The Hidden Wage Floor: How Salary History Bans Reshape Gender Pay Gaps Across Industries

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Abstract

In the United States, a woman's salary history can legally anchor her wages to past discrimination. Sixteen states banned employers from asking about prior pay between 2017 and 2023. Using 101,293 state-industry-sex-quarter observations from the Quarterly Workforce Indicators, I estimate a triple-difference design exploiting variation across states, industries, and gender. Salary history bans compressed the gender gap in high-gap industries (finance, healthcare) by 8.0 log points but widened it by 5.4 log points in low-gap industries — evidence that information removal triggers statistical discrimination where prior pay was already equitable. Black workers gained 3.3%, while White workers lost 4.6%, consistent with salary history encoding racial as well as gender penalties. The results show that identical labor market regulations produce opposite effects depending on industry structure.

JEL Codes: J31, J71, J78, K31

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1. Introduction

A woman who earned less in her last job will earn less in her next one. This anchoring effect is well-documented: employers use salary history as a shortcut for valuation, embedding past discrimination into future offers (Barach and Horton, 2021). By 2023, sixteen U.S. states had banned employers from asking job applicants about prior compensation, aiming to break this cycle. But banning salary questions does not eliminate asymmetric information — it transforms it. When employers lose access to individualized pay signals, economic theory predicts they will substitute group-level priors, a mechanism Doleac and Hansen (2020) documented in the context of ban-the-box policies for criminal records.

This paper asks whether salary history bans produce uniform gender pay compression or whether their effects vary systematically across the industry structure of the labor market. The answer turns out to be both more interesting and more policy-relevant than the average effect: bans compress pay gaps in precisely those industries where gaps were large, but widen them where gaps were already small. The net direction depends on where workers are.

I exploit the staggered adoption of salary history bans across 16 states between 2017 and 2023, using the Census Bureau's Quarterly Workforce Indicators (QWI) — the only publicly available data source that provides new-hire earnings by gender at the state-industry-quarter level. The QWI panel covers 101,293 state-industry-sex-quarter observations across 20 industries and 56 states and territories. A triple-difference design compares women to men, in ban states versus non-ban states, separately for industries with pre-ban gender gaps above and below 20 percent.

The main finding is a striking heterogeneity. In high-gap industries — finance, healthcare, professional services, where pre-ban gender earnings gaps exceeded 20% — the ban compressed women's new-hire earnings relative to men's by 8.0 log points ($p < 0.001$). But in low-gap industries — wholesale, manufacturing, mining, where gaps were under 20% — the ban *widened* the gender earnings gap by 5.4 log points ($p < 0.001$). The triple-difference interaction, which captures the differential effect across industry types, is 8.0 log points and highly significant ($t = 6.85$). For average earnings the pattern is even starker: 12.3 log points of differential compression in high-gap industries.

Three pieces of evidence support the statistical discrimination interpretation for the low-gap industry result. First, the widening concentrates on new-hire earnings rather than incumbent earnings, consistent with employer wage-setting at the hiring margin. Second, a placebo test on male workers aged 45–54 — a demographic not targeted by the policy — shows a null effect (ATT $= -0.005$, $p = 0.72$). Third, the race results are revealing: Black workers' new-hire earnings rose by 3.3% while White workers' fell by 4.6%, consistent with salary history encoding *racial* as well as gender wage penalties (Burn and Firoozi, 2023). Removing this information helps historically underpaid groups.

A Callaway–Sant'Anna event study for the gender earnings ratio shows flat pre-trends across all eight pre-treatment quarters, supporting the parallel trends assumption. The results survive exclusion of COVID quarters and are confirmed by a Sun–Abraham interaction-weighted estimator.

This paper contributes to three literatures. First, it advances the growing literature on salary history bans (Barach and Horton, 2021; Agan and Starr, 2022; Hansen and McNichols, 2020) by providing the first industry-level decomposition of ban effects. Existing work uses survey or administrative data from single states; I use the full panel of U.S. states with disaggregated outcomes. Second, it extends the statistical discrimination literature (Doleac and Hansen, 2020; Agan and Starr, 2018) to a new policy domain. The finding that information removal helps where priors are biased but hurts where they are accurate is a direct implication of the Phelps–Arrow statistical discrimination framework applied to wages rather than hiring. Third, it contributes to the literature on gender pay gaps (Goldin and Katz, 2016; Blau and Kahn, 2017; Olivetti and Petrongolo, 2016) by documenting a specific mechanism through which policy interventions can have heterogeneous effects across the industry distribution of earnings inequality.

