

# Trade Exposures in Local Retail Pricing

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**Question.** How do trade exposures affect local retail pricing patterns?

- Why should we care?
  - \* Pricing as a natural follow-up question for markets & markups<sup>1</sup>
  - \* Studies found **nearly-uniform pricing** for large retail chains,<sup>2</sup> mainly due to
    - ① *managerial inertia* & ② *brand image concerns*
- But **this** eliminates **price disparities** that may reflect trade/demand factors:
  - What about small, local retail shops that are free from ① & ②?
  - What about small, local retail shops that are more affected by trade?
- I explore data from local bike shops (LBSs) across the US and imports.

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<sup>1</sup>Also see my short discussion on Amiti and Heise (2024): [\[here\]](#).

<sup>2</sup>Also see DellaVigna and Gentzkow (2019). They found that most large US food, drugstore, and mass merchandise chains set nearly-uniform prices across stores.

**This study.** Bridges trade and associated domestic sales through “small” retail businesses,<sup>3</sup> by constructing pricing data from LBSs in the US.

$$\text{Trade exposures} \xrightarrow{?} \text{Prices} \quad (1)$$

- I make two **main contributions**:

- ① **(Novel data)**. Construct price data by **scraping** through publicly available bike listings on 96 LBSs across the US
- ② **(Implication)**. Provide a framework on assessing trade exposures to prices, which can be broadly **extended to different retail businesses/industries**

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<sup>3</sup>I focus on bike-specific industry (i.e., LBSs) mainly since ① [Trade] LBSs sell bikes, which are dominantly imported goods to the US. This allows the connection to trade data. ② [Homogeneous product] Disparity of bike prices should be driven by local/trade demand factors. ③ [Market] LBSs are retail businesses that are “small” enough to not influence national bike market, but “large” enough to reflect local demand.

- **Key literature:** DellaVigna and Gentzkow (2019) (uniform pricing patterns in “large” US retail chains) & Amiti and Heise (2024) (concentration & import penetration)
- Several more relevant studies:
  - \* **Retail prices:** Atkin et al. (2018) (Mexico; supermarket), Cavallo (2018) (US, Argentina, Brazil, Chile, Colombia; supermarket), Cavallo (2017), Sorensen (2000) (US; prescription drugs)
  - \* **Local costs & spatial:** Diamond and Moretti (2024), De Loecker et al. (2016), Atkin and Donaldson (2015), Gopinath et al. (2011) (US & Canada; grocery)
- **My takeaway:** Prior studies on retail prices focused exclusively on large retail chains [for data convenience]; nearly none addressed price disparities from small retail shops, which may reflect local demand better.

# Empirical Framework

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# Baseline Estimation

- I plan to proceed with this specification:

$$\Delta p_{irt} = \gamma \Delta IEM_{irt} + \theta_{it} + \varepsilon_{irt}, \quad (2)$$

- ①  $\Delta p_{irt}$ : %change in bike prices for bike item  $i$  at region  $r$  in time  $t$
  - ②  $\Delta IEM_{irt}$ : %change in bike import exposure measure **[IN PROGRESS]**<sup>4</sup>
  - ③  $\theta_{it}$ : item  $\times$  time FE (for across-region)
  - ④ Instrument for  $\Delta IEM_{irt}$  with a Bartik IV:  $Inst\Delta IEM_{irt} = \sum_{x \neq US} w_{irx, \Delta t} \tilde{\beta}_{irxt}$ 
    - $w_{irx, \Delta t}$ :  $\Delta t$ -year lagged total bike imports share
    - $\tilde{\beta}_{irxt}$ : foreign supply shock (Amiti and Heise (2024) & Amiti and Weinstein (2018))
- Assumption: consistent online/offline prices<sup>5</sup> (Cavallo, 2017)
  - Prediction: negative  $\gamma$

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<sup>4</sup>Adão et al. (2022) provided microfoundation of such measure.

<sup>5</sup>This assumption allows me to use the scraped [online] prices to construct my LHS variable for prices.

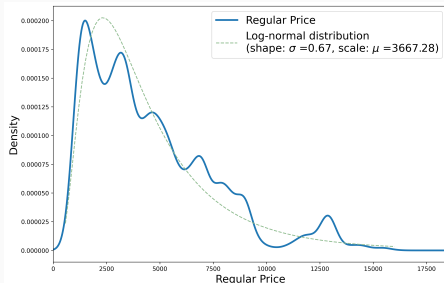
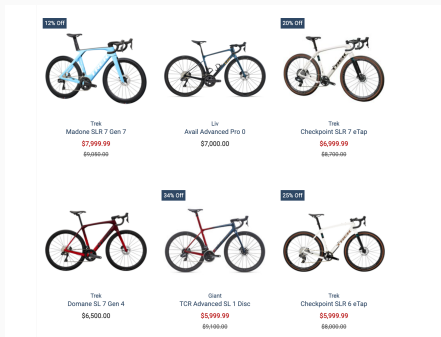
So far I prepare three main categories of datasets to approach the question:

- **(Prices).** Scraped bike price data (★)
  - \* Monthly bike prices from September 2024-present\*
  - \* 96 LBSs across 8 states: CA, CO, MN, NJ, NY, PA, TX, WI
  - \* 14,028 distinct (Items  $\times$  ZIP  $\times$  Time) pairs out of 54,853 bike listings<sup>6</sup>
- **(Trade).** Imports & Exports data on bikes (HS 8712)
  - \* USA Trade Online: Annual State Imports by HS
  - \* Census Trade Data: Monthly US imports by HS
  - \* UN COMTRADE: Annual Imports, Exports data by HS
- **(Local/HH).** 2022 5-year American Community Survey, IPUMS

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<sup>6</sup>More data to add as my Senior Thesis goes on.

# Scraped Data Example: Regular Prices



Attained from scraped data:

- Bike-related: bike brand, bike item, bike type
- Price-related: regular price, special price, discount rate
- Region/Time-related: shop, ZIP code, state code, year, month, quarter



# Limitations and Future Directions

- Limitation: level of aggregation
  - \* Does not leave much variation for RHS variable ( $\Delta IEM_{irt}$ ), or
  - \* Fails to use up as much variation as possible for LHS variable ( $\Delta p_{irt}$ )
- Future directions:
  - \* **RHS:** Write down more-granular expressions of import exposure measure  
     $\implies$  connect trade data to the ACS data
  - \* **LHS:** ① scrape prices more frequently ② match the aggregation on RHS
  - \* Better ways to utilize the other variables from my scraped data?
- More to think and explore:
  - \* Do LBSs select optimal “bike portfolio” considering their local demand?
  - \* LBSs in spatial: limited access to big market  $\leftrightarrow$  higher pricing power?
- Thanks! 😊

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