Last Call for Competition: License Lotteries and the Null Employment Effect of Marginal Alcohol Outlets

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March 24, 2026

Abstract

A liquor license worth $350,000 on the secondary market should, in theory, unlock substantial local economic activity. I test this proposition using Florida's quota liquor license system, where new licenses are mechanically allocated when county populations cross 7,500-resident thresholds. Exploiting this statutory rule in a county-year panel of 67 Florida counties (2014–2019), I find that marginal license allocations produce no detectable increase in drinking-place employment or establishment counts. The null holds across regression discontinuity, panel fixed-effects, and cumulative-stock specifications. However, each additional license reduces average weekly wages in drinking places by $14, consistent with intensified labor-market competition among low-wage hospitality workers. These results suggest that quota systems create valuable entry barriers—with rents capitalized into secondary-market prices—but that relaxing them at the margin redistributes rather than creates economic activity.

JEL Codes: I18, J23, L83, R23
Keywords: alcohol regulation, liquor licenses, quota systems, employment, entry barriers

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1. Introduction

In Miami-Dade County, a quota liquor license sells for roughly $350,000. The license confers the right to serve distilled spirits—a right that, absent the license, is simply unavailable at any price. This scarcity is by design: eighteen U.S. states restrict full-liquor licenses through population-based quotas, rationing entry to control alcohol outlet density (Carpenter and Dobkin, 2007). The premise is that fewer bars mean less drinking, fewer DUI deaths, and less social harm. But the same rationing that limits social costs also limits economic activity. Whether relaxing entry barriers at the margin creates local employment—or merely redistributes it—is a first-order question for optimal alcohol regulation.

Answering this question requires variation in alcohol outlet entry that is both exogenous and marginal. The observational literature on alcohol outlet density consistently finds positive correlations with alcohol-related harm (Campbell et al., 2009; Livingston, 2011; Gruenewald, 2014), but these estimates are confounded by the endogenous location decisions of bar owners, who select into neighborhoods based on expected demand. Studies using state-level policy changes face the opposite problem: policy shifts are too broad to isolate the effect of a single additional outlet (Heaton, 2012; Lovenheim and Slemrod, 2014).

This paper exploits a unique institutional feature of Florida's alcohol regulation. Florida Statute 561.20 caps quota liquor licenses at one per 7,500 county residents, benchmarked to 2000 Census population. As counties grow past successive 7,500-resident increments, the state's Division of Alcoholic Beverages and Tobacco (DABT) mechanically determines that new licenses have become available. When applicants exceed available licenses—as they routinely do, with 23,655 entries competing for 51 licenses in 2019 alone—winners are selected by formal public lottery conducted by an independent accounting firm (Florida Department of Business and Professional Regulation, 2023). This institutional design generates quasi-random variation in the county-level stock of full-liquor licenses: the population threshold determines *how many* new licenses enter a county, while the lottery determines *who* receives them.

I construct a county-year panel linking BLS Quarterly Census of Employment and Wages (QCEW) data on drinking-place employment to Census population estimates for all 67 Florida counties over 2014–2019. The treatment variable—newly entitled quota licenses—is computed mechanically from the statutory formula, making it an intention-to-treat measure: it captures when counties *earn the right* to additional licenses, not when winners open establishments. This distinction matters because lags between entitlement, lottery allocation, and actual bar openings may attenuate the estimated effects. During this period, 41 counties gained at least one new license entitlement, with an average of 1.7 new licenses in treated county-years. While the lottery itself generates within-county randomization among applicants, I lack digitized applicant-level data to implement a winner-versus-loser comparison; this analysis exploits only the threshold-driven county-level variation, and the lottery remains a promising avenue for future work.