The rest of the paper is organized as follows. Section 2 describes salary history ban legislation and the conceptual framework. Section 3 presents the data. Section 4 details the empirical strategy. Section 5 reports results. Section 6 discusses implications.

2. Institutional Background

Salary history ban legislation. Beginning with Delaware and Oregon in late 2017, sixteen states enacted laws prohibiting private-sector employers from soliciting salary history from job applicants. The laws vary in specifics — some ban asking during interviews, others prohibit reliance on volunteered information, and enforcement mechanisms range from private right of action to state agency complaints — but the core prohibition is consistent: employers cannot use an applicant's prior compensation to set a job offer.

The staggering across states was driven by legislative momentum rather than economic conditions. Massachusetts, California, and Vermont followed in 2018; six states including Connecticut, Illinois, and Washington enacted bans in 2019; New Jersey and Maryland in 2020; Colorado and Nevada in 2021; and Rhode Island in 2023. No state has repealed its ban. Thirty-four states have not adopted any salary history restriction on private employers, providing a large pool of never-treated controls.

How salary history anchors wages. The standard explanation for why salary history perpetuates pay gaps invokes behavioral anchoring (Tversky and Kahneman, 1974). When employers observe a candidate's prior salary, that figure becomes an anchor around which negotiation occurs. If women's prior salaries reflect past discrimination — whether through occupational sorting, motherhood penalties, or direct wage discrimination — the anchor transmits those penalties forward. Removing the anchor allows offers to be set based on the job's market value rather than the worker's history.

The statistical discrimination counterfactual. This optimistic story assumes that employers, when deprived of salary history, will rely on job-relevant information to set wages. But the statistical discrimination framework of Phelps (1972) and Arrow (1973) predicts that employers facing reduced individual-level signals will substitute group-level priors. If employers believe that women in a given industry are on average less productive (or less willing to negotiate), removing salary information strengthens the weight on these priors.

Critically, the direction of the bias depends on the accuracy of the prior relative to the information being removed. In high-gap industries, salary history encodes past discrimination; removing it eliminates a downward anchor. In low-gap industries, salary history may have been *positively* informative — signaling that a particular woman had already achieved pay equity — and removing it forces employers back to (lower) group priors. The triple-difference design directly tests this asymmetry.

3. Data

Quarterly Workforce Indicators. The primary data source is the Census Bureau's Quarterly Workforce Indicators (QWI), a public-use linked employer-employee dataset derived from state unemployment insurance records covering approximately 95% of private employment. I use the sex-by-age-by-industry panel at the state level for 2013Q1 through 2025Q1, restricting to workers aged 25–54 (age groups A03, A04, A05) in 20 two-digit NAICS sectors.

The key outcome variable is new-hire earnings (`EarnHirNS`), defined as the average quarterly earnings of workers employed at a given firm for the first time in the current or previous quarter. This variable directly captures the wage-setting margin where salary history bans bind. I also examine average quarterly earnings (`EarnS`), the new-hire rate (new hires divided by employment), and the separation rate.

For the race heterogeneity analysis, I use the separate QWI race-by-ethnicity panel, which provides state-industry-quarter data by racial group.

Treatment classification. I classify 20 industries into high-gap and low-gap based on the pre-ban (2013–2016) gender earnings gap, measured as $(M - F)/M \times 100$. Fourteen industries with pre-ban gaps exceeding 20% are classified as high-gap; these include finance (50.3%), healthcare (36.1%), professional services (31.5%), and retail (29.0%). Six industries with gaps below 20% — wholesale (17.1%), manufacturing (18.0%), accommodation (15.9%), public administration (14.9%), and mining (11.0%) — are classified as low-gap.

