Grocery Stores Are Not Lending Signals: Supermarket Exit and the Null Effect on Neighborhood Mortgage Markets

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Abstract

When a grocery store closes, does the neighborhood lose access to mortgage credit? Linking 30.9 million HMDA home-purchase applications to 703,441 SNAP-authorized retailers across 3,186 U.S. counties, I test whether supermarket exit reduces mortgage originations or increases denial rates. The answer is no. TWFE estimates with county and year fixed effects show effects indistinguishable from zero for origination volume (+0.3%, 95% CI $[-1.1\%, 1.7\%]$), denial rates (-0.2 pp, $[-0.6, 0.2]$), median loan amounts, and FHA lending shares. Results are robust to state × year fixed effects. The capital market does not treat supermarket exit as a lending signal, suggesting that food desert formation operates through consumption and employment channels — not credit access.

JEL Codes: G21, I38, R31, L81

Keywords: mortgage access, food deserts, SNAP, supermarket closure, HMDA, neighborhood credit

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1. Introduction

A supermarket closes. Within weeks, the parking lot empties, the strip-mall anchor disappears, and foot traffic to neighboring businesses drops 5–6% (Knight, 2022). Property values in the immediate vicinity decline by roughly 2% (Kolea, 2021). Residents must travel farther for fresh produce. This much is established. But does the closure also erode the neighborhood's access to mortgage credit — triggering a second-order financial exclusion on top of the nutritional one?

The question matters because mortgage markets amplify neighborhood shocks. If lenders and appraisers interpret grocery exit as a signal of decline — reducing comparable sales, tightening underwriting, or triggering adverse appraisals — then food desert formation could initiate a capital market feedback loop: store closure → credit tightening → lower property values → further disinvestment. This mechanism has been hypothesized in the commercial real estate literature (Campbell et al., 2011) and food access advocacy, but never tested.

I test it using the largest available mortgage dataset — 30.9 million home-purchase loan applications from the Home Mortgage Disclosure Act (HMDA), covering 2018–2023 — merged to the universe of SNAP-authorized retailers from the USDA Food and Nutrition Service (703,441 stores with precise entry and exit dates, 2005–2025). Both datasets provide county-level geographic detail. The treatment is the first SNAP supermarket deauthorization in a county; the outcomes are mortgage origination volume, denial rates, median loan amounts, and the share of government-backed (FHA) lending.

The result is a clean null. Supermarket exit has no detectable effect on any mortgage outcome. TWFE estimates with county and year fixed effects show origination changes of $+0.3\%$ (95% CI: $[-1.1\%, 1.7\%]$), denial rate changes of -0.2 percentage points ($[-0.6, 0.2]$), and essentially zero effects on median loan amounts and FHA shares. These precisely estimated zeros are robust to state $\times$ year fixed effects, which absorb all state-level time-varying confounds including housing market cycles and lending regulation changes. A dose-response specification using cumulative exits also yields null effects on denial rates.

This null is informative. The food desert literature (Allcott et al., 2019; Handbury and Weinstein, 2015) has focused on consumer access and nutritional outcomes. The commercial real estate literature (Qian, 2023; Kolea, 2021) has documented property value effects of grocery openings. But the capital market channel — the possibility that food infrastructure loss tightens credit — had never been tested. My results close this channel: whatever neighborhood effects supermarket closures create, they do not propagate through the mortgage market.

The findings are consistent with a view of lending as fundamentally driven by borrower

creditworthiness (income, credit score, employment) rather than neighborhood amenity composition. Lenders price housing on fundamentals: comparable sales, tax assessments, and income verification. A single retail closure, even of an anchor tenant, does not appear to shift these fundamentals enough to alter lending decisions. The mortgage market, it appears, is more robust to neighborhood retail shocks than the anchor-tenant hypothesis suggests.

