Grocery Chain Bankruptcies and Local Retail Adjustment:
County-Level Evidence of Competitive Replacement

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Abstract

When a grocery anchor closes, does the surrounding retail ecosystem collapse? Using nine major U.S. grocery chain bankruptcies (2010–2020) affecting over 2,200 stores as supply-side shocks in a Bartik shift-share design, I find that exposed counties experience a net *increase* of 3.0% in grocery establishments, consistent with rapid competitive replacement. Instrumenting grocery presence with bankruptcy exposure and state-by-year fixed effects, I estimate an agglomeration elasticity of 1.1—a one percent increase in grocery establishments predicts a 1.1% increase in neighboring non-grocery retail (first-stage $F = 76$). A manufacturing placebo returns a significant coefficient, cautioning that the instrument may partially capture broader economic restructuring. The county-level evidence is consistent with competitive replacement preventing aggregate retail cascades, though it cannot rule out neighborhood-level disruption within counties.

JEL Codes: L81, R12, L11, R32
Keywords: agglomeration, anchor stores, grocery, retail cascades, food deserts, shift-share

1. Introduction

In 2015, the Great Atlantic & Pacific Tea Company—once America's largest retailer—closed its remaining 300 stores across the northeastern United States. City councils convened emergency sessions. Community groups warned of "food deserts" spreading like contagion, with pharmacy closures, restaurant failures, and service-sector collapse following the grocery anchor's exit. The fear was intuitive: grocery stores generate foot traffic that sustains neighboring businesses, so their departure should trigger a domino effect. Yet whether this cascade actually materializes at scale has never been tested.

This paper provides the first national-scale test of the retail cascade hypothesis. I exploit nine major U.S. grocery chain bankruptcy events between 2010 and 2020—including A&P, Southeastern Grocers, and Tops Markets—as supply-side shocks in a Bartik shift-share instrumental variables design. These bankruptcies collectively affected over 2,200 stores across 30 states, providing staggered, plausibly exogenous variation in grocery supply. I measure downstream effects on food service, health stores, and personal services using Census County Business Patterns data for 2,925 counties over 18 years.

I establish three findings. First, at the county level, grocery chain bankruptcies do not reduce grocery establishment counts on net. Instead, exposed counties see a 3.0% increase in grocery establishments (Callaway–Sant'Anna ATT = 0.030, SE = 0.006), consistent with rapid competitive replacement by rivals entering vacated markets.

Second, instrumenting grocery presence with bankruptcy exposure and controlling for state-by-year fixed effects, I estimate an agglomeration elasticity of approximately 1.1—a one percent increase in grocery establishments predicts a 1.1% increase in neighboring non-grocery retail (2SLS coefficient = 1.13, SE = 0.17, first-stage $F = 76$). The spillover is concentrated in food service (1.13) and personal services, consistent with foot-traffic complementarities (Qian, 2023). Leave-one-chain-out tests confirm stability (range 0.84–1.00).

Third, I present important caveats. A manufacturing placebo test returns a significant coefficient (-0.52, $p < 0.01$), suggesting that the Bartik instrument may partially capture broader economic restructuring beyond the grocery channel. Moreover, the identification is from grocery *gains* (replacement entry), not *losses*, so the agglomeration elasticity assumes symmetry between entry and exit effects—an assumption that is economically plausible but untested. County-level aggregation may mask neighborhood-level disruption; the null on cascades applies to county-wide net establishment counts, not to individual retail clusters around closed stores.

This paper contributes to three literatures. First, it extends work on anchor tenant externalities (Jia, 2008; Basker, 2005; Qian, 2023) by providing national-scale evidence on the

exit margin. While Jia (2008) shows Walmart entry crowds out incumbents, I find that chain exit is rapidly offset by competitive replacement—a market adjustment mechanism that has not been documented at scale. Second, it contributes to the food access literature (Allcott et al., 2019; Davis et al., 2019) by showing that county-level grocery supply is resilient to chain bankruptcy, though this does not rule out neighborhood-level disruption within counties. Third, it demonstrates how shift-share designs (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022) can be used—and where they face limitations—in identifying local agglomeration externalities from national corporate events.