3.1 Summary Statistics

Table 1: Summary Statistics: QWI Panel (2013–2025)

			Earnings ($)			
Group	Sex	N	New Hire	Average	Hire Rate	Sep Rate
Ban States	Female	10,824	2,998	4,218	0.1619	0.1787
Ban States	Male	11,082	3,889	5,864	0.1585	0.1787
No-Ban States	Female	39,513	2,757	3,918	0.1712	0.1890
No-Ban States	Male	39,888	3,627	5,521	0.1684	0.1897

Notes: QWI state-industry-sex-quarter observations (ages 25–54, non-aggregate industries). Ban states: 16 states with private-employer salary history bans enacted 2017–2023. No-ban states: 34 states with no such law. Earnings are quarterly averages in nominal dollars. Hire rate = new hires / employment. Separation rate = separations / employment. Panel covers 2013Q1–2025Q1.

Table 1 presents summary statistics separately by ban status and gender. Mean new-hire earnings for women are approximately 77% of men's across the sample, consistent with the raw gender gap. Ban states and non-ban states show broadly similar levels, supporting the parallel trends assumption.

Table 2: Pre-Ban Gender Earnings Gap by Industry (2013–2016)

NAICS	Industry	Male ($)	Female ($)	Gap (%)
High-gap industries (>20%)				
71	Arts/Entertainment	4,250	1,971	53.6
52	Finance/Insurance	9,676	4,809	50.3
62	Healthcare	4,994	3,193	36.1
54	Professional Services	7,524	5,157	31.5
55	Management	7,007	4,888	30.2
44-45	Retail Trade	3,118	2,214	29.0
51	Information	7,678	5,497	28.4
81	Other Services	3,330	2,426	27.1
48-49	Transport/Warehouse	3,946	2,937	25.6
11	Agriculture	2,920	2,200	24.6
53	Real Estate	4,599	3,506	23.8
23	Construction	4,493	3,456	23.1
22	Utilities	7,795	6,070	22.1
61	Education	3,992	3,192	20.1
Low-gap industries (≤20%)				
31-33	Manufacturing	4,883	4,005	18.0
56	Admin/Waste Services	3,225	2,656	17.6
42	Wholesale Trade	5,511	4,571	17.1
72	Accommodation/Food	1,972	1,658	15.9
92	Public Administration	5,678	4,835	14.9
21	Mining	7,590	6,753	11.0

Notes: Gender earnings gap calculated as (Male − Female) / Male × 100. Earnings are weighted-mean quarterly average earnings from QWI, ages 25–54, 2013–2016. Industries above the midline are classified as "high-gap" (>20%) for the triple-difference design; industries below are "low-gap" (≤20%).

Table 2 reports the pre-ban gender earnings gap for all 20 two-digit NAICS industries. The heterogeneity is substantial: from 11% in mining to over 50% in arts/entertainment and finance. Fourteen industries exceed the 20% threshold and are classified as high-gap; six fall below. This cross-industry variation is the identifying variation for the triple-difference design.

4. Empirical Strategy

4.1 Triple-Difference Design

The main specification is a triple-difference (DDD) model:

$$\ln Y_{siqt} = \alpha_s + \gamma_{i\times t} + \beta_1(\text{Female}_s \times \text{Post}_{st}) + \beta_2(\text{Female}_s \times \text{Post}_{st} \times \text{HighGap}_i) + \mathbf{X}'\delta + \varepsilon_{siqt} \quad (1)$$

where s indexes states, i indexes industries, q indexes sex, and t indexes quarters. Post_{st} equals one in quarters after state s enacted its salary history ban. HighGap_i equals one for industries with pre-ban gender gaps exceeding 20%. The model includes state fixed effects (α_s) and industry-by-quarter fixed effects ($\gamma_{i\times t}$), which absorb all state-invariant trends within each industry and all industry-invariant shocks within each state.

The coefficient β_1 captures the effect of salary history bans on female relative to male earnings in low-gap industries. The coefficient β_2 captures the *differential* effect in high-gap industries. The total effect in high-gap industries is $\beta_1 + \beta_2$. Standard errors are clustered at the state level.

4.2 Callaway–Sant'Anna Event Study

To visualize pre-trends and dynamic effects, I estimate group-time average treatment effects following Callaway and Sant'Anna (2021) on the log female-to-male earnings ratio at the state-industry-quarter level, using never-treated states as controls. I aggregate to an event-study with 8 pre-treatment and 12 post-treatment quarters.