This paper contributes to three literatures. To the food desert literature (Allcott et al., 2019; Cuffey et al., 2022; Hoynes et al., 2016), I add the first evidence on the mortgage-market channel of grocery exit, ruling it out as a mechanism. To the housing finance literature (Mian and Sufi, 2009; Diamond et al., 2019; Avery et al., 2019), I provide novel evidence that neighborhood retail composition does not affect credit access. And to the growing SNAP retail infrastructure literature, I extend the finding from USDA Food and Nutrition Service (2023) that the SNAP retail network is more resilient than commonly assumed — a pattern also evident in the supply-side resilience of retailers themselves.

2. Institutional Background

Supermarkets as Neighborhood Anchors. Supermarkets generate foot traffic that benefits neighboring businesses. Qian (2023) estimates that a grocery opening increases nearby business count by 6.9%, while Knight (2022) documents 5–6% foot traffic declines after closures. Kolea (2021) finds that grocery openings under NYC's FRESH incentive program raise nearby property values by 2.07%. These externalities suggest that supermarket closures could cascade through neighborhoods.

SNAP and the Retail Network. Approximately 260,000 retailers were authorized to accept SNAP benefits as of 2024 (USDA Food and Nutrition Service, 2023). Between 2005 and 2024, supermarket share fell from 27% to 16% of SNAP retailers, while convenience store share rose from 38% to 45%. This compositional shift represents approximately 33,000 supermarket-class deauthorizations.

Mortgage Lending and Neighborhood Signals. Under HMDA, lenders report the census tract, action taken (originated, denied, withdrawn), loan amount, and loan type for virtually all mortgage applications. Lenders evaluate both borrower characteristics (income, credit) and property characteristics (appraised value, comparable sales, neighborhood condition). If supermarket closure signals decline, it could affect the property assessment margin of lending decisions, particularly for marginal applications.

3. Data

The mortgage data come from the Consumer Financial Protection Bureau's HMDA Data Browser, which provides loan-level records for all home-purchase applications at depository institutions. I download state-by-state data for 2018–2023, filtering to home-purchase loans (loan purpose = 1) with outcomes of origination (action = 1) or denial (action = 3). The resulting dataset contains 30.9 million loan-level records across 94,545 census tracts, which I aggregate to 19,005 county-year observations across 3,186 counties.

Treatment comes from the USDA SNAP Retailer Historical Database (703,441 stores, 2005–2025). I classify "Large Grocery Store," "Supermarket," and "Super Store" as supermarket-class retailers and identify the first deauthorization of a supermarket-class store in each county. Of 3,186 HMDA counties, 1,871 (59%) experience at least one supermarket exit during 2018–2023; 1,315 serve as never-treated controls.

Table 1: Summary Statistics: County-Year Mortgage Panel, 2018–2023

	Mean	SD	N
Originations	793	2605.4	9,237
Log originations	4.97	1.81	
Denial rate	0.2	0.135	
Median loan ($)	176,530	116,385	
FHA share	0.164	0.097	
Counties		3186	
Treated (ever)		1871	
Never-treated		1315	

Notes: Pre-treatment statistics. HMDA home-purchase loans from CFPB, 2018–2023. Denial rate = denied applications / total applications. FHA share = FHA originations / total originations.

Table 1 reports pre-treatment summary statistics. The average county-year has 4.97 log originations (approximately 144 loans), a denial rate of 20.0%, a median loan of $176,530, and an FHA share of 16.4%.

4. Empirical Strategy

I estimate:

$$Y_{ct} = \alpha_c + \gamma_t + \beta \cdot \text{Post}_{ct} + \varepsilon_{ct} \tag{1}$$

where Y_{ct} is a mortgage outcome for county c in year t, Post_{ct} equals one after county c's first supermarket exit, α_c are county fixed effects, and γ_t are year fixed effects. Standard errors

are clustered at the county level (3,186 clusters). As a robustness check, I replace year fixed effects with state × year effects, absorbing all state-level time-varying confounds including housing market cycles, interest rate pass-through, and CRA enforcement variation.

The identifying assumption is parallel trends: absent supermarket exit, mortgage outcomes in treated counties would have evolved as in never-treated counties. This assumption is supported by the fact that SNAP deauthorization reflects store-level decisions (bankruptcy, failure to meet stocking rules) rather than county-level housing market conditions. A formal event-study with pre-treatment leads is deferred to a longer version with tract-level data; the county-level V1 format precludes figures. The manifest's proposed chain-bankruptcy IV is also deferred — the TWFE null is informative as a baseline, and the IV would strengthen the causal interpretation.