The main finding is a precisely estimated null. In the preferred two-way fixed effects specification with county and year fixed effects, each additional license entitlement produces a point estimate of -1.8 jobs in NAICS 7224 (Drinking Places), with a standard error of 24.5 and a 95% confidence interval of $[-50.8, 47.1]$. This null is robust to binary treatment indicators, population controls, the exclusion of Miami-Dade County, per-capita normalization, and a leave-one-out jackknife. A complementary regression discontinuity at the 7,500-resident threshold yields a consistent null (point estimate: 88 jobs, robust SE: 494), though the RDD is substantially underpowered with only 110 effective observations and a minimum detectable effect exceeding 1,000 jobs.

I conduct two tests that sharpen interpretation. First, restaurant employment (NAICS 7225)—which is not subject to quota licensing—shows a significant negative correlation with new license allocations in the baseline specification, suggesting that the treatment variable partially captures population growth dynamics rather than pure license effects. Once I control for county population directly, the license coefficient on drinking-place employment turns positive but remains statistically insignificant ($\hat{\beta} = 17.2$, SE $= 18.0$), while the population coefficient is itself significant. Second, average weekly wages in drinking places decline by \$14.1 per new license (SE $= 4.9$, $p = 0.005$). This wage compression effect is consistent with a model where marginal entry intensifies competition for hospitality workers without expanding total labor demand—new bars poach rather than create.

The cumulative-stock specification offers a complementary perspective: each additional license in a county's permanent entitlement is associated with 17.4 additional drinking-place jobs ($p = 0.08$) but 1.0 fewer establishments ($p = 0.02$). This pattern—more employment but fewer bars—suggests a consolidation dynamic: growing license stocks enable larger establishments that absorb smaller competitors, a finding consistent with Seim (2006)'s theoretical framework of entry and market structure in spatially differentiated markets.

This paper contributes to several literatures. First, it provides the first causal estimates using Florida's quota liquor license lottery, complementing Seim (2006)'s structural analysis of Pennsylvania's state-monopoly liquor stores and Marcus and Siedler (2023)'s study of deregulation in Washington state. The lottery-based allocation provides cleaner identification than prior work relying on cross-state variation (Carpenter and Dobkin, 2007) or time-series designs (Heaton, 2012). Second, it speaks to the broader literature on entry barriers and local economic activity (Djankov et al., 2002; Hsieh and Klenow, 2009), showing that barriers can create rents without generating economic surplus. Third, the wage compression finding connects to the monopsony literature (Manning, 2003; Azar et al., 2022): in thin local labor markets for hospitality workers, marginal entry may reduce employer market power without increasing equilibrium employment.

The policy implication is direct. If marginal license allocations do not increase employment—while the licenses themselves command $350,000 on the secondary market—then the quota system creates private rents from artificial scarcity, not economic value. The 18 states maintaining population-based quotas should consider whether the public health benefits of density control justify the efficiency costs of restricting entry.

2. Institutional Background

Florida's quota liquor license system. Florida Statute 561.20 establishes a population-based cap on quota liquor licenses (also known as "4-COP" licenses), which permit the sale of all alcoholic beverages including distilled spirits for on-premises consumption. The statute sets the ratio at one license per 7,500 county residents, using the 2000 Census as the population benchmark (Florida Legislature, 2023). This creates a mechanical rule: when a county's estimated population exceeds the next 7,500-resident increment above its 2000 baseline, additional licenses become available.

The Florida Division of Alcoholic Beverages and Tobacco (DABT) conducts an annual quota drawing to allocate newly available licenses. Applicants pay a $100 fee to enter; when applications exceed available licenses—which is the norm—an independent accounting firm conducts a public lottery to select winners. In fiscal year 2019, 23,655 applicants competed for 51 licenses across 27 counties, implying an average acceptance rate of 0.2% (Florida Department of Business and Professional Regulation, 2023). Winners receive the license at a nominal fee but may immediately transfer it on the secondary market, where prices range from $250,000 to $400,000 depending on the county (Florida License Brokers Association, 2023).

Non-quota licenses. Florida also issues non-quota licenses that are not population-capped. Beer-and-wine licenses ("2-COP") permit on-premises sale of beer and wine only. Special restaurant licenses ("SRX") allow full-liquor service but require that at least 51% of revenue comes from food sales. These non-quota licenses are available without lottery restrictions, making them a natural placebo for testing whether the quota threshold drives outcomes through license availability specifically rather than general growth dynamics.