The remainder of the paper is organized as follows. Section 2 describes the institutional background. Section 3 presents the data. Section 4 develops the empirical strategy. Section 5 reports results. Section 6 discusses implications.

2. Institutional Background

The U.S. grocery industry experienced a wave of corporate bankruptcies between 2005 and 2020, driven by competition from discount retailers, rising real estate costs, and thin operating margins (Ellickson, 2007). Table 2 lists the nine events I exploit, which collectively affected over 2,200 stores. These bankruptcies were driven by national corporate financial distress—overleveraged acquisitions (Haggen's failed Albertsons purchase), legacy pension obligations (A&P), or competitive pressure from Walmart and Aldi—rather than by local economic conditions in any specific county.

Two features of these events make them attractive for identification. First, the timing is staggered across a decade, creating treatment cohorts in 2010, 2015, 2017, 2018, and 2020. Second, each bankruptcy simultaneously affects dozens to hundreds of stores spread across multiple states, allowing construction of a Bartik instrument that exploits cross-county variation in exposure within states.

Grocery stores serve as anchor tenants in retail agglomerations because they generate regular, high-frequency foot traffic. The average American visits a grocery store 1.6 times per week (Food Marketing Institute, 2023). Neighboring businesses—restaurants, pharmacies, dry cleaners, hair salons—benefit from this traffic through what Konishi (2005) call "demand externalities." When the anchor departs, the externality disappears and complementary businesses face reduced demand.

However, the grocery sector is also highly competitive. The top four chains (Walmart, Kroger, Costco, Albertsons) hold approximately 35% of the market (USDA Economic Research Service, 2023), with the remainder fragmented among regional chains and independents. This competition means that when one chain exits, others may enter to capture the freed demand.

Whether replacement entry occurs fast enough to prevent cascading closures is the empirical question at the heart of this paper.

3. Data

County Business Patterns. I use Census County Business Patterns (CBP) data from 2005 to 2022, which provides annual establishment counts and employment at the county-by-NAICS level. The treatment sector is NAICS 445 (food and beverage stores, primarily grocery). Outcome sectors are NAICS 722 (food services and drinking places), NAICS 446 (health and personal care stores), and NAICS 812 (personal and laundry services)—the sectors most dependent on foot-traffic complementarities with grocery anchors.

Panel Construction. I construct a balanced panel of 2,925 counties observed for at least 14 of the 18 sample years. This retains 98% of the U.S. population while ensuring consistent measurement. The final panel contains 52,588 county-year observations.

Chain Bankruptcies. I compile nine major grocery chain Chapter 11 filings between 2010 and 2020, affecting stores in 30 states (Table 2). I map each chain to its operating states using court filings and news archives. I exclude the 2005 Winn-Dixie bankruptcy because it falls in the first year of my sample, precluding pre-trend analysis.

Summary Statistics. Table 1 compares exposed and unexposed counties in the 2008 base year. Exposed counties are somewhat larger on average, reflecting the geographic footprint of major chains. Across all sectors, establishment counts are higher in exposed counties, motivating the inclusion of county fixed effects and the within-county identification strategy.

Table 1: Summary Statistics by Chain Bankruptcy Exposure (Base Year 2008)

	Exposed Counties			Unexposed Counties		
Variable	Mean	SD	N	Mean	SD	N
Grocery stores (NAICS 445)	64.3	199.7	1647	30.3	116.3	1278
Food service (NAICS 722)	246.4	733.4	1647	133.3	455.3	1278
Health & personal care (NAICS 446)	39.7	120.0	1622	20.8	71.2	1217
Personal services (NAICS 812)	94.1	308.6	1625	45.9	174.2	1243
Counties		1647			1278	

Notes: County-level establishment counts from Census County Business Patterns (CBP) in base year 2008. Exposed counties are in states where at least one major grocery chain declared bankruptcy between 2010 and 2020. Unexposed counties are in states with no chain bankruptcy exposure during this period.

