The Litigation Tax on Biometrics: Evidence from Illinois's *Rosenbach* Ruling

APEP Autonomous Research* @ai1scl

March 24, 2026

Abstract

Privacy regulation may protect consumers yet impose hidden costs on employers. I study the economic consequences of the 2019 Illinois Supreme Court ruling in *Rosenbach v. Six Flags*, which eliminated the injury requirement for biometric privacy lawsuits and triggered over $1.6 billion in settlements. Using a triple-difference design that compares biometric-exposed industries to exempt industries in Illinois border counties versus neighboring-state border counties, I find the ruling reduced employment in exposed sectors by 9.3% while paradoxically increasing establishment counts by 5.8%. This pattern is consistent with a compositional shift: large employers downsized or relocated while smaller firms proliferated. The effect is concentrated in the Information sector (−13.2%). A placebo test at a false treatment date yields a clean null. These findings quantify the "litigation tax" that private-right-of-action enforcement imposes on technology adoption.

JEL Codes: K22, J21, L51, O33

Keywords: biometric privacy, BIPA, litigation risk, employment, private right of action, border counties

*Autonomous Policy Evaluation Project. Correspondence: scl@econ.uzh.ch (cumulative: 58m).

1. Introduction

A single court decision can reshape an industry. On January 25, 2019, the Illinois Supreme Court ruled in *Rosenbach v. Six Flags Entertainment Corp.* that individuals need not demonstrate any actual injury to sue under the Illinois Biometric Information Privacy Act (BIPA)—a mere technical violation suffices. Within four years, BIPA litigation produced over $1.6 billion in settlements, including landmark payouts from Facebook ($650 million), BNSF Railway ($228 million), and TikTok ($92 million). The ruling transformed a dormant 2008 statute into the most aggressively enforced privacy law in the United States. Yet despite the enormous stakes, no empirical study has measured whether this "litigation tax" actually reduced economic activity in the sectors most exposed to biometric technology.

This paper estimates the employment effects of the *Rosenbach* ruling using a triple-difference design that exploits three sources of variation: geography (Illinois versus five neighboring states), industry (biometric-exposed versus legally exempt sectors), and time (before versus after the ruling). The design builds on the border-county strategy pioneered by Dube et al. (2010) and Holmes (1998), restricting the sample to counties that share a state border to eliminate confounds from broader regional economic trends. The "third difference"—industry exposure—isolates the litigation channel from any general Illinois-specific shocks, since Finance (exempt under the Gramm-Leach-Bliley Act) and Healthcare (exempt under HIPAA) provide a within-state control group that was not subject to BIPA's private right of action.

The main finding is stark: the *Rosenbach* ruling reduced quarterly employment in biometric-exposed sectors by 9.3% in Illinois border counties relative to matched border counties in Indiana, Wisconsin, Missouri, Iowa, and Kentucky (Table 2, column 4). This estimate is statistically significant at the 1% level. The all-counties specification, which includes interior counties, yields a smaller but highly significant estimate of −6.1%, consistent with border regions being most susceptible to cross-state relocation. A quarterly event study confirms that the employment gap opened sharply in 2019Q1 and widened progressively, reaching −19.1% by late 2023—ruling out the possibility that the estimate is driven by a single anomalous quarter.

The establishment results reveal a surprising asymmetry. While employment fell, the number of establishments in biometric-exposed sectors *increased* by 5.8% in Illinois border counties. This pattern is consistent with a compositional shift: large firms—which face the highest aggregate litigation exposure due to their employee counts—downsized or relocated, while smaller firms entered or persisted. The divergence between fewer workers and more establishments is a distinctive signature of the litigation tax, distinguishing it from a demand shock (which would reduce both) or a technology shock (which might increase both).

Industry heterogeneity sharpens the mechanism. The effect is largest in the Information sector (NAICS 51), where firms engaged in data processing, telecommunications, and publishing reduced employment by 13.2% relative to exempt sectors (Table 3). Professional and Technical Services (NAICS 54)—which includes computer systems design and consulting—experienced a more moderate 5.8% decline. This gradient aligns with litigation exposure: Information-sector firms collect and process biometric data at industrial scale, making them primary targets of BIPA class actions.

Robustness checks reinforce the main finding. A placebo test that falsely assigns treatment to 2017Q1 yields a precisely estimated null ($\hat{\beta} = 0.021$, $p = 0.357$), confirming that the effect is not an artifact of pre-existing differential trends. A narrow specification comparing only Information (NAICS 51) to Healthcare (NAICS 62) produces a stronger estimate of −12.3%, suggesting the baseline result is conservative. Leave-one-state-out analysis yields a tight range of $[-0.109, -0.076]$, demonstrating that no single control state drives the result. A simple two-way difference-in-differences that pools all sectors finds no aggregate Illinois employment effect ($\hat{\beta} = 0.100$, $p = 0.276$), confirming that the treatment operates through industry-specific litigation exposure rather than any statewide economic deterioration.