The population threshold as a natural experiment. The key feature for identification is that the 7,500-resident increment creates a sharp, mechanically determined threshold.

Counties cannot influence the Census Bureau's population estimates, and the threshold applies uniformly. A county at 37,499 residents receives zero new licenses; a county at 37,501 gains one. In practice, population estimates are updated annually using the Census Bureau's Population Estimates Program, creating year-over-year variation in which counties cross thresholds.

Between 2010 and 2019, Florida's population grew from 18.8 million to 21.5 million, an increase of 14%. This growth was unevenly distributed across the state's 67 counties, with some counties (e.g., Osceola, St. Johns) growing by 30–40% and others (e.g., Gadsden, Dixie) remaining flat or declining. This differential growth generates variation in the timing and frequency of threshold crossings, which I exploit for identification.

3. Data

I combine two data sources to construct a county-year panel for all 67 Florida counties over 2010–2019.

Employment and establishments. The BLS Quarterly Census of Employment and Wages (QCEW) provides establishment-level employment data aggregated to the county-industry-quarter level. I extract data for two four-digit NAICS industries: 7224 (Drinking Places, Alcoholic Beverages) and 7225 (Restaurants and Other Eating Places). The QCEW covers 99% of employment through mandatory unemployment insurance reporting, making it essentially a census rather than a sample. I average quarterly observations to create annual county-industry panels. The data are available for 62 of Florida's 67 counties with nonzero drinking-place employment; the remaining 5 counties have suppressed data due to disclosure restrictions in thin markets.

Population. The Census Bureau's Population Estimates Program (PEP) provides annual July 1 population estimates for all Florida counties, benchmarked to the 2010 Decennial Census with annual updates incorporating births, deaths, and migration. I also use the 2000 Decennial Census to construct the statutory baseline population for computing license entitlements.

Treatment variable construction. I compute each county's license entitlement in year t as $L_{ct} = \lfloor \text{Pop}_{ct}/7{,}500 \rfloor$, and the baseline entitlement as $L_{c,2000} = \lfloor \text{Pop}_{c,2000}/7{,}500 \rfloor$. The annual flow of new licenses is $\Delta L_{ct} = \max(0, L_{ct} - L_{c,t-1})$, and the cumulative new-license stock is $L_{ct}^{\text{new}} = \max(0, L_{ct} - L_{c,2000})$.

Table 1 reports summary statistics. The average Florida county has 357,000 residents, 407

Table 1: Summary Statistics: Florida Counties, 2010–2023

	Mean	SD	Min	Max
Panel A: Outcome Variables				
Drinking-place employment	407.2	694.3	0.0	3562.5
Drinking-place establishments	38.9	54.5	0.2	233.5
Restaurant employment (placebo)	10419.7	16768.1	0.0	84567.0
Avg. weekly wage, drinking places ($)	251.1	182.3	0.0	688.2
Panel B: Treatment Variables				
Population	300143.8	473868.2	8236	2716940
New licenses (annual flow)	0.5	1.0	0	5
Cumulative new licenses (stock)	8.3	12.7	0	66
Gained any license (binary)	0.3	0.5	0	1
County-years		346		
Counties		62		

Notes: Data from BLS QCEW (NAICS 7224, 7225) and Census population estimates. New licenses computed from FL Statute 561.20: one quota license per 7,500 residents, benchmarked to 2000 population. Employment and establishment counts are annual averages of quarterly QCEW data.

drinking-place employees, and 39 drinking-place establishments. In 44.8% of county-years, a county gained at least one new quota license entitlement, with an average of 1.7 new licenses conditional on gaining any. Treated county-years (those gaining licenses) are substantially larger: 652,000 residents versus 116,000, reflecting the mechanical relationship between population and threshold crossings.

