The Pass-through of Retail Crime

Carl Hase

Goethe University Frankfurt
JGU Mainz

Johannes Kasinger

Tilburg University

EEA 2024

Introduction

Institutional context

Data and empirical strategy

Main results

Policy analysis

Conclusion

Motivation

BUSINESS

Walmart closing stores in this large U.S. city on heels of CEO warning about high theft levels

Updated: Apr. 07, 2023, 11:02 a.m. | Published: Mar. 07, 2023, 11:11 a.m.

Robberies are becoming an increasing concern for retailers.

About 69 percent of stores said they have seen an increase in organized theft in the past year.

HOME > RETAIL

Target said it's lost $400 million this year due to 'inventory shrink' — and organized retail crime is mostly to blame

Avery Hartmans

Business | Northwest | Retail

REI to close only Portland store, citing break-ins, theft

April 17, 2023 at 2:33 pm | *Updated April 17, 2023 at 7:34 pm*

BAY AREA // SAN FRANCISCO

Westfield mall blamed 'rampant criminal activity' for Nordstrom closing in S.F. Here's what the data says

Roland Li, Sam Whiting

May 3, 2023 | Updated: May 4, 2023 5:39 p.m.

BUSINESS

Downtown SF Whole Foods Slashes Store Hours Due to 'High Theft' and Hostile People

Written by **Garrett Leahy**

Published Nov. 09, 2022 • 1:57pm

CBS EVENING NEWS

U.S. cities, retailers boost security as crime worries grow among potential shoppers

Motivation

- (Organized) retail crime has surged to the forefront of public discourse in the United States
  - The U.S. Chamber of Commerce (2022) declared organized retail crime a "national crisis"
  - Numerous policy initiatives to fight organized retail crime
- Retail crime imposes costs on businesses, individuals, and society
- Understanding these costs is central for determining optimal level of public crime prevention

Motivation

- Retail crime can also affect market outcomes, in particular market prices
  - 46% of retailers have increased the use of third-party security personnel in their stores, and 34% said they increased payroll to support their risk efforts (National Retail Federation, 2022)
  - 64% of small business owners reported increasing prices in response to retail crime (Forbes, 2022)
- Crime-induced price changes—**the cost pass-through of retail crime**—have distributional implications and can introduce an excess burden by distorting firms' and consumers' decisions
- Evidence of a causal link between retail crime and market prices is nonexistent

What we do

- **Investigate the impact of organized retail crime on prices** using the retail cannabis industry as a natural laboratory
- Match detailed scanner data with store-level records of armed robberies and burglaries between 2018 and 2021 in Washington state
- Exploit quasi-random timing of store-level retail crime incidents
- Use stacked DiD framework to estimate the effect of crime on prices at **victimized stores** and nearby **rival stores**
- Characterize the welfare effects of retail crime pass-through using a sufficient statistics approach

Main findings

1. Retail crime incidents cause a 1.8% increase in prices at victimized stores
   - No effect on quantity sold or wholesale cost
2. Rival stores increase prices by 1.6% with a two month lag
   - Cannot be explained by demand substitution or strategic complementarity in prices
   - Consistent with an own-cost shock (e.g. from precautionary security expenditures or higher business crime insurance premia)
3. Retail crime resembles a 1% unit tax on retailers
   - Annual welfare reduction of $30.5 million
   - 2/3 of tax incidence borne by consumers

Related literature

1. **Economic effects of crime:** (Gibbons, 2004; Linden and Rockoff, 2008), consumption of conspicuous and entertainment goods (Mejia and Restrepo, 2016; Fe and Sanfelice, 2022) and crop yields (Dyer, 2023)

    - Crime and market outcomes: violent crime and drug-trafficking in Columbia and Mexico (Rozo, 2018; Stolkin, 2023) or on larceny thefts of cars and computers (Jackson and Tran, 2020)

2. **Pass-through of cost shocks:** Nakamura and Zerom (2010); Ganapati et al. (2020); Conlon and Rao (2020); Hollenbeck and Uetake (2021); Muehlegger and Sweeney (2022)

Introduction

Institutional context

Data and empirical strategy

Main results

Policy analysis

Conclusion

Retail cannabis industry

- Approx. 50% of U.S. states have legal recreational cannabis markets, $25 billion in annual sales
- Washington state market established in 2014, now one of the largest agricultural products in the state
- 30-40% of adults in WA regularly consume cannabis (Washington State Department of Health, 2024)
- Market is regulated by the Liquor and Cannabis Board (LCB)
- 508 cannabis retailers and 692 producers in WA
- Brick-and-mortar stores (no online sales) $\Rightarrow$ retailers compete in local markets

▸ Usage ▸ Categories ▸ Descriptive stats

Organized Retail Crime in Cannabis

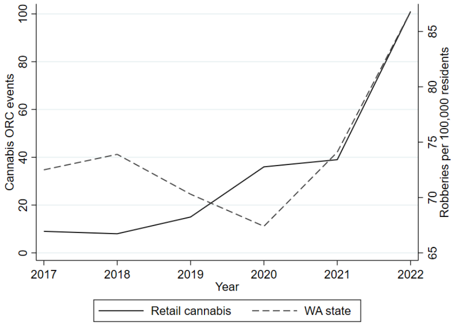


Figure 1: State vs cannabis crime rates

- 210 reported armed robberies and burglaries at cannabis retailers in WA state from 2017-2023
  - Typically extracting cash and/or merchandise, often violent in nature
- Prompted policy response from state lawmakers
- Many retailers invest heavily in strategies to prevent retail crime, including security guards, surveillance and training

