Supermarket Price Setting on the Two Sides of the Atlantic - Evidence from Scanner Data

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Pascal Seiler    Jesse Wursten

European Central Bank

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The views expressed here are solely those of the authors and do not necessarily reflect the views of the ECB or the Eurosystem
Motivation

- Food inflation is more volatile in the US and euro area
  - Responded more forcefully to the Covid-19 lockdowns
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- Food inflation matters
  - Accounts for around 20% of consumption
  - Affects inflation expectations (D’Acunto et al., 2021)
Motivation

食品通胀在美国和欧元区更为波动。

- 受到Covid-19封锁的有力响应

食品通胀很重要。

- 占消费的20%左右
- 影响通胀预期（D’Acunto等人，2021年）

波动受到名义刚性差异的影响

- 多少价格调整（频率）
- 哪些价格调整（状态依赖）：大型价格变化被选中吗？
What do we do?

- Introduce new supermarket scanner data (PRISMA Network) from
  - 4 euro area countries: Germany, France, Italy and the Netherlands,
  - Contrast it to the US
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- Document price-setting facts
  - Contrast frequency and dispersion of price changes,
  - Assess state-dependence through estimating generalized- and duration hazard functions

(Woodford, 2009)
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- Interpret the evidence through the lens of a micro-founded price-setting model
  (Woodford, 2009)
What do we find?

- A state-dependent price-setting model (Woodford, 2009) captures facts
  - Price adjustment is infrequent (menu costs)
  - Price changes are large (product-level shocks)
  - Adjustment probability depends on misalignment (state dependence)
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- Both frequency and size are larger in the US than in the euro area
  - Implies more volatile product-level environment (shocks) in the US
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- Both frequency and size are larger in the US than in the euro area
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- State dependence also stronger in the US
  - Comes predominantly from more misaligned prices
  - In line with more volatile product-level shocks
Selected literature

- We contrast euro area and US price setting as Gautier et al. (2022a) (see also Dhyne et al., 2006)
  - CPI microdata
  - Confirms higher frequency and size in the US
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  - CPI microdata
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- Estimation of state-dependence in price setting
  - Increasing generalized hazard (Gagnon et al., 2012; Campbell and Eden, 2014; Eichenbaum et al., 2011; Gautier et al., 2022b)
  - Increasing duration hazard as Fougère et al. (2007) (differently from Nakamura and Steinsson, 2008; Klenow and Malin, 2010; Alvarez et al., 2021)
Selected literature, cont.

- Interpret evidence through the lens of a state-dependent price-setting model (Woodford, 2009)
  - Model matches evidence well
  - State-dependence plays limited role in flexibility of price level (Woodford, 2009; Costain and Nakov, 2011; Alvarez et al., 2020)
  - Higher idiosyncratic shock volatility in the US explains difference relative to euro area
Selected literature, cont.

▶ Interpret evidence through the lens of a state-dependent price-setting model (Woodford, 2009)
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  ▶ Higher idiosyncratic shock volatility in the US explains difference relative to euro area

▶ Role of sales as and adjustment margin
  ▶ Supermarkets in Germany and Italy did adjust their sales during Covid-19 lockdowns
Supermarket scanner data

- Weekly \((w)\) panel of
  - Revenues \((TR_{psw})\) and units sold \((Q_{psw})\) from
  - Products \((p)\) identified at the barcode level in
  - Uniquely-identified stores \((s)\).
Supermarket scanner data

- Weekly ($w$) panel of
  - Revenues ($TR_{psw}$) and units sold ($Q_{psw}$) from
  - Products ($p$) identified at the barcode level in
  - Uniquely-identified stores ($s$).