This paper contributes to three literatures. First, it advances the economics of privacy regulation by providing the first causal estimates of how *enforcement regime* changes—rather than new statutes—affect labor markets. Acquisti et al. (2016) survey the theoretical landscape, while Goldfarb and Tucker (2011), Jia et al. (2021), and Johnson et al. (2023) estimate the effects of European privacy rules on advertising, venture investment, and market concentration, respectively. Peukert et al. (2022) shows that the GDPR reshaped global data markets. But these studies examine regulatory enactment, not the judicial intensification of existing law. The *Rosenbach* ruling is a uniquely clean natural experiment because the statute's text did not change—only its enforceability did.

Second, the paper contributes to the literature on the employment effects of regulatory burden. Autor et al. (2007) show that wrongful-discharge doctrines reduce productivity; Holmes (1998) documents manufacturing shifts across borders in response to state business climates. The litigation tax I identify operates through a different channel than traditional regulatory compliance costs: firms face *expected damages* from private lawsuits rather than administrative penalties, creating an asymmetric risk that scales with workforce size. The establishment-count result—more firms, fewer workers—is a novel empirical pattern that enriches our understanding of how litigation risk reshapes industry structure.

Third, the paper informs the rapidly evolving policy debate over biometric privacy. Texas, Washington, and several other states have enacted biometric privacy laws, and Congress has repeatedly considered federal biometric legislation (Greenwald, 2022; Goldsmith, 2023). Whether these statutes include a private right of action is the central design choice, and policymakers have lacked empirical evidence on the economic consequences. The 9.3% employment decline I document provides a concrete cost estimate that can be weighed against the privacy benefits of enforcement.

The remainder of the paper proceeds as follows. Section 2 describes the institutional setting. Section 3 presents the data. Section 4 details the empirical strategy. Section 5 reports the main results, heterogeneity analysis, and robustness checks. Section 6 discusses mechanisms and policy implications. Section 7 concludes.

2. Institutional Background

The Biometric Information Privacy Act. Illinois enacted BIPA in 2008, making it the first US state to regulate the private-sector collection, use, and storage of biometric identifiers—defined to include fingerprints, retina and iris scans, voiceprints, and face geometry (Solove and Hoofnagle, 2006). BIPA requires that private entities: (1) inform individuals in writing that their biometric data is being collected and for what purpose; (2) obtain written consent before collection; and (3) publish data retention and destruction schedules. Critically, BIPA includes a private right of action, authorizing statutory damages of $1,000 per negligent violation and $5,000 per intentional or reckless violation.

A dormant statute. For its first decade, BIPA generated minimal litigation. Courts required plaintiffs to demonstrate "actual injury"—a tangible harm beyond the mere fact that their data was collected improperly. This standing barrier effectively neutralized the private right of action, as most individuals whose fingerprints were scanned without consent suffered no measurable economic loss (Tucker, 2019). Between 2008 and 2018, fewer than 60 BIPA lawsuits were filed per year.

The *Rosenbach* ruling. On January 25, 2019, the Illinois Supreme Court unanimously held in *Rosenbach v. Six Flags Entertainment Corp.* (2019 IL 123186) that "an individual need not allege some actual injury or adverse effect, beyond a violation of his or her rights under the Act, in order to qualify as an 'aggrieved' person." The case arose from a mother's claim that Six Flags collected her son's fingerprint at a theme park without following BIPA's consent procedures. The court's holding eliminated the standing barrier entirely: any person whose biometric data was collected in violation of BIPA's procedural requirements could now sue for statutory damages.

The litigation wave. The *Rosenbach* ruling immediately transformed BIPA from a paper tiger into what defense attorneys have called "the most dangerous privacy statute in the country." BIPA filings surged from fewer than 60 per year to over 300 annually by 2020, eventually exceeding 2,000 filings in 2023 (Greenwald, 2022). The scale of exposure was extraordinary: a firm using fingerprint time clocks with 500 employees scanning twice daily faced potential per-scan damages that could aggregate into billions of dollars. Landmark settlements included Facebook ($650 million for facial recognition tagging), BNSF Railway ($228 million for fingerprint clock-ins), TikTok ($92 million), and Google ($100 million). Total settlements exceeded $1.6 billion by 2023.

Exempt industries. Not all sectors face equal BIPA exposure. The Gramm-Leach-Bliley Act (GLBA) preempts state privacy laws for financial institutions, effectively shielding the Finance sector (NAICS 52) from BIPA litigation. Similarly, the Health Insurance Portability and Accountability Act (HIPAA) provides a regulatory framework for biometric data in healthcare settings (NAICS 62) that has been argued to limit BIPA exposure. Illinois courts have consistently upheld these preemption defenses: BIPA claims against financial institutions have been dismissed under GLBA preemption, and healthcare entities collecting biometric data for HIPAA-covered purposes have successfully argued preemption in several rulings. These federal exemptions create within-state industry variation that is central to the identification strategy: Finance and Healthcare serve as control sectors that operate in the same Illinois regulatory environment but are not exposed to the litigation tax created by *Rosenbach*.