Introduction

Institutional context

Data and empirical strategy

Main results

Policy analysis

Conclusion

Price data

- Source: Top Shelf Data, March 2018 - December 2021
- At the transaction level, the scanner data contains:
  - The **price and quantity of each product sold by a producer to a retailer**
  - The subsequent **price and quantity of that very same product sold at the retail level**
- **Main dependent variable**: establishment-level Young price index that aggregates price changes across product subcategories (see Renkin et al., 2022; Leung, 2021)

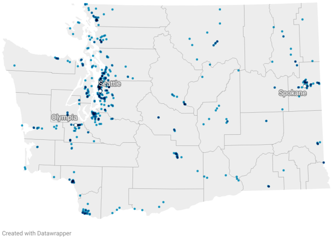
$$\pi_{j,t} = \ln I_{j,t}, \text{ with } I_{j,t} = \prod_{c} I_{c,j,t}^{\omega_{c,j,y(t)}} \tag{1}$$

- Additional dependent variables: quantity index, wholesale cost index, margins index

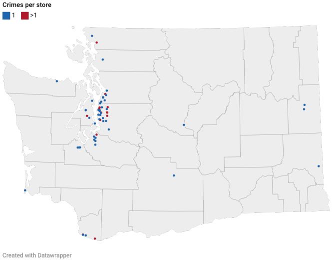
Price indexes

Crime data

- Store-level retail crime tracker maintained by Uncle Ike's on behalf of the industry at large
- For each crime incident: **date, retail establishment**, link to police report, newspaper articles, etc.
- 62 armed robberies, 14 burglaries during sample period (March 2018-December 2021)



(a) Retail stores



(b) Stores with a reported crime

▸ Descriptive statistics

Treatment groups

1. **Victimized stores**: stores that directly experience a robbery or burglary ($n = 57$)
2. **Rival stores**: stores located within a 5-mile radius of a victimized store ($n = 264$)
   - Mechanisms: Demand substitution, strategic complementarity in prices, own-cost shock (precautionary security expenditures or insurance premium hike)

Table 1: Estimation sample descriptive statistics

	(1) Victimized	(2) Rivals	(3) Never-treated
Unit price (in dollars)	26.24	25.47	26.00
	(4.33)	(4.49)	(4.50)
Units sold per month	13,260	12,304	10,908
	(12,409)	(11,931)	(11,617)
Monthly revenue (in dollars)	248,516	215,201	210,416
	(234,911)	(217,957)	(235,890)

Notes: The table summarizes store-level variables prior to being treated. Statistics for the never-treated group are based on the entire sample period. Standard deviations are in parentheses.

Control group

- Control group: stores in unaffected local markets, i.e. stores located 30-50 miles from a victimized store ($n = 329$)
  - 30-mile buffer limits potential bias from treatment effect spillovers, e.g., due to strategic price competition
    - 30-mile radius is based on estimating stores' price response to competitors' wholesale costs
      ▸ Strategic pricing
  - 50-mile boundary ensures that the control group remains comparable to the treated stores

Empirical strategy

- Stacked DiD estimator (Cengiz et al., 2019; Deshpande and Li, 2019; Baker et al., 2022)
- Identifies clean controls for event-specific sub-experiments, stacks sub-experiments $d \in D$ on top of each other, estimates model on stacked data (SEs clustered at the store level)
- Distributed lag model in first-differences (Renkin et al., 2022; Leung, 2021):

$$\pi_{j,t,d} = \sum_{l=-4}^{5} \beta_l \Delta T_{j,d,t-l} + \gamma_{t,d} + \epsilon_{j,d,t} \quad (2)$$

- $\gamma_{t,d}$: sub-experiment x time FE
- Report cumulative effects relative to normalized baseline period (numerically equivalent to event study coefficients) (see e.g. Schmidheiny and Siegloch, 2023; Renkin et al., 2022; Leung, 2021)
  - Treatment effect on price *level*: $E_L = \sum_{l=0}^{L} \beta_l$. Pre-treatment effects: $P_{-L} = -\sum_{l=-1}^{-L+1} \beta_l$

Introduction

Institutional context

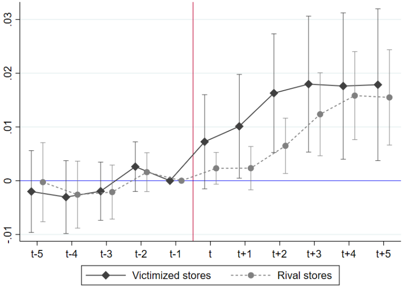
Data and empirical strategy

Main results

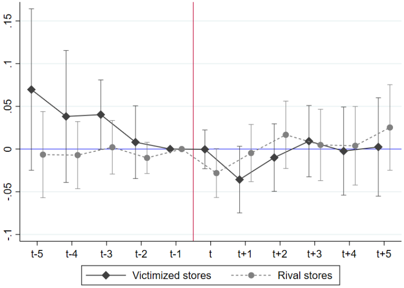
Policy analysis

Conclusion

Main results



(a) Effect on price level



(b) Effect on quantity sold

Notes: Both panels show cumulative price level effects E_L, relative to the normalized baseline period $t-1$, with SE of the sums clustered at the store level. Data: Top Shelf Data (August 2018-July 2021) and Washington ESD, 2018-2021.

