. Running variable distribution by country. The figure plots the distribution of the running variable — the official SCImago best-category percentile ranking — for Thailand, Malaysia, and Singapore over the full sample period. Vertical dashed lines indicate the institutional quartile thresholds corresponding to the Q1/Q2 (75th percentile), Q2/Q3 (50th percentile), and Q3/Q4 (25th percentile) cutoffs used throughout the analysis. The running variable is constructed from each journal's official best-category percentile in the SCImago Journal Rank (SJR) system, rather than from sample-specific percentile rankings.

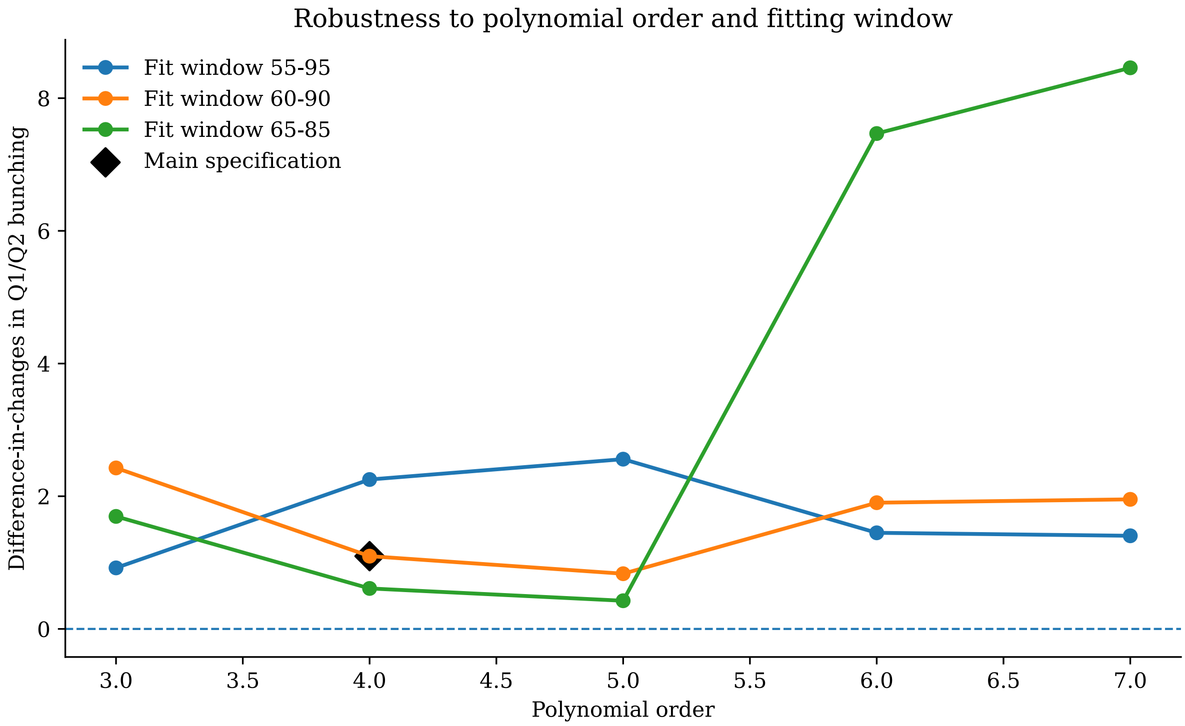

Figure A2. Robustness of Thailand–Singapore difference-in-differences estimates to polynomial order and fitting window. The figure presents robustness checks for the Thailand–Singapore difference-in-differences estimates of Q1/Q2 bunching, using alternative polynomial orders and fitting windows. The horizontal axis reports the polynomial order used to estimate the smooth counterfactual distribution, while the vertical axis reports the estimated difference-in-differences coefficient. Separate lines correspond to alternative fitting windows around the Q1 threshold (55–95, 60–90, and 65–85 percentile ranges). The vertical dashed line indicates the main specification used in the paper: a fourth-order polynomial fitted locally within the 60–90 percentile range.