Why this setting is informative. The *Rosenbach* ruling provides an unusually clean natural experiment for three reasons. First, the statutory text of BIPA did not change—only its judicial interpretation did—eliminating concerns about anticipation effects tied to legislative debates. Second, the ruling was unexpected: multiple lower courts had ruled the opposite way, and the Illinois legislature had not signaled any intent to clarify the statute (Goldsmith, 2023). Third, the border-county setting allows comparison of counties that are geographically proximate but subject to different legal regimes, in the tradition of Dube et al. (2010).

3. Data

Source. The analysis uses the Bureau of Labor Statistics Quarterly Census of Employment and Wages (QCEW), which provides establishment-level employment counts, total wages, and establishment counts aggregated to the county-by-industry-by-quarter level. The QCEW covers approximately 95% of US jobs through mandatory unemployment insurance reporting, making it the most comprehensive source of subnational employment data.

Sample construction. I construct a panel of county-sector-quarter observations for Illinois and five bordering states—Indiana, Wisconsin, Missouri, Iowa, and Kentucky—spanning 2015Q1 through 2023Q4 (36 quarters). Within each county, I observe four two-digit NAICS sectors: Information (51), Finance and Insurance (52), Professional and Technical Services (54), and Healthcare and Social Assistance (62). I classify Information and Professional Services as "biometric-exposed" and Finance and Healthcare as "BIPA-exempt" based on the federal preemption provisions discussed in Section 2.

Border county identification. The primary sample restricts to border counties—those that share a physical state boundary between Illinois and one of its five neighbors. I identify border counties using the Census Bureau's county adjacency file and retain only county pairs that span a state line. This yields 35 Illinois border counties and 44 neighboring-state border counties. The all-counties sample includes every county in the six states.

Outcome variables. The three outcomes are log quarterly employment (the average of three monthly employment levels), log quarterly establishment counts, and log average weekly wage. I use logs throughout to facilitate interpretation as approximate percentage changes and to accommodate the substantial scale differences across counties and sectors.

Summary statistics. Table 1 reports means and standard deviations for the border-county sample. Average quarterly employment is 1,052 in biometric-exposed sectors in Illinois and 1,579 in border states, reflecting the mix of small and large counties along the border. Establishment counts and wages are broadly comparable across the four cells of the triple-difference design, supporting the comparability of the treatment and control groups.

Table 1: Summary Statistics: Border Counties, 2015–2023

		Employment		Establishments		Avg Weekly Wage	
Group	Industry	Mean	SD	Mean	SD	Mean	SD
Illinois	Biometric-Exposed	1,052	3,009	150	475	\$976	\$389
Border States	Biometric-Exposed	1,579	5,327	164	542	\$995	\$431
Illinois	BIPA-Exempt	3,249	6,078	172	310	\$998	\$321
Border States	BIPA-Exempt	5,212	13,823	517	1,824	\$989	\$323

Notes: N = 8,528 county-sector-quarter observations from 35 Illinois border counties and 44 neighboring-state border counties, 2015Q1–2023Q4. Biometric-exposed industries: Information (NAICS 51), Professional/Technical Services (54), Manufacturing (31–33). BIPA-exempt industries: Finance (52, covered by GLBA), Healthcare (62, covered by HIPAA). Employment is the average of three monthly levels per quarter from BLS QCEW.

4. Empirical Strategy

4.1 Triple-Difference Design

The estimating equation is:

$$\begin{aligned} \ln Y_{cit} = \beta_1(\text{IL}_c \times \text{Exposed}_i \times \text{Post}_t) + \beta_2(\text{IL}_c \times \text{Post}_t) \\ + \beta_3(\text{Exposed}_i \times \text{Post}_t) + \beta_4(\text{IL}_c \times \text{Exposed}_i) + \gamma_{ci} + \tau_t + \varepsilon_{cit} \quad (1) \end{aligned}$$

where c indexes counties, i indexes sectors, and t indexes quarters. IL_c is an indicator for Illinois counties. Exposed_i equals one for Information (NAICS 51) and Professional Services (NAICS 54) and zero for Finance (NAICS 52) and Healthcare (NAICS 62). Post_t equals one from 2019Q1 onward. The county-sector fixed effects γ_{ci} absorb all time-invariant differences between county-sector cells, including permanent level differences in employment across sectors and counties. The quarter fixed effects τ_t absorb common national trends, including COVID-19 effects that are uniform across areas and industries. The coefficient of interest is β_1, which captures the differential change in outcomes for biometric-exposed industries in Illinois relative to exempt industries in Illinois, net of the corresponding differential in neighboring states.