▸ Victimized table ▸ Rivals table ▸ Heterogeneity ▸ Other outcomes

Robustness checks and alternative specifications

- Using a canonical TWFE estimator, and the estimators by Borusyak et al. (2024) and Callaway and Sant'Anna (2021) produce very similar results Alternative estimators
- Results are robust to extending the event window Extended window
- Placebo tests, shifting treatment by 12 months, show no significant effects Placebo
- Results are robust to adjusting definition of rivals (up to 10-mile radius) and control group definition Inner ring Outer ring
- Robust to adding controls (local house price index, avg county wages and county population), accounting for outliers, using price per gram as dependent variable and restricting to a balanced panel/weighting as in (Wing et al., 2024) Victimizied stores Rival stores

Mechanisms

- **Victimized** stores' price effect consistent with a security cost shock
  - Aligns with state legislative activity, the WA State Retail Crime Task Force, industry reports, and news media
- **Rivals'** price effect not due to demand substitution or strategic complementarity in prices
  - Consistent with own-cost shock (precautionary security expenditures or higher insurance premium)
    - Delay could reflect victimized stores' reluctance to share information about robberies and burglaries
    - "Following a robbery, store owners "**keep it a secret**" (Ian Eisenberg, CEO at Uncle Ike's)
    - "[We] need to start talking and communicating with each other across the retail stores...**once robbed, nobody knows**." (Sara Eltinge, CEO at Herbery)

Introduction

Institutional context

Data and empirical strategy

Main results

Policy analysis

Conclusion

Policy analysis - Crime as a hidden tax

- We model crime as marginal cost shock that can be understood as a hidden crime tax levied on retailers
- Our policy analysis follows three steps:
    1. Derive general welfare implications and sufficient statistics from the symmetric oligopoly model by Weyl and Fabinger (2013)
    2. Estimate own and competitors marginal cost pass-through rates to examine strategic complementarity in pricing and quantify the hidden tax rate
    3. Combine estimates and theoretical insights to quantify the welfare effect in our context

▸ Model ▸ MC pass-through

Policy analysis - Crime as a hidden tax

- Crime increases prices by 1.6% in affected local markets (DiD estimates)
  - Equivalent to a \$0.45 increase in unit price (at avg. unit price of \$28)
- Marginal cost pass-through rate: 1.65 (from pass-through regression)
- Hidden crime tax: \$0.45/1.65 = \$0.27, equivalent to a **1% unit tax**
- ΔCS = \$0.45 × 45,520,552 units sold = \$20.5 million
- ΔPS = \$10 million
  - Based on conduct parameter $\hat{\theta} = 0.89$ from Hollenbeck and Uetake (2021) who study the same industry
- Total annual welfare effect = \$30.5 million

Introduction

Institutional context

Data and empirical strategy

Main results

Policy analysis

Conclusion

Conclusion

- Retail crime incidents cause a 1.8% increase in prices at victimized stores
- Rivals' prices increase by 1.6% with a two-month lag
  - Implies that **retail crime pass-through extends beyond victimized stores and affects local market prices more generally**
- The costs of retail crime are equivalent to a 1% hidden unit tax levied on cannabis retailers
- Annual welfare reduction of $30.5 million for market participants
- **When evaluating the costs of retail crime, it is important to consider its effects on market outcomes**

Conclusion and discussion

- Welfare implications of retail crime extend beyond our context:
  - Retail crime is a common concern across various industries, as evidenced by numerous reports and articles (National Retail Federation, 2022; Jackson and Tran, 2020)
  - Increasing security expenditures reported across many retail sectors, hinting at that these costs are passed-through onto consumers
    - 46% of retailers have increased the use of third-party security personnel in their stores, and 34% said they increased payroll to support their risk efforts (National Retail Federation, 2022)
    - 64% of small business owners reported increasing prices in response to retail crime (Forbes, 2022)
- The cannabis industry similar to traditional retail sectors in terms of variable cost structure and (to a certain extent) demand elasticities (Hollenbeck and Uetake, 2021)

References I

Baker, A. C., Larcker, D. F., and Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, 144:370–395.

Borusyak, K., Jaravel, X., and Spiess, J. (2024). Revisiting event study designs: Robust and efficient estimation. *Review of Economic Studies*, page rdae007.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225:200–230.

Cengiz, D., Dube, A., Lindner, A., and Zipperer, B. (2019). The effect of minimum wages on low-wage jobs*. *The Quarterly Journal of Economics*, 134:1405–1454.

Conlon, C. T. and Rao, N. L. (2020). Discrete prices and the incidence and efficiency of excise taxes. *American Economic Journal: Economic Policy*, 12:111–143.