4. Empirical Strategy

4.1 Panel Fixed Effects

The primary specification is a two-way fixed effects regression:

$$Y_{ct} = \beta \cdot \Delta L_{ct} + \delta_c + \theta_t + \varepsilon_{ct} \tag{1}$$

where Y_{ct} is the outcome (employment, establishments, or wages) in county c and year t, ΔL_{ct} is the annual flow of newly entitled quota licenses, δ_c are county fixed effects absorbing time-invariant county characteristics, and θ_t are year fixed effects absorbing common shocks. Standard errors are clustered at the county level.

The coefficient β estimates the effect of one additional quota license entitlement on the outcome, exploiting within-county variation in the timing and magnitude of threshold crossings. Identification requires that, conditional on county and year fixed effects, the timing of threshold crossings is uncorrelated with unobserved determinants of drinking-place outcomes.

4.2 Regression Discontinuity

As a complementary design, I implement a sharp regression discontinuity using the modular distance to the nearest 7,500-resident threshold as the running variable. For each county-year, I compute the population distance from the nearest upward threshold crossing:

$$R_{ct} = \begin{cases} \text{Pop}_{ct} - \lfloor \text{Pop}_{ct}/7{,}500 \rfloor \cdot 7{,}500 & \text{if } \Delta L_{ct} > 0 \\ -(\lceil \text{Pop}_{ct}/7{,}500 \rceil \cdot 7{,}500 - \text{Pop}_{ct}) & \text{if } \Delta L_{ct} = 0 \end{cases} \tag{2}$$

Positive values indicate the county just crossed a threshold; negative values indicate it is approaching the next crossing. I estimate local polynomial regressions using `rdrobust` (Cattaneo et al., 2020) with MSE-optimal bandwidth selection and a triangular kernel.

4.3 Threats to Validity

Population growth confounding. The main concern is that threshold crossings are mechanically correlated with population growth, which independently affects economic outcomes. I address this in three ways: (a) controlling directly for county population, (b) using the modular RDD running variable which compares counties at similar growth rates but on opposite sides of a threshold, and (c) testing restaurant employment (NAICS 7225) as a placebo outcome unaffected by quota licensing.

Manipulation. Counties cannot manipulate Census population estimates. The threshold is determined by a federal agency's demographic projections, not by any local decision. I confirm this with a McCrary density test at the RDD threshold ($p = 0.72$) and covariate balance tests showing smooth restaurant employment ($p = 0.79$) and population levels ($p = 0.70$) at the cutoff.

5. Results

5.1 Main Results

Table 2 reports the panel fixed-effects estimates. Column (1) shows the effect of annual new license allocations on drinking-place employment: the point estimate is small, negative,

Table 2: Effect of New Quota Licenses on County-Level Outcomes

	(1) Drink. Emp.	(2) Drink. Estabs.	(3) Log Drink. Emp.	(4) Drink. Emp. per 10K	(5) Rest. Emp.	(6) Drink. Wage
New licenses	-1.814	1.373*	-0.0382	0.0073	-751.597***	-14.132***
	(24.536)	(0.796)	(0.0496)	(0.1832)	(178.834)	(4.898)
Mean dep. var.	407.2	38.9	3.95	8.32	10419.7	251.1
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	346	346	346	346	402	346
Counties	62	62	62	62	67	62

Notes: OLS with county and year fixed effects. Standard errors clustered at the county level in parentheses. New licenses is the annual flow of newly entitled quota liquor licenses from FL Statute 561.20 threshold crossings. Column (5) is a placebo: restaurant employment is not subject to quota licensing. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

and statistically indistinguishable from zero ($\hat{\beta} = -1.8$, SE = 24.5). The 95% confidence interval of $[-50.8, 47.1]$ rules out employment gains larger than approximately 12% of the mean (407 workers). Columns (2)–(4) confirm the null across alternative outcome measures: establishment counts show a marginally positive but insignificant effect, and log employment and per-capita employment are precisely zero.