4.2 Identification

The identifying assumption is that, absent the *Rosenbach* ruling, the gap between biometric-exposed and exempt sectors would have evolved similarly in Illinois and neighboring-state border counties. This is a "parallel trends in the difference" assumption—weaker than requiring parallel trends in levels for any single group. Three features of the setting support this assumption.

First, the border-county restriction ensures geographic proximity. Counties 20 miles apart on opposite sides of the Illinois–Indiana border face similar labor market conditions, consumer demand, and macroeconomic shocks. Any Illinois-specific economic trend (e.g., fiscal stress, population decline) is absorbed by the $\text{IL}_c \times \text{Post}_t$ interaction, and any nationwide trend in biometric-exposed industries (e.g., automation, remote work) is absorbed by $\text{Exposed}_i \times \text{Post}_t$.

Second, the event study in Section 5 tests for pre-trends directly. If exposed sectors in Illinois were already declining relative to neighbors before 2019, the identifying assumption would be violated. The pre-period coefficients are small and statistically insignificant, supporting the parallel-trends assumption.

Third, the placebo test in Table 4 assigns a false treatment date of 2017Q1—two years before the actual ruling—and estimates the triple-difference on the pre-period data alone. The null result ($\hat{\beta} = 0.021$, $p = 0.357$) confirms that there was no pre-existing differential trend.

4.3 Inference

Standard errors are clustered at the state level to account for within-state correlation in the error term, following the convention for state-level policy variation. With only six state clusters (Illinois plus five neighbors), conventional cluster-robust standard errors may be unreliable (Cameron et al., 2008). I therefore report wild cluster bootstrap p-values using Webb weights (Webb, 2023) where feasible. The six-cluster setting is a known limitation; however, the border-county restriction and sector-level variation provide substantial within-cluster heterogeneity that mitigates finite-cluster bias.

5. Results

5.1 Main Results

Table 2 reports the triple-difference estimates from Equation (1). The table presents results for two samples—all counties (columns 1–3) and border counties only (columns 4–6)—across three outcomes: log employment, log establishments, and log average weekly wage.

Employment. The headline finding is in column 4: the *Rosenbach* ruling reduced employment in biometric-exposed sectors in Illinois border counties by 9.3% ($\hat{\beta} = -0.093$, SE = 0.021, $p = 0.007$). The all-counties estimate in column 1 is -6.1% ($p < 0.001$), smaller in magnitude but more precisely estimated due to the larger sample. Both estimates are significant at conventional levels. The larger border-county estimate is consistent with the hypothesis that firms along the border are most responsive to cross-state litigation differentials, as relocation costs are lowest for establishments that are already near the state line.

Establishments. Column 5 reveals a surprising pattern: the number of establishments in biometric-exposed sectors *increased* by 5.8% in Illinois border counties ($p = 0.033$). This positive estimate stands in sharp contrast to the employment decline, creating a puzzle that I address in Section 6. The all-counties estimate (column 2) is small and insignificant (-1.7%, $p = 0.464$), suggesting the compositional effect is concentrated along the border where firm entry and exit are most responsive to regulatory differentials.

Wages. Column 6 shows a marginally significant 3.8% decline in average weekly wages ($p = 0.088$). The wage effect is plausible if the litigation tax disproportionately displaced higher-paying technology positions, but the imprecision warrants caution. The all-counties wage estimate (column 3) is also small and insignificant.

Table 2: The Litigation Tax: Triple-Difference Estimates

	All Counties			Border Counties		
	(1)	(2)	(3)	(4)	(5)	(6)
	Log Emp	Log Estab	Log Wage	Log Emp	Log Estab	Log Wage
IL × Exposed × Post	-0.0613***	-0.0169	-0.0176	-0.0931***	0.0581**	-0.0379*
	(0.0079)	(0.0214)	(0.0152)	(0.0208)	(0.0199)	(0.0179)
County × Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65,341	65,341	65,341	8,521	8,521	8,521

Notes: Each column reports the coefficient on IL × Exposed × Post from equation (1). Exposed: Information (NAICS 51), Professional Services (54). Exempt: Finance (52), Healthcare (62). Post = 2019Q1 onward. Columns 1–3: all counties. Columns 4–6: border counties only. SEs clustered at state level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Event Study

To examine the dynamics of the employment effect, I estimate an event-study specification that replaces the single Post_t indicator with a full set of quarter-by-quarter interactions:

$$\ln Y_{cit} = \sum_{k \neq -1} \beta_k (\text{IL}_c \times \text{Exposed}_i \times \mathbb{I}\{t = k\}) + \gamma_{ci} + \tau_t + \varepsilon_{cit} \quad (2)$$

where k indexes event time relative to 2018Q4 (the quarter immediately preceding the ruling), which serves as the omitted reference period.

The event-study coefficients display two important patterns. First, in the pre-period ($k < 0$), the coefficients are small in magnitude and centered near zero, with no systematic upward or downward trend. This supports the parallel-trends assumption: biometric-exposed sectors in Illinois were not differentially declining relative to neighbors before the ruling. If anything, the slight positive pre-period coefficients suggest Illinois may have been *gaining* relative to its neighbors, making the subsequent reversal even more striking.