Deshpande, M. and Li, Y. (2019). Who is screened out? application costs and the targeting of disability programs. *American Economic Journal: Economic Policy*, 11:213–248.

Dyer, J. (2023). The fruits (and vegetables) of crime: Protection from theft and agricultural development. *Journal of Development Economics*, 163:103109.

References II

Fe, H. and Sanfelice, V. (2022). How bad is crime for business? evidence from consumer behavior. *Journal of Urban Economics*, 129:103448.

Ganapati, S., Shapiro, J. S., and Walker, R. (2020). Energy cost pass-through in us manufacturing: Estimates and implications for carbon taxes. *American Economic Journal: Applied Economics*, 12:303–342.

Gibbons, S. (2004). The costs of urban property crime. *The Economic Journal*, 114(499):F441–F463.

Hollenbeck, B. and Uetake, K. (2021). Taxation and market power in the legal marijuana industry. *The RAND Journal of Economics*, 52:559–595.

Jackson, O. and Tran, T. (2020). Larceny in the product market: A hidden tax? *Federal Reserve Bank of Boston Research Department Working Papers No. 20-14*.

Leung, J. H. (2021). Minimum wage and real wage inequality: Evidence from pass-through to retail prices. *The Review of Economics and Statistics*, 103:1–16.

Linden, L. and Rockoff, J. E. (2008). Estimates of the impact of crime risk on property values from megan's laws. *American Economic Review*, 98(3):1103–1127.

References III

Mejia, D. and Restrepo, P. (2016). Crime and conspicuous consumption. *Journal of Public Economics*, 135:1–14.

Muehlegger, E. and Sweeney, R. L. (2022). Pass-through of own and rival cost shocks: Evidence from the us fracking boom. *Review of Economics and Statistics*, 104(6):1361–1369.

Nakamura, E. and Zerom, D. (2010). Accounting for incomplete pass-through. *Review of Economic Studies*, 77:1192–1230.

National Retail Federation (2022). National retail security survey organized retail crime 2022. https://cdn.nrf.com/sites/default/files/2022-09/National%20Retail%20Security%20Survey%20Organized%20Retail%20Crime%202022.pdf. Retrieved November 17, 2023.

Renkin, T., Montialoux, C., and Siegenthaler, M. (2022). The pass-through of minimum wages into u.s. retail prices: Evidence from supermarket scanner data. *The Review of Economics and Statistics*, 104:890–908.

Rozo, S. V. (2018). Is murder bad for business? evidence from colombia. *Review of Economics and Statistics*, 100:769–782.

References IV

Schmidheiny, K. and Siegloch, S. (2023). On event studies and distributed-lags in two-way fixed effects models: Identification, equivalence, and generalization. *Journal of Applied Econometrics*.

Stolkin, G. (2023). Paying for violence: The effect of drug trafficking organization presence on consumer prices. *Working Paper. Available at SSRN 4428016*.

Washington State Department of Health (2024). Tobacco and cannabis use dashboard.

Weyl, E. G. and Fabinger, M. (2013). Pass-through as an economic tool: Principles of incidence under imperfect competition. *Journal of Political Economy*, 121(3):528–583.

Wing, C., Freedman, S. M., and Hollingsworth, A. (2024). Stacked difference-in-differences.

Appendix

Usage

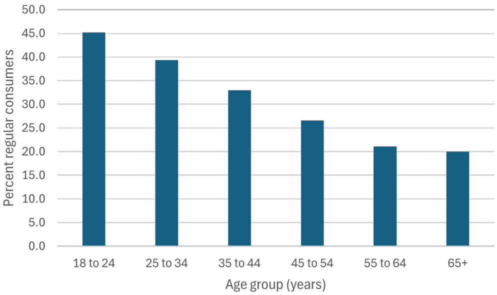


Figure 4: Share of regular cannabis users by age group

Notes: Data from the 2021 Behavioral Risk Factor Surveillance System. Source: Washington State Department of Health, Center for Health Statistics.

Back

Table 2: Market share by product category

Product category	Monthly sales (in millions of $)	Market share
Usable marijuana	$58.77	0.52
Concentrate for inhalation	$34.70	0.31
Solid edible	$8.45	0.08
Infused mix	$5.40	0.05
Liquid edible	$2.96	0.03
Other	$2.16	0.02

Notes: Column 1 reports the average monthly retail sales across Washington state for the major product categories; Column 2 shows the corresponding market shares. Sales are tax-inclusive. Data source: Top Shelf Data (March 2018 through December 2021).

Back

Table 3: Descriptive statistics

	Monthly average per store	Sample total
Establishments		508
Units sold	15,157 (5,829)	263 million
Distinct products	470 (305)	210,842
Sales	$282,857 ($273,082)	$5.07 billion

Notes: Column 1 reports monthly averages at the store level. Standard deviations are in parentheses. Column 2 reports totals across all stores and months in the sample period. Sales are tax-inclusive. Data source: Top Shelf Data (March 2018 through December 2021).