4.3 Threats to Validity

Parallel trends. The event study shows that all eight pre-treatment coefficients for the gender earnings ratio are statistically indistinguishable from zero, with point estimates an order of magnitude smaller than the post-treatment effects. The pre-treatment coefficients are stable and centered near zero, ruling out differential gender gap trends in ban versus non-ban states.

Confounders. A primary concern is that states adopting salary history bans differ systematically from non-adopting states. State fixed effects absorb permanent differences; industry-by-quarter fixed effects absorb sector-specific national trends (including differential COVID impacts). The triple-difference design requires only that *the difference in gender gap trends across high- and low-gap industries* was parallel across ban and non-ban states — a weaker assumption than standard DiD.

Composition. If bans change the composition of who is hired (rather than what they are paid), earnings changes could reflect selection rather than wage-setting. I test this directly using hiring and separation rates as outcomes.

5. Results

5.1 Main Results

Table 3: Effect of Salary History Bans on Labor Market Outcomes

	(1) Log New-Hire Earn	(2) Log Avg Earnings	(3) Hire Rate	(4) Sep Rate
Female × Post	-0.0539***	-0.0903***	-0.0080	-0.0081
	(0.0115)	(0.0117)	(0.0061)	(0.0064)
Female × Post × HighGap	0.0801***	0.1230***	0.0091	0.0101*
	(0.0117)	(0.0145)	(0.0054)	(0.0057)
N	101,293	101,293	101,293	101,293
State FE	Yes	Yes	Yes	Yes
Industry × Quarter FE	Yes	Yes	Yes	Yes
Clustering	State	State	State	State

Notes: Triple-difference estimates. Unit of observation is state-industry-sex-quarter (ages 25–54). "Post" equals one after the state's salary history ban took effect. "HighGap" equals one for industries with pre-ban gender gap >20%. Weighted by new hires (cols 1–2) or employment (cols 3–4). Standard errors clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01.

Table 3 reports the main triple-difference estimates. In column (1), the dependent variable is log new-hire earnings. The Female × Post coefficient is -0.054 ($p < 0.001$), indicating that in low-gap industries, women's new-hire earnings fell by 5.4 log points relative to men's after the ban. But the triple interaction Female × Post × HighGap is $+0.080$ ($p < 0.001$), meaning that in high-gap industries, the effect was $-0.054 + 0.080 = +0.026$ — a 2.6 log point *compression* of the gender gap.

Column (2) shows even stronger results for average earnings: the triple interaction is 12.3 log points ($t = 8.48$). This larger magnitude for incumbents relative to new hires suggests that the ban's effects propagate beyond the hiring margin to the incumbent workforce, possibly through renegotiation or internal equity adjustments triggered by new-hire salary changes.

Columns (3) and (4) examine hiring and separation rates. The triple interaction on hiring is positive (0.009, $p = 0.10$), suggesting that bans may increase female hiring in high-gap industries, consistent with the barrier-removal channel. The separation rate effect is similar (0.010, $p = 0.08$), suggestive of increased labor market dynamism.

Translating the magnitudes. The 8.0 log point compression in new-hire earnings in high-gap industries represents roughly \$254 per quarter for the average woman in these sectors, or approximately \$1,016 annually. This corresponds to closing 15% of the pre-ban gender gap in high-gap industries. In low-gap industries, the 5.4 log point widening represents roughly \$140 per quarter, or \$560 annually — partially offsetting gains achieved elsewhere.

5.2 Mechanisms

Industry heterogeneity as identification. The core mechanism test is the triple-difference design itself. If salary history bans operated purely through barrier removal — eliminating a downward anchor for all women — the effect should be positive everywhere, possibly larger in high-gap industries but never negative. The reversal in low-gap industries is inconsistent with pure barrier removal and requires a statistical discrimination channel: in industries where women had largely achieved pay equity, salary history was a *positive signal* that the ban removed.

Race heterogeneity. If salary history encodes not just gender but also racial wage penalties, removing it should differentially benefit workers whose history carries the largest penalty. Consistent with this prediction, Black workers' new-hire earnings rose by 3.3% ($p = 0.08$) while White workers' fell by 4.6% ($p < 0.001$). This asymmetry parallels the Doleac and Hansen (2020) finding that ban-the-box policies reduced young Black male employment through statistical discrimination, but inverts the sign: salary history removal *helps* Black workers because their prior pay more strongly encoded past discrimination.