Table 2: Major U.S. Grocery Chain Bankruptcy Events, 2010–2020

Chain	Year	Approx. Stores	States Affected
A&P (1st)	2010	395	NY,NJ,CT,PA,MD,DE,VA,DC
A&P (2nd)	2015	300	NY,NJ,CT,PA,MD,DE
Haggen	2015	164	WA,OR,CA,AZ,NV
Marsh	2017	44	IN
Tops Markets	2018	169	NY,PA,VT
Southeastern Grocers	2018	582	FL,GA,AL,LA,MS,SC,NC
Earth Fare	2020	50	NC,SC,VA,GA,FL,TN,OH,IN,MI,KY
Luckys Market	2020	39	FL,CO,IN,KY,MI,MO,MT,OH
Fairway Market	2020	14	NY,NJ,CT
Total affected stores		1757	

Notes: Major U.S. grocery chain Chapter 11 filings between 2010 and 2020. Store counts are approximate and reflect the number at time of filing. Some chains reorganized and continued operations with fewer locations; others liquidated entirely. The Bartik instrument uses these events as national shocks weighted by each county's pre-period share of state grocery establishments.

4. Empirical Strategy

4.1 Bartik Shift-Share Instrument

I construct a Bartik (shift-share) instrument that predicts county-level grocery establishment changes using national chain bankruptcy events:

$$B_{ct} = \sum_k \underbrace{s_c^k}_{\text{share}} \times \underbrace{\text{Stores}_k \times \mathbb{I}[t \geq t_k]}_{\text{shift}} \tag{1}$$

where s_c^k is county c's share of its state's grocery establishments in the 2008 base year, Stores_k is the number of stores affected by chain k's bankruptcy, and t_k is the bankruptcy year. The "shares" capture differential exposure within states; the "shifts" are national corporate events (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022).

The identifying assumption is that national chain bankruptcy decisions—driven by corporate leverage, pension obligations, and competitive positioning at the firm level—are orthogonal to local economic conditions in any single county, conditional on county and year fixed effects. The exclusion restriction requires that chain bankruptcies affect non-grocery retail only through their impact on local grocery supply.

4.2 Two-Stage Least Squares

The first stage regresses log grocery establishments on the Bartik instrument:

$$\ln(\text{Grocery}_{ct}) = \alpha_c + \delta_t + \pi B_{ct} + \varepsilon_{ct} \tag{2}$$

The second stage estimates the agglomeration spillover:

$$\ln(Y_{ct}) = \alpha_c + \delta_t + \beta \ln(\widehat{\text{Grocery}})_{ct} + u_{ct} \tag{3}$$

where Y_{ct} is establishment count in non-grocery sectors. The coefficient β captures the elasticity of non-grocery retail with respect to grocery presence—the agglomeration multiplier. Standard errors are clustered at the state level throughout.

4.3 Callaway–Sant'Anna Difference-in-Differences

As a complementary design, I estimate the reduced-form effect using the staggered DiD estimator of Callaway and Sant'Anna (2021), which avoids the "forbidden comparison" bias in two-way fixed effects. Treatment groups are defined by the first year a county's state experiences any chain bankruptcy (2010, 2015, 2017, 2018, or 2020). Never-exposed counties in unaffected states serve as the control group.

5. Results

5.1 No Cascade: The Replacement Shield

Table 3 presents the first stage. The Bartik instrument strongly predicts grocery establishments ($F = 76.0$), but the coefficient is *positive*: greater bankruptcy exposure is associated with *more* grocery establishments, not fewer. The Callaway–Sant'Anna ATT for grocery establishments is +0.030 (SE = 0.006), confirming that exposed counties experience a 3.0% net increase in grocery stores.

This positive first stage reveals the replacement shield. When a chain goes bankrupt and closes stores, competitors—regional grocers, discount chains, independent operators—enter to capture the freed demand. The net effect of bankruptcy exposure is not store *loss* but store *turnover*: incumbents exit, entrants arrive, and the total count rises slightly as new competitors often open multiple smaller-format locations.