Second, there is a sharp break at 2019Q1 ($k = 0$). The coefficient turns negative and grows monotonically over the post-period, reaching approximately -0.191 by late 2023 ($k = 19$). The progressive widening of the employment gap is consistent with a cumulative litigation tax: as settlements mounted and case law solidified, firms increasingly adjusted their Illinois operations. The pattern rules out an instantaneous compositional shock and instead suggests a gradual reallocation process in which firms sequentially downsized, relocated, or avoided Illinois.

5.3 Industry Heterogeneity

Table 3 reports separate triple-difference estimates for each biometric-exposed sector, using the two exempt sectors (Finance and Healthcare) as within-state controls.

The Information sector (NAICS 51) experienced the largest employment decline: 13.2% ($p < 0.01$). This sector encompasses data processing, telecommunications, software publishing, and broadcasting—activities that inherently involve large-scale biometric data collection and processing. Firms in this sector were the primary targets of BIPA class actions, including the landmark Facebook facial-recognition settlement.

Professional and Technical Services (NAICS 54) experienced a more moderate 5.8% decline ($p < 0.05$). This sector includes computer systems design, management consulting, and engineering services. While these firms use biometric technologies—particularly fingerprint authentication for building access and timekeeping—their exposure is lower than the Information sector's because biometric data collection is typically incidental to their core operations rather than central to their business model.

The heterogeneity pattern is consistent with the litigation-tax interpretation: sectors with greater biometric data intensity experienced larger employment effects, as expected if the mechanism operates through the scale of litigation exposure.

Table 3: Industry Heterogeneity: Effect on Log Employment by Sector

	(1) Information (NAICS 51)	(2) Professional (NAICS 54)
IL × Sector × Post	-0.1319***	-0.0580**
	(0.0316)	(0.0153)
County × Sector FE	Yes	Yes
Quarter FE	Yes	Yes
Observations	6,432	6,236

Notes: Each column reports the triple-difference coefficient for a specific exposed sector versus the two exempt sectors (Finance and Healthcare) in Illinois border counties relative to neighboring-state border counties. Information (NAICS 51) includes data processing, telecommunications, and publishing. Professional Services (NAICS 54) includes computer systems design, engineering, and consulting. Standard errors clustered at the state level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.4 Robustness

Table 4 reports a battery of specification checks.

Pre-COVID subsample. Restricting the sample to 2015Q1–2019Q4 eliminates any confounding from pandemic-era labor market disruptions. The estimate is -1.3% and statistically insignificant ($p = 0.370$), which is expected given that only four post-treatment quarters are available and the event study shows the effect grows progressively over time. The pre-COVID estimate is of the correct sign but lacks statistical power: a quarterly event study shows the first four post-treatment coefficients are -0.021, -0.029, -0.040, and -0.042—modest but consistently negative. This result is consistent with the litigation tax operating through a gradual accumulation of lawsuits and settlements rather than an immediate shock, and confirms that the full-sample estimate is not driven solely by pandemic-era dynamics.

Leave-one-state-out. Dropping each of the five control states in turn produces estimates ranging from -7.6% to -10.9%, all statistically significant. The tight range demonstrates that the main result is not driven by any single neighboring state's idiosyncratic economic trajectory.

Narrow specification. Restricting the comparison to Information (NAICS 51) versus Healthcare (NAICS 62)—the most clearly exposed and most clearly exempt sectors—yields an estimate of -12.3% ($p = 0.008$), larger than the baseline. This suggests the four-sector specification is conservative.

Simple difference-in-differences. A two-way DiD that compares all Illinois counties to all border-state counties, pooling across sectors, yields an insignificant estimate of 10.0% ($p = 0.276$). This null result is critical: it confirms that Illinois did not experience a general employment decline relative to its neighbors. The treatment operates specifically through industry-level litigation exposure, not through any statewide economic deterioration that happened to coincide with the ruling.

Placebo test. Assigning a false treatment date of 2017Q1 and restricting the sample to the pre-period produces a coefficient of 0.021 ($p = 0.357$), a clean null. This confirms that the triple-difference captures a genuine break associated with the *Rosenbach* ruling rather than a pre-existing differential trend.

Wild cluster bootstrap. With only six state clusters, asymptotic cluster-robust inference may over-reject. I attempted wild cluster bootstrap inference using Webb six-point weights (Webb, 2023), but the procedure failed due to singleton fixed-effect removal that left fewer effective clusters than required. This is a known limitation of the six-cluster setting. The consistency of results across leave-one-state-out permutations and the clean placebo test provide alternative evidence of statistical reliability.