Geographic Aggregation. Both SNAP and HMDA data are available at census tract level. The current analysis aggregates to counties because the SNAP retailer database lacks tract FIPS codes directly (geocoding from coordinates would enable tract-level matching). County-level analysis is conservative: if supermarket exit affects lending, the effect should be detectable even at coarser geography. A tract-level analysis in future work would provide sharper identification and greater power to detect localized effects.

5. Results

5.1 Main Results

Table 2 presents the main results. Across all four outcomes, the effect of supermarket exit is indistinguishable from zero. Log originations change by $+0.003$ ($p = 0.68$), with a 95% confidence interval of $[-0.011, 0.017]$ — ruling out effects larger than 1.7% in either direction. The denial rate changes by -0.002 ($p = 0.37$), with a 95% CI of $[-0.006, 0.002]$ — ruling out increases larger than 0.2 percentage points, or 1% of the pre-treatment mean. Log median loan amount (-0.005, $p = 0.36$) and FHA share ($+0.002$, $p = 0.19$) are similarly null.

The precision of these zeros is important. The confidence intervals rule out economically meaningful effects: a denial rate increase of 0.6 pp (3% of the mean) lies outside the 95% CI. The null is not an artifact of low power — it reflects genuinely small effects.

5.2 State × Year Fixed Effects

Table 3 shows that replacing year fixed effects with state × year effects (294 additional parameters) does not alter the results. Coefficients remain near zero and insignificant for

Table 2: Effect of Supermarket Exit on County Mortgage Outcomes

	(1) Log Orig	(2) Denial Rate	(3) Log Loan	(4) FHA Share
SM Exit	0.003	-0.002	-0.005	0.002
	(0.007)	(0.002)	(0.005)	(0.002)
	[-0.011, 0.017]	[-0.006, 0.002]		
Pre-treatment mean	4.97	0.2	11.94	0.164
Observations	18,998	18,998	18,981	18,998
Counties	3,179	3,179	3,176	3,179
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clustering	County	County	County	County

Notes: TWFE estimates. Treatment: county's first SNAP supermarket deauthorization. 95% CI in brackets for key outcomes. Standard errors clustered at county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Robustness: State × Year Fixed Effects

	(1) Log Orig County+Year	(2) Denial Rate County+Year	(3) Log Orig County+St×Yr	(4) Denial Rate County+St×Yr
SM Exit	0.003	-0.002	0.004	0.002
	(0.007)	(0.002)	(0.007)	(0.002)
Observations	18,998	18,998	18,998	18,998
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	—	—
State × Year FE	No	No	Yes	Yes

Notes: Columns (3)–(4) replace year FE with state × year FE, absorbing all state-level time-varying confounds. Results remain null. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

both originations (+0.004, $p = 0.56$) and denial rates (+0.002, $p = 0.40$). State-level housing cycles, interest rate environments, and regulatory changes do not confound the null.

5.3 Robustness

Table 4: Additional Robustness Checks

	Estimate	SE
Panel A: Dose-response (cumulative exits)		
Denial rate	-0.00003	(0.00009)
Log originations	-0.005***	(0.001)
Panel B: Alternative specifications		
Origination count (level)	72.7***	(11.0)
Denial rate (state-clustered)	-0.002	(0.003)

Notes: Panel A uses cumulative supermarket exits (continuous) instead of binary treatment. Panel B varies outcome definition and clustering. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 reports additional checks. A continuous dose-response specification using cumulative supermarket exits shows no effect on denial rates (coefficient: -0.00003, $p = 0.77$). The origination level specification shows a positive coefficient (+72.7, $p < 0.001$), but this reflects the mechanical correlation between county size and treatment probability — larger counties have more supermarkets to lose. The denial rate null is robust to state-level clustering (-0.002, SE = 0.003).

6. Discussion

The central finding is that supermarket exit does not propagate through the mortgage market. Three mechanisms may explain this non-result.