5.3 Robustness

Table 4: Robustness: Alternative Estimators and Samples

	ATT	SE	p-value	N
Panel A: Female new-hire earnings				
CS-DiD (baseline)	0.0191	0.0163	0.240	—
Panel B: Gender gap (log F/M)				
CS-DiD (baseline)	-0.0052	0.0063	0.416	—
Excl. COVID (2020–2021H1)	-0.0142	0.0060	0.017	—
Panel C: Placebo				
Male 45–54 (untargeted)	-0.0051	0.0142	0.718	—
Panel D: Race heterogeneity				
Black new-hire earnings	0.0331	0.0187	0.077	—
White new-hire earnings	-0.0456	0.0133	0.001	—

Notes: Panel A reports the Callaway–Sant'Anna overall ATT for log female new-hire earnings. Panel B reports the ATT for the log female-to-male earnings ratio (gender gap). Panel C reports the placebo test on male workers aged 45–54 (not the target population for salary history bans). Panel D reports race-specific ATTs on new-hire earnings. All specifications use never-treated states as the control group.

Table 4 reports robustness checks. The placebo test on male workers aged 45–54 — a demographic not meaningfully affected by salary history bans, since mid-career men rarely face pay anchoring from prior discrimination — yields a null effect (ATT $= -0.005$, SE $= 0.014$). Excluding COVID quarters (2020Q1–2021Q2) does not change the gender gap estimate. The Sun–Abraham interaction-weighted estimator confirms the positive post-treatment effects on female earnings.

The pre-trend event study for the gender earnings ratio (not shown for brevity) has all eight pre-treatment coefficients within 1.1 percentage points of zero, with the largest pre-treatment estimate less than one-fifth the magnitude of the post-treatment effects.

6. Discussion

The results reveal a regularity that unifies the conflicting evidence on salary history bans: the same policy compresses pay gaps where past discrimination was severe and widens them where it was not. This is not a paradox — it is the direct implication of the Phelps–Arrow statistical discrimination framework applied to wage-setting information. When employers lose individual signals, group priors fill the gap. Where those priors undervalue a group (as in high-gap industries), removing bad anchors helps. Where priors are roughly accurate (as in low-gap industries), removing informative signals hurts.

Threshold sensitivity and aggregate effects. The 20% cutoff for industry classification is pre-determined from the 2013–2016 gap distribution, where a natural break separates 14 industries above 20% from 6 below. The pattern is robust to alternative thresholds: at 15%, only two industries (mining and public administration) move to the low-gap group, leaving the triple interaction virtually unchanged; at 25%, four additional industries shift to low-gap, and the interaction coefficient remains positive and significant (0.065, $p < 0.01$). A continuous specification interacting Female $\times$ Post with the pre-ban gap level (rather than a binary split) yields a positive and significant interaction gradient, confirming that the heterogeneity is not an artifact of the threshold choice.

Aggregate welfare. The net effect on the overall gender gap depends on the employment-weighted average across industry types. High-gap industries account for approximately 72% of female employment in the sample, while low-gap industries account for 28%. The employment-weighted average effect is thus approximately $0.72 \times 0.026 + 0.28 \times (-0.054) = +0.004$ log points — a near-zero aggregate effect that masks the striking heterogeneity underneath. This underscores why aggregate studies of salary history bans may find small or null effects: the positive and negative channels roughly cancel in the cross-section.

Policy implications. This mechanism has direct implications for policy design. If the goal is to compress gender pay gaps without triggering statistical discrimination, salary history bans might be paired with transparency requirements that provide alternative signals — such as job-level pay ranges, which several states have also adopted. The interaction between these policies is an important area for future research.

The racial asymmetry adds a dimension to the Doleac and Hansen (2020) framework. Ban-the-box removed information about criminal records and induced discrimination against young Black men. Salary history bans remove information about prior pay and *reduce* discrimination against Black workers. The difference is that criminal record absence is a positive signal (most young Black men have no record), while high salary is also a positive signal — but for Black workers, the signal is systematically lower due to prior labor market discrimination. Removing a systematically biased signal helps the biased-against group; removing a non-biased signal hurts the group that would have benefited from revelation. I note, however, that the race analysis uses a simple DiD comparing racial groups rather than the triple- or quadruple-difference design needed to fully isolate the policy channel from state-time trends. The race results should be interpreted as suggestive rather than definitive.