Back

Table 4: Estimation sample descriptive statistics

(a) Pre-treatment characteristics

	(1) Victimized	(2) Rivals	(3) Never-treated
Unit price (in dollars)	26.24	25.47	26.00
	(4.33)	(4.49)	(4.50)
Units sold per month	13,260	12,304	10,908
	(12,409)	(11,931)	(11,617)
Monthly revenue (in dollars)	248,516	215,201	210,416
	(234,911)	(217,957)	(235,890)
Unique products per month	505	425	393
	(388)	(346)	(324)

(b) Treatment group sizes

Stores	57	264	137
Control stores	329	321	
Total store-months	15,949	17,055	

Notes: Panel (a) summarizes store-level variables prior to being treated. Panel (b) shows the number of stores in each treatment group. Data: Top Shelf Data and Uncle Ike's robbery tracker (March 2018 through December 2021).

Back

Table 5: Crime descriptive statistics

(a) Stores affected

	Stores with crime	Stores with no crime	Total stores
	57	450	508
Stores with single crime	46		
Stores with > 1 crime	12		

(b) Type of crime

	Armed robbery	Burglary	Total
	62	14	76

Notes: Data: Uncle Ike's robbery tracker (March 2018 through December 2021).

Back

Construction of price indexes

1. Calculate average monthly price of product i at establishment j:

$$P_{i,j,t} = \frac{TR_{i,j,t}}{TQ_{i,j,t}} \tag{3}$$

2. Construct a geometric index of month-to-month price changes for each product subcategory at establishment j:

$$I_{c,j,t} = \prod_i \left(\frac{P_{i,j,t}}{P_{i,j,t-1}} \right)^{\omega_{i,c,y(t)}} \tag{4}$$

$\omega_{i,j,y(t)}$: product i's share of total revenue from category c at establishment j in month t

3. Aggregate across categories to get establishment-level index:

$$I_t = \frac{P_t}{P_{t-1}} = \prod_c I_{c,t}^{\omega_{c,y(t)}} \tag{5}$$

Back

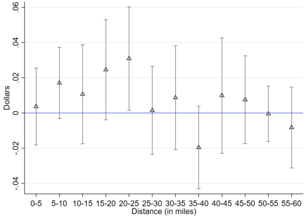
Strategic pricing

- Leverage scanner data on universe of vertical transactions between producers and retailers
- Measure sensitivity of retail prices to rivals' marginal unit costs
- Sort competitors into bins $r \in R$ based on geographic distance from retailer j (baseline bin size: 5 miles)
- Estimate product-level linear panel regression in logs (similar to Hollenbeck and Uetake (2021))

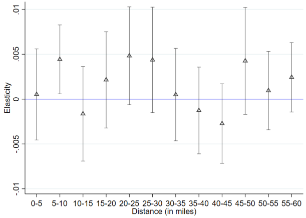
$$\Delta p_{i,j,t} = \alpha \Delta w_{i,j,t} + \sum_{r=1}^{R} \beta_r \Delta w_{i,r,t} + \gamma_t + \Delta \varepsilon_{i,j,t}. \tag{6}$$

Back

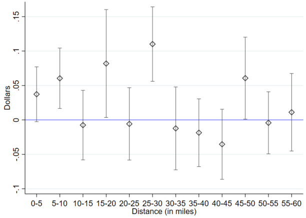
Strategic pricing



(a) Dollars, first-differenced



(b) First difference of logs



(c) Dollars

Back

Table 6: Effect of crime on prices at victimized stores

	(1) Baseline	(2) Controls	(3) Price per gram	(4) Wins.	(5) Alt. weights	(6) Mult. treat-ments	(7) Balanced (un-weighted)	(8) Balanced (weighted)
E_0	0.008	0.008	0.009	0.008	0.007	0.016*	0.009	0.009
	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)	(0.009)	(0.009)	(0.009)
E_2	0.016**	0.016**	0.024***	0.016**	0.013*	0.022**	0.019*	0.019*
	(0.007)	(0.007)	(0.009)	(0.007)	(0.008)	(0.009)	(0.010)	(0.010)
E_4	0.018*	0.017*	0.026**	0.018*	0.015	0.015**	0.019*	0.019*
	(0.009)	(0.009)	(0.011)	(0.009)	(0.010)	(0.007)	(0.011)	(0.011)
$\sum$ Pre-event	-0.001	-0.000	-0.004	-0.002	0.001	0.009	-0.002	-0.002
	(0.005)	(0.005)	(0.008)	(0.005)	(0.004)	(0.010)	(0.007)	(0.007)
N	15,294	15,294	15,258	15,294	15,294	17,294	11,182	11,182

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data from Top Shelf Data.

Back

Table 7: Effect of crime on prices at rival stores

	(1) Baseline	(2) Controls	(3) Price per gram	(4) Wins.	(5) Alt. weights	(6) Mult. treatments	(7) Balanced (un-weighted)	(8) Balanced (weighted)
E_0	0.002	0.002	0.003	0.001	0.003	0.000	0.001	-0.0003
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)
E_2	0.005	0.005	0.008	0.005	0.004	0.002	0.002	0.002
	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)
E_4	0.017***	0.016***	0.020***	0.014***	0.014**	0.005*	0.012*	0.011*
	(0.006)	(0.006)	(0.007)	(0.005)	(0.006)	(0.002)	(0.006)	(0.006)
$\sum$ Pre-event	-0.002	-0.001	-0.005	-0.001	0.001	-0.003*	-0.007	-0.008
	(0.005)	(0.005)	(0.006)	(0.005)	(0.004)	(0.002)	(0.006)	(0.006)
N	16,142	16,142	16,084	16,142	16,142	21,898	12,406	10,579

Notes: $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$. Data from Top Shelf Data.