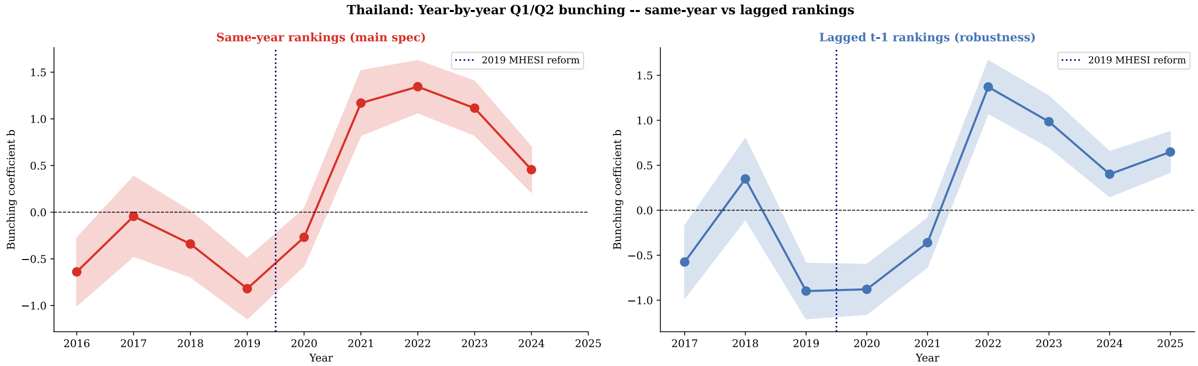

Figure A3. Thailand year-by-year Q1/Q2 bunching: same-year versus lagged journal rankings. The figure compares year-by-year Thailand Q1/Q2 bunching estimates using the same year SCImago ranking specification and a lagged t-1 ranking specification. The vertical dashed line indicates the 2019 MHESI reform period. The lagged specification assigns journals to quartile categories using rankings from the previous year rather than contemporaneous rankings. This robustness check is motivated by the fact that publication decisions are typically made during earlier submission and revision stages before articles formally appear in publication databases.

Appendix B. Back-of-the-envelope calculation of publication-related expenditure associated with excess bunching

This appendix provides a stylised calculation intended to illustrate the potential scale of institutional resources associated with the estimated post-2019 excess concentration around the Q1 threshold. The exercise is not intended to estimate actual fiscal expenditure, but rather to give an order-of-magnitude sense of how localised threshold-oriented publication behaviour may translate into cumulative institutional resource commitments over time.

The calculation begins with the estimated excess mass from the post-2019 Thailand Q1/Q2 bunching analysis reported in Section 4.2: approximately 1,575 excess publications concentrated within five percentile points above the Q1 threshold during 2020–2025, relative to the estimated smooth counterfactual distribution.

To translate this excess mass into stylised institutional expenditure, three conservative assumptions are applied.

First, the calculation assumes an average publication-related support value of 50,000 THB per qualifying Q1 publication. This figure is substantially below the support schedules reported by several leading Thai research universities — Chulalongkorn University, for example, provides a support ceiling of 500,000 THB for Q1 publications — and is adopted to reflect heterogeneity in payment schedules across institutions.

Second, only 50% of excess publications are assumed to qualify for institutional support, on the grounds that many university schemes restrict eligibility to first authors or corresponding authors.

Third, the calculation counts only publications concentrated locally within the bunching window immediately above the Q1 threshold, intentionally excluding any wider behavioural or spillover effects outside the threshold region.

Under these assumptions, the implied expenditure is:

$$1{,}575 \times 0.50 \times 50{,}000 = 39{,}375{,}000 \text{ THB}$$

This corresponds to approximately 39 million THB, or roughly US$1.1 million at an approximate exchange rate of 35 THB per USD.

Actual publication-support schemes differ substantially across universities in both magnitude and eligibility criteria, and the estimated excess mass itself depends on the maintained bunching specification. The figure should therefore be read as an order-of-magnitude illustration rather than a fiscal estimate.