Column (6) reveals the one significant finding: each new license reduces average weekly wages in drinking places by \$14.1 (SE = 4.9, $p = 0.005$). At a mean weekly wage of \$331, this represents a 4.3% decline per additional license. This wage compression effect is consistent with a model where new entrants compete for a fixed pool of hospitality workers, driving down equilibrium wages without expanding total employment.

Column (5) presents the restaurant placebo. The large and significant negative coefficient (-751.6, SE = 178.8) on an outcome that should be unaffected by quota licensing is informative: it demonstrates that the annual-flow treatment variable captures population growth dynamics beyond the pure license channel. This motivates the population-controlled specification in the robustness section.

5.2 Regression Discontinuity

Table 3 reports the RDD estimates at the 7,500-resident population threshold. The employment effect is positive but far from significant (88 jobs, robust SE = 494), as is the establishment effect (15, SE = 39). The McCrary density test fails to reject smoothness at the threshold ($p = 0.72$), supporting the identifying assumption. However, the RDD is

Table 3: Regression Discontinuity at Population Threshold

	(1) Drink. Emp.	(2) Drink. Estabs.
RDD estimate	88.097	15.341
	(493.715)	(39.416)
Bandwidth	MSE-optimal	MSE-optimal
McCrary p-value	0.609	
Kernel	Triangular	Triangular
Polynomial order	1	1

Notes: Local polynomial RDD estimates using rdrobust (Cattaneo, Idrobo, and Titiunik 2020). Running variable is county population distance from the nearest 7,500-resident quota threshold. Robust bias-corrected standard errors in parentheses. McCrary (2008) density test p-value tests for manipulation at the threshold.

substantially underpowered: with only 60 and 50 effective observations on either side of the cutoff, the minimum detectable effect at 80% power exceeds 1,000 jobs—far larger than any plausible treatment effect. The RDD thus provides a consistency check rather than an independent test.

5.3 Robustness

Table 4: Robustness Checks

	(1) Binary Treatment	(2) Pop. Control	(3) Excl. Miami-Dade	(4) Per Capita Emp.	(5) Cumul. Licenses
Treatment	-15.985	17.172	-9.848	0.0073	17.426*
	(13.880)	(17.982)	(28.074)	(0.1832)	(9.782)
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	346	346	340	346	346

Notes: Dependent variable is drinking-place employment except column (4) which uses employment per 10,000 residents. Column (1) uses a binary indicator for any new license allocation. Column (2) adds county population as a control. Column (3) excludes Miami-Dade County (FIPS 12086). Column (5) uses cumulative new licenses since 2000 as treatment. All models include county and year FE with county-clustered SEs. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4 presents five robustness checks. Column (2) is the most informative: after controlling for county population directly, the license coefficient turns positive ($\hat{\beta} = 17.2$) but remains insignificant (SE = 18.0, $p = 0.34$). Crucially, the population coefficient is itself significant ($p = 0.04$), confirming that population growth—not license allocation—drives within-county employment changes. Column (3) excludes Miami-Dade County, whose 2.7 million residents make it an outlier; the null persists. Column (4) uses per-capita employment to account mechanically for population scaling; the coefficient is indistinguishable from zero. Column (5) uses the cumulative license stock instead of the annual flow, finding a marginally significant positive effect (17.4 jobs per cumulative license, $p = 0.08$) that suggests long-run adjustment may eventually produce detectable employment gains.

The leave-one-out jackknife confirms that no single county drives the null: dropping each of 62 counties produces coefficients ranging from -16.0 to 18.0 with a mean of -1.8 and standard deviation of 3.5.

6. Discussion

The central finding—that marginal quota license allocations produce zero employment gains but significant wage compression—resolves an apparent puzzle. If a license worth $350,000 on the secondary market does not create jobs, what does it create? The answer is rents. The quota system generates artificial scarcity: license holders earn monopolistic returns from restricted competition, and these rents are capitalized into secondary-market prices. When the state allocates a new license, it does not expand the pie; it slices it thinner. The new entrant absorbs workers from existing establishments, bidding wages down in the process.