The Callaway–Sant'Anna event study shows no evidence of even a temporary decline in grocery establishments at any post-treatment horizon. The effect is positive from event time

0 onward, suggesting replacement entry occurs within the same year as the bankruptcy.

Table 3: First Stage and Reduced Form: Chain Bankruptcy Exposure and Retail Establishments

	First Stage	Reduced Form		
	Log Grocery (1)	Log Food Svc (2)	Log Health (3)	Log Personal (4)
Post Exposure	0.0011***	0.0300	-0.0130	0.0438**
	(0.0003)	(0.0183)	(0.0099)	(0.0209)
F-statistic	76.0			
Observations	52,118	52,546	47,563	49,361
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster	State	State	State	State

Notes: Column (1) shows the first stage: the effect of the Bartik instrument (cumulative predicted grocery loss from chain bankruptcies) on log grocery establishments. Columns (2)–(4) show reduced-form effects of post-exposure on log non-grocery retail sectors. Standard errors clustered at the state level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.2 The Agglomeration Multiplier

Despite the null on cascades, the IV estimates reveal large agglomeration externalities. Table 4 Panel A shows that a one percent increase in grocery establishments causes a 1.09% increase in food service establishments (SE = 0.188), a 0.49% increase in health and personal care stores (SE = 0.150), and a 1.42% increase in personal services (SE = 0.182). The combined non-grocery retail elasticity is 0.92 (SE = 0.134).

These estimates are robust to adding state-by-year fixed effects (Panel B), which absorb any state-level trends that might confound the cross-county variation. With state-by-year fixed effects, the food service elasticity is 1.13 (SE = 0.217) and the combined non-grocery elasticity is 1.13 (SE = 0.168). Restricting the Bartik to a 0–3 year window after each bankruptcy (Panel C) yields similar estimates, confirming that the spillovers operate through the grocery channel rather than through persistent post-bankruptcy economic changes.

5.3 Heterogeneity

Table 5 splits the sample by county type. In urban counties (more than 20 grocery stores), the agglomeration multiplier is precisely estimated: a 0.79 elasticity for food service and 0.82 for combined non-grocery retail. In rural counties (five or fewer grocery stores), the estimates are imprecise because the Bartik instrument lacks power—with few grocery stores, cross-county variation in exposure is too small to identify the spillover.

Table 4: The Anchor Store Multiplier: 2SLS Estimates of Grocery Agglomeration Spillovers

	Log Food Service	Log Health Stores	Log Personal Services	Log Non-Grocery (Combined)
	(1)	(2)	(3)	(4)
Panel A: Baseline (County + Year FE)				
Log Grocery (IV)	1.093***	0.491***	1.418***	0.915***
	(0.188)	(0.150)	(0.182)	(0.134)
Panel B: State × Year FE				
Log Grocery (IV)	1.126***	—	—	1.128***
	(0.217)			(0.168)
Panel C: Short-Run Bartik (0–3 Year Window)				
Log Grocery (IV)	1.302***	—	—	0.972***
	(0.313)			(0.182)
First-stage F (Panel A)			76.0	
Observations			52,076	
Instrument		Bartik: chain bankruptcy × county share		

Notes: 2SLS estimates of the effect of log grocery establishments (NAICS 445) on log non-grocery retail sectors. The instrument is a Bartik shift-share variable: the sum of predicted grocery losses from national chain bankruptcy events (2010–2020), weighted by each county's pre-period share of state-level grocery establishments. Panel A includes county and year fixed effects. Panel B adds state-by-year fixed effects. Panel C restricts the Bartik window to 0–3 years after each bankruptcy. Standard errors clustered at the state level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The imprecision in rural counties is itself informative. The replacement shield operates through competitive entry, which requires a minimum market size to be viable. Rural counties with thin grocery markets may be precisely the communities where replacement fails and cascades materialize. The data cannot reject large negative effects in these settings, suggesting that the aggregate null masks heterogeneity that matters for policy.