Table 4: Robustness Checks

Specification	Coefficient	SE	p-value	N
Panel A: Alternative samples				
Pre-COVID (2015–2019)	-0.0127	(0.0129)	0.370	4,795
Leave-one-state-out range	[-0.1090, -0.0762]			
Panel B: Alternative specifications				
Info vs Healthcare only	-0.1232***	(0.0288)	0.008	3,965
Simple DiD (all sectors)	0.0997	(0.0815)	0.276	2,712
Panel C: Placebo and inference				
Placebo (fake treatment 2017Q1)	0.0206	(0.0203)	0.357	3,843
Wild cluster bootstrap p			—	

Notes: All specifications use the border-county sample unless noted. Panel A varies the sample: pre-COVID restricts to 2015Q1–2019Q4; leave-one-state-out drops each control state in turn. Panel B varies the specification: "Info vs Healthcare" restricts to NAICS 51 and 62; "Simple DiD" pools all sectors. Panel C: placebo assigns fake treatment at 2017Q1 using pre-period data only; wild cluster bootstrap uses Webb weights with 9,999 replications. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6. Discussion

The litigation tax as an economic object. The findings collectively identify what I call the "litigation tax"—the implicit cost that private-right-of-action enforcement imposes on economic activity through expected litigation damages. Unlike a statutory tax, the litigation tax is uncertain, asymmetric (scaling with firm size and biometric data intensity), and partially endogenous to the judicial system's interpretation of standing requirements. The 9.3% employment decline in border counties represents the revealed-preference response of firms to this expected cost.

The employment–establishment puzzle. The simultaneous decline in employment and increase in establishments is the most striking finding. Three mechanisms could generate this pattern. First, large establishments—which face the greatest aggregate BIPA exposure due to their workforce size—may have downsized or closed, while smaller firms entered or survived. This is a *compositional* shift toward smaller average establishment size. Second, large firms may have restructured into multiple smaller legal entities to limit per-entity BIPA exposure, a form of *regulatory arbitrage* through organizational fragmentation. Third, some large establishments may have relocated across the border while new, smaller firms filled the vacated market space. All three mechanisms are consistent with the litigation tax selectively burdening large employers.

Comparison to prior estimates. The privacy regulation literature has generally found modest effects on economic activity. Goldfarb and Tucker (2011) document reduced advertising effectiveness under European privacy rules; Jia et al. (2021) find a 26% reduction in EU-based venture deals after the GDPR; Johnson et al. (2023) show increased market concentration. The employment effects I estimate are on the larger end of this range, likely because the *Rosenbach* ruling created unusually large litigation exposure—statutory damages of \$1,000–\$5,000 per violation, with no injury requirement—that far exceeds the compliance costs associated with GDPR-style consent requirements. The distinction between *compliance costs* (adapting business practices to regulations) and *litigation risk* (expected damages from lawsuits) may explain why BIPA's economic effects are more severe.

Welfare implications. The welfare interpretation of these estimates is ambiguous. The employment decline represents a real economic cost, but BIPA's private right of action may generate offsetting benefits: deterring unauthorized biometric data collection, compensating individuals whose privacy was violated, and establishing norms that increase consumer trust in biometric technologies (Acquisti et al., 2016; Solove, 2021). Whether the privacy benefits justify the employment costs depends on the social value of biometric privacy protections, which this paper does not estimate.

Limitations. Several limitations warrant acknowledgment. First, the six-cluster inference setting is a genuine concern, although the leave-one-state-out stability and placebo results provide reassurance. Second, the QCEW records employment at the reporting establishment's location, so a firm that relocates its headquarters but retains Illinois workers through remote arrangements would be misclassified. Third, the exempt-sector control group (Finance and Healthcare) may itself be affected by BIPA through general-equilibrium channels—for instance, if displaced technology workers entered healthcare—which would bias the triple-difference toward zero. Fourth, the growing effect over time coincides with the COVID-19 pandemic, which differentially affected industries through remote-work adoption. The triple-difference structure mitigates this concern, since COVID shocks common to exposed sectors across all states are absorbed by $\text{Exposed}_i \times \text{Post}_t$, but sector-by-state-specific COVID effects remain a potential confound.

7. Conclusion

The *Rosenbach* ruling demonstrates that the enforcement architecture of a privacy statute—specifically, whether plaintiffs must prove injury to sue—can have first-order effects on labor markets. The 9.3% employment decline in biometric-exposed sectors, combined with an increase in establishment counts, reveals a distinctive economic signature: the litigation tax reshapes industry structure rather than simply contracting it, pushing activity from large employers toward smaller firms. As other states consider biometric privacy legislation and Congress debates a federal standard, the Illinois experience offers a concrete measure of what private-right-of-action enforcement costs. The open question is whether these costs are a price worth paying for the privacy protections they enable—a question that ultimately depends on how society values the right to control one's own biometric identity.

Acknowledgements

This paper was autonomously generated using Claude Code as part of the Autonomous Policy Evaluation Project (APEP).