Back

Table 8: Price effects by market concentration and chain size

	Victimized				Rivals			
	(1) Independent stores	(2) Chain stores	(3) Low concentration	(4) High concentration	(5) Independent stores	(6) Chain stores	(7) Low concentration	(8) High concentration
E_0	0.010	0.0014	0.012	0.0019	0.0025	0.0033	0.0019	0.0038
	(0.0078)	(0.0027)	(0.0097)	(0.0027)	(0.0022)	(0.0029)	(0.0026)	(0.0023)
E_2	0.021**	0.0063	0.024**	0.0075	0.010***	0.00062	0.0077	0.0062*
	(0.0096)	(0.0050)	(0.011)	(0.0060)	(0.0037)	(0.0048)	(0.0049)	(0.0033)
E_4	0.024**	0.0035	0.031**	0.0011	0.024***	0.0042	0.022***	0.011*
	(0.012)	(0.0056)	(0.013)	(0.0088)	(0.0060)	(0.0076)	(0.0073)	(0.0063)
$\sum$ Pre-event	-0.0016	-0.0013	0.0015	-0.0059	-0.0030	-0.00014	0.00049	-0.0053
	(0.0063)	(0.0055)	(0.0063)	(0.0067)	(0.0050)	(0.0075)	(0.0073)	(0.0058)
N	15,355	14,929	15,197	15,087	13,863	11,657	13,231	12,289

Notes: Dependent variable: the establishment-level monthly inflation rate. Listed coefficients are sums of the distributed lag coefficients E_L, L months after a crime, relative to the normalized baseline period in $t-1$. SE of the sums are clustered at the establishment level and are shown in parentheses. Sample period: March 2018 through December 2021. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Data from Top Shelf Data.

Back

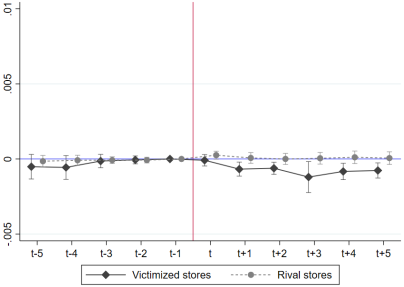
Table 9: Effect of robberies on prices at robbed stores

	Stacked				Staggered	
	(1) Baseline	(2) Controls	(3) Trimmed	(4) Expanded control group	(5) Baseline	(6) Multiple treatments
E_0	0.007	0.007	0.009	0.007	0.007	0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
E_2	0.016**	0.015**	0.018**	0.015**	0.014**	0.011***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.004)
E_4	0.018**	0.016**	0.020**	0.014*	0.014*	0.009*
	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.005)
$\sum$ Pre-event	-0.002	-0.001	-0.002	-0.001	-0.001	0.003
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)
N	15,949	15,949	15,788	84,137	17,610	17,763

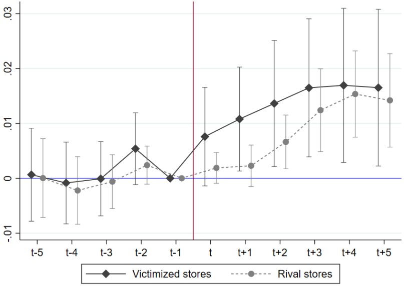
Notes: Dependent variable: the establishment-level monthly inflation rate. Listed coefficients are sums of the distributed lag coefficients E_L, L months after a robbery, relative to the normalized baseline period in $t-1$. SE of the sums are clustered at the establishment level and are shown in parentheses. Sample period: March 2018 through December 2021. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data from Top Shelf Data.

Back

Other store-level outcomes



(a) Effect on wholesale cost



(b) Effect on retail margins

Back

Alternative specifications

Table 10: Effect of retail crime on prices at victimized stores

	(1) Baseline	(2) Controls	(3) Price per gram	(4) Wins.	(5) Alt. weights	(6) Mult. treat-ments	(7) Balanced (un-weighted)	(8) Balanced (weighted)
E_0	0.008	0.008	0.009	0.008	0.007	0.016*	0.009	0.009
	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)	(0.009)	(0.009)	(0.009)
E_2	0.016**	0.016**	0.024***	0.016**	0.013*	0.022**	0.019*	0.019*
	(0.007)	(0.007)	(0.009)	(0.007)	(0.008)	(0.009)	(0.010)	(0.010)
E_4	0.018*	0.017*	0.026**	0.018*	0.015	0.015**	0.019*	0.019*
	(0.009)	(0.009)	(0.011)	(0.009)	(0.010)	(0.007)	(0.011)	(0.011)
$\sum$ Pre-event	-0.001	-0.000	-0.004	-0.002	0.001	0.009	-0.002	-0.002
	(0.005)	(0.005)	(0.008)	(0.005)	(0.004)	(0.010)	(0.007)	(0.007)
N	15,294	15,294	15,258	15,294	15,294	17,294	11,182	11,182

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data from Top Shelf Data.