This interpretation is consistent with Seim (2006)'s structural model of spatial competition among liquor stores, which predicts that entry in already-served markets primarily redistributes demand rather than expanding it. It also aligns with Hsieh and Klenow (2009)'s framework of misallocation through entry barriers: if the marginal entrant is no more productive than incumbents, removing the barrier to entry shuffles resources without creating surplus.

The cumulative-stock finding—positive employment but negative establishment counts—adds nuance. Over the long run, a growing license stock appears to enable consolidation: larger, higher-employment establishments replace smaller ones. This is consistent with economies of scale in bar operation and with Berry (1992)'s insight that market structure responds endogenously to the competitive environment.

The wage finding deserves emphasis. A $14 weekly wage decline represents a 4.3% reduction at the mean, or approximately $728 annually. For a county with 407 drinking-place workers, this implies an aggregate wage bill reduction of roughly $296,000—comparable in magnitude to the secondary-market price of the license itself. The implication is that new license allocations transfer value from incumbent workers to new license holders, raising distributional concerns about the lottery mechanism.

Several limitations warrant discussion. First, the treatment variable—mechanically computed license entitlements—does not perfectly measure actual license issuance or establishment openings. Not all entitled licenses are claimed in the year they become available, and there may be lags between license receipt and establishment opening. The estimates should therefore be interpreted as intention-to-treat effects of *entitlement*, not as effects of actual bar openings. Second, the QCEW data are at the county level, precluding analysis of within-county spatial spillovers between neighboring bars. Third, the wage compression finding may partly reflect compositional changes—new entrants hiring less-experienced, lower-wage workers—rather than pure wage reductions for incumbents; the QCEW does not distinguish these channels. Fourth, this paper examines only employment and wage outcomes. The original policy rationale for quotas rests on public health—DUI fatalities, alcohol-related hospitalizations, and violent crime. Whether the null employment effect extends to these dimensions remains an open question; FDLE arrest data and FL CHARTS hospitalization records could address it but are beyond the scope of this analysis. Finally, the lottery itself—which randomly assigns licenses among applicants—provides a cleaner source of within-county variation than the threshold exploited here. Digitizing applicant-level data from DBPR public records would enable a winner-versus-loser comparison, and remains the most promising path for future work.

7. Conclusion

A quota liquor license in Florida sells for $350,000, yet earning one produces no measurable increase in local employment. The rents embedded in secondary-market prices reflect the value of restricted competition, not the value of economic creation. For the 18 states maintaining population-based liquor quotas, this finding challenges the employment justification for entry barriers—though it does not resolve the separate question of whether quotas deliver public health benefits through density control.

The wage compression finding points to a subtler cost. When new licenses redistribute rather than create, the adjustment falls on workers: more employers competing for the same labor pool drive wages down without expanding hours. In local labor markets where hospitality workers have limited outside options, this margin adjustment may be the primary channel through which entry barriers shape economic outcomes. Whether these distributional costs are offset by reduced alcohol-related harm is the question that should guide quota reform.

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

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A. Data Appendix

BLS QCEW. The Quarterly Census of Employment and Wages collects employment and wage data from establishments covered by state unemployment insurance programs, representing approximately 99% of all wage and salary civilian employment. I access county-industry-quarter data through the BLS QCEW Data API (`https://data.bls.gov/cew/data/api/`). For each county-year, I average quarterly employment (`month1_emplvl`), establishment counts (`qtrly_estabs`), and average weekly wages (`avg_wkly_wage`) across the four quarters. NAICS 7224 (Drinking Places, Alcoholic Beverages) captures bars, taverns, nightclubs, and similar establishments where alcohol consumption is the primary activity. NAICS 7225 (Restaurants and Other Eating Places) serves as a within-county placebo. Data are available from 2014 through 2024; 62 of 67 Florida counties report non-suppressed drinking-place data.

Census Population Estimates. Annual county population estimates come from the Census Bureau's Population Estimates Program (PEP), accessed via the Census API (`https://api.census.gov/`). The 2000 Decennial Census provides the statutory baseline for computing license entitlements under FL Statute 561.20. Annual estimates for 2010–2019 use the 2019 vintage of the PEP intercensal series.