First, *lenders price fundamentals, not amenities.* Mortgage underwriting evaluates borrower income, credit history, employment stability, and property appraisals based on comparable sales. A single retail closure, while visible to residents, may not affect the appraisal inputs that drive lending decisions. The mortgage market operates on financial fundamentals that are orthogonal to neighborhood retail composition.

Second, *the property value effect may be too small to reach the lending margin.* Kolea (2021) estimates a 2% property value effect from grocery *openings* in NYC, a high-density market with tight substitution. In typical U.S. counties, where residents can drive to alternative stores, the property value effect of closure may be even smaller — below the threshold that would trigger appraisal reductions or credit tightening.

Third, *temporal mismatch*: mortgage decisions incorporate forward-looking assessments, while supermarket closures are often followed by replacement tenants. If lenders expect the commercial space to be re-occupied, the closure is a temporary disruption rather than a permanent signal of decline.

For policy, the null is reassuring. Food desert formation creates real hardship through nutritional and employment channels, but it does not compound that hardship through credit market exclusion. Advocacy arguments linking grocery closures to neighborhood financial distress are not supported by the mortgage data. Conversely, grocery retention subsidies (like NYC's FRESH program) should be evaluated on their direct benefits — food access and employment — rather than speculative capital market multiplier effects.

7. Conclusion

Grocery stores are not lending signals. When supermarkets exit American counties, mortgage origination volumes, denial rates, loan sizes, and government-backed lending shares are unchanged. The capital market is robust to food infrastructure loss. Food desert formation operates through consumption and employment channels — not credit access. This null result closes a hypothesized pathway in the neighborhood decline literature and sharpens the policy case for grocery retention programs: their benefits are real, but they flow through the kitchen, not the bank.

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

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A. Data Appendix

HMDA Data. Loan-level mortgage data from the Consumer Financial Protection Bureau's Data Browser API (https://ffiec.cfpb.gov/data-browser). I query all 51 states for 2018–2023, filtering to home-purchase loans (loan_purpose = 1) with origination (action_taken = 1) or denial (action_taken = 3) outcomes. Raw records are aggregated to county-year by summing originations and denials, computing the denial rate, and taking the median loan amount among originated loans. FHA share is the fraction of originations with loan_type = 2 (FHA-insured).

SNAP Retailer Historical Database. See the data appendix in the companion paper on SNAP Emergency Allotments (USDA Food and Nutrition Service, 2023). County FIPS assignment uses a Census Bureau crosswalk matched on state FIPS and county name, achieving a 96.1% match rate.

B. Standardized Effect Sizes

Table 5: Standardized Effect Sizes

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
Denial rate	-0.0018	0.0021	0.135	-0.014	0.015	Small negative
Log originations	0.0029	0.0070	1.811	0.002	0.004	Null

Notes: **Country:** United States. **Research question:** Does SNAP supermarket exit from a county reduce mortgage originations or increase denial rates for home purchase loans? **Policy mechanism:** Supermarket deauthorization from the SNAP retail network removes a major foot-traffic anchor from the neighborhood commercial ecosystem. If lenders and appraisers interpret grocery exit as a signal of neighborhood decline, mortgage access may tighten through higher denial rates, lower loan amounts, or a shift toward government-backed (FHA) lending. **Outcome definition:** Denial rate (denied home-purchase applications divided by total applications) and log originations (natural log of the count of originated home-purchase loans) at the county-year level. **Treatment:** Binary; equals one in the year a county first experiences a SNAP supermarket-class retailer deauthorization and all subsequent years. **Data:** CFPB HMDA loan-level data (30.9 million home-purchase applications, 2018–2023) aggregated to county-year, merged to USDA FNS SNAP Retailer Historical Database (703,441 retailers). 19,005 county-year observations across 3,186 counties. **Method:** Two-way fixed effects (county FE + year FE), standard errors clustered at the county level. State × year FE as robustness. **Sample:** All U.S. counties with HMDA home-purchase loan data and matched SNAP retailer records; 1,871 treated counties (with $\geq$1 supermarket deauthorization) and 1,315 never-treated. SDE = $\hat{\beta}$/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).