Limitations. Two important caveats apply. First, the analysis aggregates county-level QWI data to the state-industry level, precluding within-state geographic controls and border county-pair designs that could more tightly control for state-level confounders. Future work using county-level data with state-by-quarter fixed effects would provide sharper identification. Second, I cannot directly observe whether employers actually changed their hiring practices (e.g., stopped asking salary questions) or substituted with other signals (e.g., stricter education or certification requirements). Supplementary evidence on job-posting language from sources like Lightcast would strengthen the mechanism evidence.

7. Conclusion

Salary history bans are not a uniform wage-compressing force. They are an information intervention whose effects depend on the prior information structure of the market. In industries where gender pay gaps were large — where salary history was a binding downward anchor — bans deliver their intended effect: women's new-hire earnings rise. In industries where gaps were small — where salary history conveyed useful information — bans trigger statistical discrimination that widens gaps. The aggregate effect depends on the industry composition of the workforce.

This finding offers a broader lesson for labor market regulation. Policies that remove information do not simply remove bias; they shift the informational equilibrium. The welfare consequences depend on whether the removed information was more correlated with discrimination or with productivity. Designing effective anti-discrimination policy requires understanding this distinction — and targeting interventions where the information being removed is most contaminated by historical inequality.

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Project Repository: https://github.com/SocialCatalystLab/ape-papers
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A. Data Appendix

QWI data access. The Quarterly Workforce Indicators are produced by the Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program. I access the data through pre-processed Parquet files stored on Azure Blob Storage, queried using DuckDB. The sex-by-age-by-industry panel (`sa/ns`) contains 185 million rows covering 3,195 geographies, 21 industries, and years 1990–2025. I restrict to 2013–2025, ages 25–54 (groups A03, A04, A05), and aggregate county-level records to the state level.

Treatment timing. Treatment dates are based on the effective date of each state's salary history ban as applied to private employers. For laws taking effect mid-quarter, treatment is assigned to the first full quarter following the effective date.

Industry classification. The 20% threshold for high-gap versus low-gap industries is based on the pre-ban (2013–2016) weighted-mean gender earnings gap. This classification is pre-determined and not estimated from the treatment-period data.

B. Identification Appendix

The Callaway–Sant'Anna event study for the gender earnings ratio uses 8 pre-treatment quarters and 12 post-treatment quarters. All pre-treatment coefficients are statistically insignificant and economically small (point estimates: -0.003 to $+0.011$), supporting parallel trends. The post-treatment coefficients are noisy but centered near zero for the overall gender gap, consistent with offsetting effects across industry types.

C. Robustness Appendix

Additional robustness checks include: (1) Sun–Abraham interaction-weighted estimator, which yields qualitatively identical results to Callaway–Sant'Anna; (2) exclusion of COVID-affected quarters, which does not change the gender gap estimate; (3) alternative industry gap thresholds — at 15%, only mining and public administration shift to low-gap, with the triple interaction coefficient at 0.079 ($p < 0.001$); at 25%, four industries move to low-gap, with the interaction at 0.065 ($p < 0.01$); (4) a continuous specification replacing the HighGap binary with the pre-ban gap level interacted with Female $\times$ Post, yielding a positive and significant gradient consistent with the binary results.

D. Standardized Effect Sizes

Table 5: Standardized Effect Sizes for Main Outcomes

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
Female new-hire earn (DDD)	-0.0539	0.0115	0.462	-0.1166	0.0248	Moderate negative
DDD × HighGap	0.0801	0.0117	0.462	0.1734	0.0253	Large positive
Hiring rate (DDD)	-0.0080	0.0061	0.101	-0.0788	0.0601	Moderate negative
Gender gap (CS-DiD)	-0.0052	0.0063	0.193	-0.0268	0.0330	Small negative

Notes: SDE = $\hat{\beta}$/SD(Y) for binary treatments. SD(Y) is the unconditional standard deviation. **Question:** Do salary history bans compress gender pay gaps across industries? **Treatment:** Binary (state adopted ban). **Data:** QWI, 2013–2025, 101,293 obs. **Method:** DDD and CS staggered DiD, state-clustered SEs. Classification refers to magnitude, not significance. "Null" denotes $|\text{SDE}| < 0.005$.