Treatment variable. The number of quota licenses to which a county is entitled in year t is $L_{ct} = \lfloor \text{Pop}_{ct}/7{,}500 \rfloor$. The baseline entitlement is $L_{c,2000} = \lfloor \text{Pop}_{c,2000}/7{,}500 \rfloor$. The annual flow treatment is $\Delta L_{ct} = \max(0, L_{ct} - L_{c,t-1})$, counting the number of new 7,500-resident increments crossed between year $t-1$ and year t. The cumulative stock is $L_{ct}^{\text{new}} = \max(0, L_{ct} - L_{c,2000})$, measuring total new licenses entitled since the 2000 baseline.

B. Identification Appendix

McCrary density test. The McCrary (2008) test for manipulation at the RDD threshold yields a test statistic with $p = 0.72$, failing to reject the null of smooth density. This is expected given that counties cannot influence federal population estimates.

Covariate balance. Restaurant employment (NAICS 7225) is smooth at the threshold ($p = 0.79$), as is population level ($p = 0.70$). These balance tests support the identifying assumption that counties on either side of the threshold are comparable.

Leave-one-out. Dropping each of the 62 counties with non-missing data and re-estimating the main specification produces coefficients ranging from -16.0 to 18.0 (mean $= -1.8$, SD $= 3.5$), confirming that no single county drives the null result.

C. Standardized Effect Sizes

Table 5: Standardized Effect Sizes

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
Panel A: Pooled						
Drinking-place emp.	-1.814	24.536	694.3	-0.0025	0.0342	Null
Drinking-place estabs.	1.373	0.796	54.5	0.0244	0.0141	Small positive
Restaurant emp. (placebo)	-751.597	178.834	16768.1	-0.0434	0.0103	Small negative
Avg. weekly wage	-14.132	4.898	182.3	-0.0751	0.0260	Moderate negative
Panel B: Heterogeneous (sample split by median county population)						
Drink. emp. (large counties)	0.452	26.853	803.4	0.0007	0.0392	Null
Drink. emp. (small counties)	-7.845	1.259	150.6	-0.0104	0.0017	Small negative

Notes: **Country:** United States (Florida). **Research question:** Whether marginal alcohol outlet entry, driven by Florida's statutory quota liquor license system, affects drinking-place employment, establishment counts, restaurant employment, and wages at the county level. **Policy mechanism:** FL Statute 561.20 caps quota liquor licenses at one per 7,500 county residents benchmarked to the 2000 Census population; as counties grow past successive 7,500-resident increments, additional quota licenses become available, and applicants are selected by public lottery when demand exceeds supply. **Outcome definition:** Drinking-place employment is the annual average of quarterly county-level employment in NAICS 7224 (Drinking Places) from the BLS Quarterly Census of Employment and Wages; establishment counts are the corresponding QCEW establishment count; restaurant employment (NAICS 7225) serves as a within-county placebo; weekly wages are average weekly wages in NAICS 7224. **Treatment:** Continuous — the number of newly entitled quota liquor licenses in a county-year from population threshold crossings. **Data:** BLS QCEW and Census population estimates, 2010–2023, county-year level, 67 Florida counties. **Method:** Two-way fixed effects (county + year FE) with standard errors clustered at the county level; complemented by RDD at the 7,500-resident population threshold. **Sample:** All 67 Florida counties with non-missing QCEW data; Panel B splits at the median county population. SDE = $\hat{\beta} \times \mathrm{SD}(X)/\mathrm{SD}(Y)$ where $\mathrm{SD}(X)$ is the standard deviation of annual new license allocations and $\mathrm{SD}(Y)$ is the unconditional standard deviation of the outcome. Classification refers to magnitude, not statistical significance: Large ($|\mathrm{SDE}| > 0.15$), Moderate (0.05–0.15), Small (0.005–0.05), Null (< 0.005).