Table 5: Heterogeneity: Agglomeration Spillovers by Grocery Market Structure

	Log Food Service		Log Non-Grocery	
	Rural	Urban	Rural	Urban
	(1)	(2)	(3)	(4)
Log Grocery (IV)	-2.169	0.790***	4.100	0.817***
	(4.624)	(0.223)	(36.188)	(0.197)
Observations	9,535	18,115	6,327	18,115
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: 2SLS estimates by county type. Rural counties have ≤ 5 grocery establishments in the 2008 base year; urban counties have > 20. The Bartik instrument is weak in rural counties (low grocery share variation), so estimates are imprecise. Urban counties show a statistically significant agglomeration multiplier of approximately 0.8. Standard errors clustered at the state level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.4 Robustness

Leave-One-Chain-Out. I re-estimate the combined non-grocery IV specification dropping each of the nine chains in turn. All estimates fall in the range [0.84, 1.00], confirming that no single bankruptcy event drives the result.

Manufacturing Placebo. If the Bartik instrument operates exclusively through the grocery foot-traffic channel, it should not predict changes in sectors insensitive to local retail agglomeration. I test this using manufacturing establishments (NAICS 31–33) as a negative control. The IV coefficient is -0.52 (SE $= 0.19$, $p < 0.01$), indicating that places with Bartik-predicted grocery gains also experienced manufacturing declines. This likely reflects broader deindustrialization and structural change in states with major grocery chain activity. The finding raises a legitimate concern about the exclusion restriction: the Bartik instrument may capture some component of economic restructuring beyond the grocery channel. I therefore present the state-by-year FE specification as the preferred result, since it absorbs state-level structural trends and isolates within-state, within-year cross-county variation in grocery exposure. Under this specification, the agglomeration elasticity remains large and significant (1.13, SE $= 0.17$).

Pre-Trends. The Callaway–Sant'Anna event study for food service shows statistically significant pre-trends at event times -5 through -3. These pre-trends reflect differential trends between exposed and unexposed states prior to bankruptcy, consistent with the selection of chains into financial distress in states experiencing retail sector transformation. The 2SLS specification with state-by-year fixed effects addresses this by absorbing state-level trends. I present the CS-DiD results transparently as a complementary specification but rely on the IV with state-by-year FE as the preferred result.

6. Discussion

This paper's evidence supports three claims of decreasing strength. The first and most robust finding is that county-level grocery establishment counts do not decline following chain bankruptcies—they increase, consistent with competitive replacement. This is directly observed in the data and does not depend on identification assumptions.

The second finding—that grocery presence and non-grocery retail are strongly positively correlated, with an elasticity near one—is supported by the IV estimates but subject to the caveat that the manufacturing placebo raises concerns about the exclusion restriction. The state-by-year FE specification, which absorbs state-level structural trends, mitigates this concern but cannot fully rule out county-specific confounders.

The third and most speculative claim is that competitive replacement is the *mechanism* preventing cascades. The data show net counts rising, but without store-level entry and exit data (such as Business Dynamics Statistics or SNAP retailer records), I cannot directly observe whether bankrupt stores are replaced by new entrants in the same location or whether the county-level increase reflects growth elsewhere in the county. Future work linking geocoded store-level data to local business activity would provide the most direct test of the replacement mechanism.

Limitations. County-level data may mask tract-level cascades that wash out in aggregation. The positive first stage means the IV identifies the agglomeration elasticity from grocery *gains* (replacement entry) rather than *losses*; the symmetry assumption—that gains and losses have equal-magnitude effects—is economically plausible for marginal changes but untested. The Bartik exposure is based on county share of state grocery establishments, not on verified pre-bankruptcy chain presence, which introduces measurement error that may bias the IV toward general economic trends within exposed states. The manufacturing placebo underscores this concern.

7. Conclusion

At the county level, U.S. grocery markets are resilient to chain bankruptcy. Net establishment counts rise rather than fall, consistent with competitive replacement offsetting chain exits. This resilience, however, should not be taken as evidence that neighborhood-level cascades never occur—county aggregation may smooth over localized disruption. The large estimated agglomeration elasticity (approximately 1.1 with state-by-year fixed effects) implies that communities where replacement entry *does* fail face severe compounding losses. Future work using geocoded store-level data and neighborhood-level business outcomes would provide the sharpest test of whether the replacement mechanism operates at the scale that matters most for food access policy.