Back

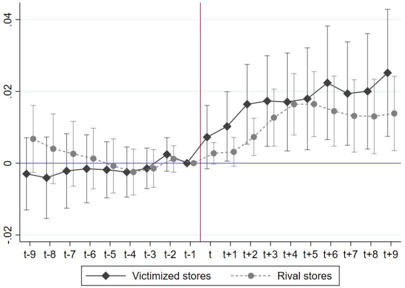
Alternative specifications

Table 11: Effect of retail crime on prices at rival stores

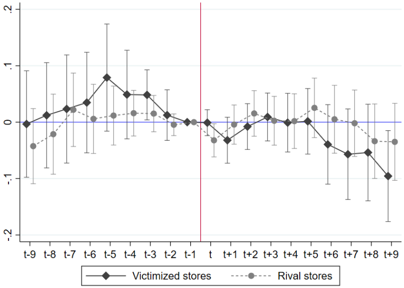
	(1) Baseline	(2) Controls	(3) Price per gram	(4) Wins.	(5) Alt. weights	(6) Mult. treatments	(7) Balanced (un-weighted)	(8) Balanced (weighted)
E_0	0.002	0.002	0.003	0.001	0.003	0.000	0.001	-0.0003
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)
E_2	0.005	0.005	0.008	0.005	0.004	0.002	0.002	0.002
	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)
E_4	0.017***	0.016***	0.020***	0.014***	0.014**	0.005*	0.012*	0.011*
	(0.006)	(0.006)	(0.007)	(0.005)	(0.006)	(0.002)	(0.006)	(0.006)
$\sum$ Pre-event	-0.002	-0.001	-0.005	-0.001	0.001	-0.003*	-0.007	-0.008
	(0.005)	(0.005)	(0.006)	(0.005)	(0.004)	(0.002)	(0.006)	(0.006)
N	16,142	16,142	16,084	16,142	16,142	21,898	12,406	10,579

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data from Top Shelf Data.

Back



(a) Effect on price level



(b) Effect on quantity sold

Back

Alternative estimators

Table 12: Alternative estimators

	Victimized			Rivals		
	(1) TWFE	(2) BJS	(3) CS	(4) TWFE	(5) BJS	(6) CS
E_0	-0.001	-0.001	0.009	0.001	0.002	0.002
	(0.004)	(0.005)	(0.006)	(0.002)	(0.002)	(0.003)
E_2	0.010**	0.016***	0.025**	0.003	0.004	0.007
	(0.004)	(0.006)	(0.011)	(0.003)	(0.003)	(0.007)
E_4	0.014*	0.016**	0.035**	0.010**	0.010*	0.015
	(0.008)	(0.007)	(0.017)	(0.004)	(0.005)	(0.012)
$\sum$ Pre-event	-0.001	-0.001	0.012	-0.001	-0.002	0.001
	(0.005)	(0.006)	(0.012)	(0.004)	(0.005)	(0.010)
N	17,606	17,110	17,517	17,606	13,489	16,698

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Back

Table 13: Placebo treatment and Staggered TWFE

	Placebo				Staggered			
	(1) Vict. -12 mo	(2) Vict. +12 mo	(3) Riv. -12 mo	(4) Riv. +12 mo	(5) Vict.	(6) Vict. (30-50 mi)	(7) Riv.	(8) Riv. (30-50mi)
E_0	-0.000	-0.011	-0.002	-0.004*	0.007	0.007	0.001	0.001
	(0.004)	(0.009)	(0.004)	(0.003)	(0.005)	(0.005)	(0.002)	(0.002)
E_2	-0.001	-0.019	-0.004	-0.004	0.014**	0.014**	0.002	0.003
	(0.008)	(0.013)	(0.006)	(0.005)	(0.006)	(0.006)	(0.003)	(0.003)
E_4	0.004	-0.020	-0.002	-0.006	0.013*	0.014*	0.007*	0.009**
	(0.010)	(0.015)	(0.006)	(0.007)	(0.007)	(0.007)	(0.004)	(0.004)
$\sum$ Pre-event	-0.007	-0.001	-0.003	-0.005	-0.001	-0.002	0.001	0.000
	(0.020)	(0.009)	(0.006)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)
N	11,015	7,827	10,897	8,393	17,610	12,916	17,610	15,017

Notes: Dependent variable: the establishment-level monthly inflation rate. Listed coefficients are sums of the distributed lag coefficients E_L, L months after a crime, relative to the normalized baseline period in $t-1$. SE of the sums are clustered at the establishment level and are shown in parentheses. Sample period: March 2018 through December 2021. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data from Top Shelf Data.