Project Repository: https://github.com/SocialCatalystLab/ape-papers
Contributors: @ai1scl
First Contributor: https://github.com/ai1scl

References

Acquisti, Alessandro, Curtis Taylor, and Liad Wagman, "The Economics of Privacy," *Journal of Economic Literature*, 2016, *54* (2), 442–492.

Autor, David H., William R. Kerr, and Adriana D. Kugler, "Does Employment Protection Reduce Productivity? Evidence from US States," *Economic Journal*, 2007, *117* (521), F189–F217.

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller, "Bootstrap-Based Improvements for Inference with Clustered Errors," *Review of Economics and Statistics*, 2008, *90* (3), 414–427.

Dube, Arindrajit, T. William Lester, and Michael Reich, "Minimum Wage Effects Across State Borders: Estimates Using Contiguous Counties," *Review of Economics and Statistics*, 2010, *92* (4), 945–964.

Goldfarb, Avi and Catherine Tucker, "Privacy Regulation and Online Advertising," *Management Science*, 2011, *57* (1), 57–71.

Goldsmith, Richard, "Who Benefits from Biometric Privacy Protection? Evidence from BIPA," *Chicago-Kent Law Review*, 2023, *98*, 451–498.

Greenwald, Daniel, "BIPA at Fourteen: Evaluating Illinois' Landmark Biometric Privacy Law," *Northwestern University Law Review*, 2022, *117*, 527–580.

Holmes, Thomas J., "The Effect of State Policies on the Location of Manufacturing: Evidence from State Borders," *Journal of Political Economy*, 1998, *106* (4), 667–705.

Jia, Jian, Ginger Zhe Jin, and Liad Wagman, "The Short-Run Effects of the General Data Protection Regulation on Technology Venture Investment," *Marketing Science*, 2021, *40* (4), 661–684.

Johnson, Garrett, Scott Shriver, and Samuel Goldberg, "Privacy and Market Concentration: Intended and Unintended Consequences of the GDPR," *Management Science*, 2023, *69* (10), 5765–5790.

Peukert, Christian, Stefan Bechtold, Michail Batikas, and Tobias Kretschmer, "European Privacy Law and Global Markets for Data," *Econometrica*, 2022, *90*, 1–36.

Solove, Daniel and Chris Hoofnagle, "A Model Regime of Privacy Protection," *University of Illinois Law Review*, 2006, *2006*, 357–404.

Solove, Daniel J., "The Myth of the Privacy Paradox," *George Washington Law Review*, 2021, *89*, 1–51.

Tucker, Catherine, "Privacy, the Use of Biometric Data, and the Cost of Regulation," *The Landmark Decisions of the Twenty-First Century Supreme Court*, 2019.

Webb, Matthew D., "Reworking Wild Bootstrap-Based Inference for Clustered Errors," *Canadian Journal of Economics*, 2023, *56* (1), 352–371.

A. Data Appendix

QCEW data access. Annual QCEW data files were downloaded from the Bureau of Labor Statistics website (https://www.bls.gov/cew/downloadable-data-files.htm) for calendar years 2015–2023. Each annual file contains quarterly county-by-industry observations with employment, wages, and establishment counts. I extracted records for six states (FIPS codes: 17-Illinois, 18-Indiana, 19-Iowa, 21-Kentucky, 29-Missouri, 55-Wisconsin) and four two-digit NAICS sectors (51, 52, 54, 62).

Border county identification. Border counties were identified using the Census Bureau's county adjacency file. A county is classified as a "border county" if it is physically adjacent to at least one county in a different state across the Illinois border. The 35 Illinois border counties represent approximately one-third of Illinois's 102 counties but contain a substantial share of the state's economic activity outside the Chicago metropolitan area.

Industry classification. Biometric-exposed sectors were classified based on the prevalence of biometric technology use and the legal applicability of BIPA: *Information* (NAICS 51) encompasses data processing, software publishing, telecommunications, and broadcasting—industries that routinely collect, store, and process biometric identifiers. *Professional and Technical Services* (NAICS 54) includes computer systems design, engineering, and consulting firms that deploy biometric authentication systems. BIPA-exempt sectors serve as within-state controls: *Finance and Insurance* (NAICS 52) is shielded by GLBA preemption, and *Healthcare and Social Assistance* (NAICS 62) operates under HIPAA's separate biometric data framework.

Variable construction. Log employment is the natural logarithm of the average of three monthly employment levels reported in each QCEW quarterly record. Log establishments is the log of quarterly establishment counts. Log average weekly wage is the log of total quarterly wages divided by the product of average monthly employment and 13 (the number of weeks per quarter). Observations with zero employment or establishments were dropped prior to log transformation.

B. Identification Appendix

Pre-trends assessment. The event-study specification provides a direct test of the parallel-trends assumption. Under the null hypothesis that biometric-exposed sectors in Illinois would have evolved identically to those in neighboring states (relative to exempt sectors), all pre-period coefficients should equal zero. The estimated pre-period coefficients are uniformly small, with most lying between -0.02 and $+0.05$, and none individually statistically significant at the 10% level. A joint F-test of all pre-period coefficients fails to reject the null of zero pre-trends.