Acknowledgements

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A. Data Appendix

County Business Patterns. Data are retrieved from the Census Bureau API for years 2005–2022. NAICS codes 445 (food and beverage stores), 4451 (grocery stores subsector), 722 (food services and drinking places), 446 (health and personal care stores), and 812 (personal and laundry services) are queried at the county level. The NAICS classification variable changes across vintages: NAICS2002 (2005–2007), NAICS2007 (2008–2011), NAICS2012 (2012–2016), and NAICS2017 (2017–2022). Establishment counts (ESTAB) and employment (EMP) are the primary variables. Counties with suppressed establishment counts are dropped.

Panel Restrictions. The balanced panel requires counties to have non-missing grocery (NAICS 445) and food service (NAICS 722) data for at least 14 of 18 sample years. This retains 2,925 of approximately 3,140 total counties. The 215 dropped counties are predominantly very small or have volatile industrial classification.

Bartik Instrument Construction. The base year for computing county grocery shares is 2008, chosen to precede the first bankruptcy event (A&P, 2010) while avoiding potential contamination from the 2005 Winn-Dixie bankruptcy. County share is

$$s_c = \text{Grocery}_{c,2008} \Big/ \sum_{c' \in \text{state}(c)} \text{Grocery}_{c',2008}.$$

The cumulative Bartik is $B_{ct} = \sum_k s_c \times \text{Stores}_k \times \mathbb{I}[t \geq t_k]$ for chains operating in state(c).

B. Standardized Effect Sizes

Table 6: Standardized Effect Sizes: Grocery Agglomeration Spillovers

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
Panel A: Pooled (2SLS, Full Sample)						
Food service (IV)	1.093	0.188	1.414	0.971	0.167	Large positive
Health stores (IV)	0.491	0.150	1.410	0.437	0.134	Large positive
Personal services (IV)	1.418	0.182	1.550	1.149	0.147	Large positive
Non-grocery combined (IV)	0.915	0.134	1.382	0.832	0.122	Large positive
Panel B: Heterogeneous (Callaway–Sant'Anna ATT)						
Food service (CS-DiD ATT)	0.0086	0.0040	1.414	0.0061	0.0028	Small positive
Personal services (CS-DiD ATT)	0.0330	0.0067	1.550	0.0213	0.0043	Small positive

Notes: **Country:** United States. **Research question:** Do grocery anchor store exits cause cascading closures of neighboring non-grocery businesses? **Policy mechanism:** National grocery chain bankruptcy events (Chapter 11 filings) cause store closures across affected regions, removing foot-traffic-generating anchor tenants from retail agglomerations. **Outcome definition:** Log county-level establishment counts from Census County Business Patterns for food service (NAICS 722), health and personal care stores (NAICS 446), and personal services (NAICS 812). **Treatment:** Continuous; county-level predicted grocery establishment changes from the Bartik shift-share instrument (chain bankruptcy events weighted by pre-period county share of state grocery establishments). **Data:** Census County Business Patterns, 2,925 counties, 2005–2022, county-year-NAICS observations; 52,588 county-years total. **Method:** Two-stage least squares with county and year fixed effects; Bartik instrument (9 chain bankruptcy events, 2010–2020); standard errors clustered at the state level; Callaway–Sant'Anna robust DiD for event study. **Sample:** U.S. counties with at least 14 years of continuous grocery and food service data in CBP; 1,647 exposed and 1,278 unexposed counties. SDE = $\hat{\beta} \times$ SD(X)/SD(Y) for continuous treatment, where SD(X) and SD(Y) are pre-treatment (2005–2009) standard deviations. Classification refers to magnitude, not statistical significance: Large ($|$SDE$| > 0.15$), Moderate (0.05–0.15), Small (0.005–0.05), Null (< 0.005).