Back

Alternative inner rings

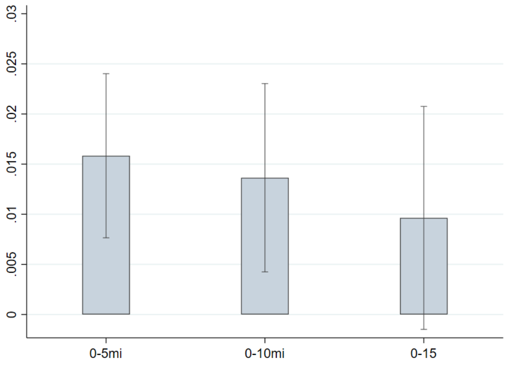


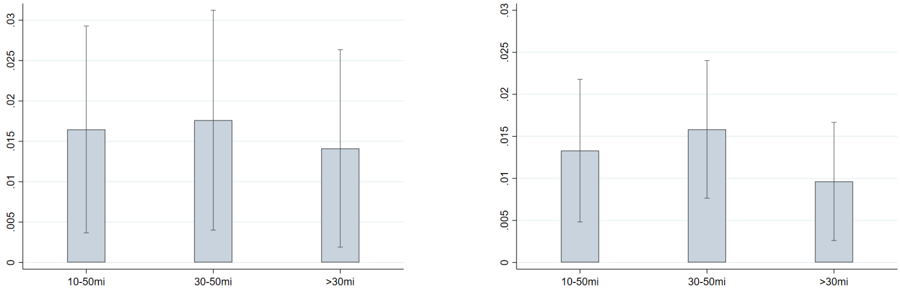
Figure 8: Price effects with alternative inner rings

*Notes:*The figures show estimated rival price level effects for different inner ring specifications.

Back

Alternative outer rings

Figure 9: Price effects with alternative outer rings



(a) Victimized stores, outer ring (b) Rival stores, outer ring

Notes: The figures show estimated rival price level effects for different outer ring specifications.

Back

Policy analysis - Oligopoly model

- We build on the symmetric oligopoly model by Weyl and Fabinger (2013), nesting common imperfect competition models (e.g. Cournot and differentiated products Nash-in prices), as well as the monopoly and perfect competition cases:

  - N firms produce one single good with marginal cost equal to $mc_j = c'(q_j) + \tau$, where τ is the hidden crime tax
  - Demand system is assumed fully symmetric and smooth
  - Firm j maximizes profits by setting a unidimensional strategic variable, r_j, that can be price, p_j, or quantity, q_j
  - We further assume that the hidden crime tax applies equally to all N firms in the affected local market (i.e. stores within a 5-mile radius of the crime)

Back

Policy analysis - Oligopoly model

Weyl and Fabinger (2013) show that the pass-through rate (in dollars) for a small unit tax is:

$$\rho = \frac{dp}{d\tau} = \frac{1}{1 + \frac{\epsilon_D - \theta}{\epsilon_S} + \frac{\theta}{\epsilon_{ms}} + \frac{\theta}{\epsilon_\theta}}$$

- ϵ_S and ϵ_D are the supply and (market) demand elasticities
- $0 \geq \theta \geq 1$ is a conduct parameter summarizing the degree of market competition
- ϵ_θ is the elasticity of θ with respect to quantity
- ϵ_{ms} is the elasticity of the inverse marginal surplus function, which describes the curvature of the demand function.

Back

Policy analysis - Oligopoly model

The incidence of the hidden crime tax equals the ratio of the marginal effect on consumer to producer surplus:

$$I = \frac{\frac{dCS}{d\tau}}{\frac{dPS}{d\tau}} = \frac{-\rho q}{-\left[1-\rho(1-\theta)\right]q} = \frac{\rho}{1-\rho(1-\theta)} \tag{7}$$

- Crime-induced price hikes lead to a deadweight loss (DWL) under imperfect competition. DWL increases with firms' market power
- The crime pass-through rate serves as a sufficient statistic (in combination with θ and q) for deriving the welfare effects of a unit tax, its incidence, and the DWL.

Back

Policy analysis - The unit cost pass-through rate

- Next, we estimate ρ by how changes in wholesale unit cost are passed through to unit prices. Two reasons:
  - Important for implications of our results, welfare analysis, our definition of a valid control group and serves as a test for strategic complementarity in pricing
  - Enables us to calculate the hidden unit tax and fictional tax revenue
- We estimate the following model at the store-product level, including own changes in wholesale costs ($\Delta w_{i,j,t}$) and changes in wholesale costs of your competitors ($\Delta w_{i,r(j),t}$):

$$\Delta p_{i,j,t} = \rho \Delta w_{i,j,t} + \sum_{r=1}^{R} \beta_r \Delta w_{i,r(j),t} + \gamma_t + \Delta \varepsilon_{i,j,t},$$

Back

Policy analysis - The unit cost pass-through rate

Table 14: Unit cost pass-through rates

	(1)	(2)	(3)	(4)
	Δp	$\Delta \ln p$	p	Store-level index
Own wholesale cost	1.654***	0.712***	1.294***	1.023***
	(0.035)	(0.008)	(0.375)	(0.159)
Competitors' wholesale cost (0-5 miles)	0.017**	0.003	0.105***	0.029
	(0.007)	(0.002)	(0.026)	(0.045)
N	3,580,835	3,580,835	5,695,425	11,840

Notes: The table reports the pass-through rates of wholesale unit cost to retail unit price, at the store-product-month level. Dependent variables are: the first-difference of price (column 1); the first-difference of the log price (column 2); price in dollars (column 3); log store-level monthly price index (columns 4). SE are clustered at the store level and are shown in parentheses. $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Back