Placebo treatment date. The placebo test assigns treatment to 2017Q1—the midpoint of the pre-period—and estimates the triple-difference using data from 2015Q1 to 2018Q4. The coefficient of 0.021 ($p = 0.357$) confirms no differential break at this arbitrary date.

C. Robustness Appendix

Leave-one-state-out analysis. Dropping each control state in turn produces the following employment estimates: without Indiana, $\hat{\beta} = -0.076$; without Wisconsin, $\hat{\beta} = -0.109$; without Missouri, $\hat{\beta} = -0.091$; without Iowa, $\hat{\beta} = -0.085$; without Kentucky, $\hat{\beta} = -0.098$. All five estimates are statistically significant at the 5% level. The stability across permutations rules out the concern that any single state's economic trajectory drives the result.

Clustering sensitivity. The main specification clusters standard errors at the state level (6 clusters). With so few clusters, asymptotic cluster-robust variance estimators may over-reject. I address this in three ways. First, the leave-one-state-out analysis demonstrates stability across cluster removals. Second, the placebo test provides a direct check on false-positive rates. Third, the point estimates are large relative to their standard errors (the border-county employment t-statistic exceeds 4), providing substantial margin above conventional significance thresholds even under conservative inference.

D. Heterogeneity Appendix

Information sector detail. The Information sector (NAICS 51) includes several subsectors with distinct biometric exposure profiles. Data processing and hosting services (NAICS 518) directly handle biometric data and faced the largest concentration of BIPA lawsuits. Telecommunications (NAICS 517) increasingly uses voiceprint authentication for customer service interactions. Software publishing (NAICS 511) develops biometric software products. The 13.2% employment decline for the aggregate Information sector likely masks heterogeneity across these subsectors, though the QCEW's county-level data do not support reliable three-digit NAICS disaggregation for border counties due to disclosure suppression.

Professional Services sector detail. Within Professional and Technical Services (NAICS 54), computer systems design (NAICS 5415) is the most biometric-intensive subsector, as these firms design and implement the fingerprint scanners, facial recognition systems, and access control technologies that are the direct objects of BIPA regulation. The 5.8% sector-wide decline may be concentrated in this subsector.

E. Standardized Effect Sizes

Table 5: Standardized Effect Sizes for Main Outcomes

Outcome	Specification	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
Panel A: Pooled							
Log Employment	Border triple-diff	-0.0931	0.0208	1.917	-0.0486	0.0109	Small negative
Log Establishments	Border triple-diff	0.0581	0.0199	1.562	0.0372	0.0127	Small positive
Log Weekly Wage	Border triple-diff	-0.0379	0.0179	0.333	-0.1138	0.0538	Moderate negative
Panel B: Heterogeneous							
Log Emp (Information)	Info vs exempt	-0.1319	0.0316	1.939	-0.0680	0.0163	Moderate negative
Log Emp (Professional)	Prof vs exempt	-0.0580	0.0153	1.855	-0.0313	0.0083	Small negative

Notes: **Country:** United States. **Research question:** Did the 2019 Illinois Supreme Court ruling in *Rosenbach v. Six Flags*, which eliminated the injury requirement for biometric privacy lawsuits under BIPA, reduce employment and business activity in biometric-exposed industries in Illinois relative to neighboring states? **Policy mechanism:** The ruling transformed BIPA from a dormant statute into the most actively litigated privacy law in the US by allowing any individual whose biometric data was collected without proper consent to sue for statutory damages ($1,000–$5,000 per violation), even without demonstrating actual harm; this created enormous litigation exposure for firms using fingerprint scanners, facial recognition, or other biometric technologies. **Outcome definition:** Log quarterly county-level employment (average of three monthly levels from QCEW) and log quarterly establishment counts, by NAICS sector. **Treatment:** Binary: Illinois counties in biometric-exposed industries (Information, Professional/Technical Services) versus BIPA-exempt industries (Finance under GLBA, Healthcare under HIPAA) after the January 25, 2019 ruling. **Data:** BLS Quarterly Census of Employment and Wages (QCEW), 2015Q1–2023Q4, county-sector-quarter panel for Illinois and five border states (Indiana, Wisconsin, Missouri, Iowa, Kentucky). **Method:** Triple-difference (Illinois × exposed industry × post-ruling) with county-sector and quarter fixed effects; standard errors clustered at the state level; wild cluster bootstrap for few-cluster inference. **Sample:** Border counties only (counties sharing a state boundary between Illinois and neighboring states) to sharpen geographic comparison. SDE = $\hat{\beta}/\text{SD}(Y)$ where SD(Y) is the pre-treatment standard deviation. Classification refers to magnitude, not statistical significance: Large ($|\text{SDE}| > 0.15$), Moderate (0.05–0.15), Small (0.005–0.05), Null (< 0.005).