- Coverage
  - Germany, France, Italy, Netherlands, US
Representative sample of stores of participating supermarket chains (US: >3000; EA: 6000-15000 stores)
Store coverage

- Representative sample of stores of participating supermarket chains (US: >3000; EA: 6000-15000 stores)

- Chains
  - Include: regular and discounter supermarkets, drug stores
  - Exclude: ‘hard’ discounters (e.g. Aldi, Lidl, Walmart)
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  - Only census: US, NL, IT, FR (almost)
  - Both: DE, IT (sample stores are ‘up-weighted’ using regional store-population)
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- EA: random 75% of IRi sample
Product coverage ▶ Table

▶ Food and health care products ($\approx 20$ percent of CPI/HICP)
Product coverage

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- EA: All products sold in the store (400,000-800,000 products)
  - Identified by EAN
  - Private label products: masked ID
Product coverage

- Food and health care products (≈ 20 percent of CPI/HICP)
- EA: All products sold in the store (400,000-800,000 products)
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- US: All products within 31 broad categories (200,000 products)
Product coverage

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  - Identified by EAN
  - Private label products: masked ID
- US: All products within 31 broad categories (200,000 products)
  - Covers most main categories reasonably well
Geographic coverage

- EA: geographically representative
  - Stores from all 2-digit ZIP areas (around 100, e.g. Frankfurt area)
Geographic coverage

- **EA**: geographically representative
  - Stores from all 2-digit ZIP areas (around 100, e.g. Frankfurt area)

- **US**: covers the most populous areas
  - 50 markets (e.g. Chicago) out of 384 MSAs
  - 73% of US population
  - Store is dropped if too large in a market (to protect anonymity)
Cleaning

- Time aggregation (unit-value prices)
  - Weekly averages, include coupons, within-week changes (not membership cards)
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  - Weekly averages, include coupons, within-week changes (not membership cards)

- Posted-price filter
  - Filter consecutive same-direction price changes (2-8% of changes)
  - Round upward remaining fractional prices (7-12%)
Cleaning, cont.

- Monthly aggregation

\[ P_{pst} = \text{mode}_{w \in t} P_{psw}. \]

\[ TR_{pst} = \frac{52}{12} \frac{\sum_{w \in t} \sum TR_{psw}}{\sum_{w \in t} 1}, \]
Cleaning, cont.

- Monthly aggregation

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\[ TR_{pst} = \frac{52}{12} \sum_{w \in t} \frac{\sum TR_{psw}}{\sum_{w \in t} 1}, \]

- We work with a 5% representative sample by country
  - Baseline: 5% random sample of items (product-store)
  - For some analysis: 5% random sample of products
Frequency is higher in the US

- Frequency of price changes key moment of price rigidity

- Most price changes are caused by sales (2/3): fully undone within a quarter

<table>
<thead>
<tr>
<th>Frequency (monthly, mean)</th>
<th>EA4</th>
<th>US</th>
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<tbody>
<tr>
<td>Posted</td>
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- Sales-filtered reference prices (Kehoe and Midrigan, 2015) change infrequently

- Reference (and posted) prices are stickier in EA4 (once in 12m) than in US (7.5m)
Distribution of price changes: size is larger in the US

- Absolute price change distribution
  - Price-change distribution is dispersed: small as well as large price changes
  - Size of reference price changes lower in EA (10%) than in the US (14%)
Distribution of price changes: size is larger in the US

- **Absolute price change distribution**
  - Price-change distribution is dispersed: small as well as large price changes
    - **Absolute price-change distribution**
  - Size of reference price changes lower in EA (10%) than in the US (14%)

- **Standardized price change distribution**
  - Standardize price changes at item level (at least 5 reference-price changes per item)
  - Kurtosis (EA: 2.5; US: 2.3)
State dependence

- State dependence can affect price-rigidity as much as frequency: if *large* price changes are selected (Golosov and Lucas, 2007)
State dependence

- State dependence can affect price-rigidity as much as frequency: if *large* price changes are selected (Golosov and Lucas, 2007)

- Granularity of scanner data: moments revealing state dependence
  - Generalized (price gap) hazard: probability of adjustment as a function of misalignment; Constant in time-dependent Calvo (1983) model; ‘upside-down top-hat’ shape in state-dependent menu cost models (Golosov and Lucas, 2007); in-between in partially state-dependent models (e.g. Woodford, 2009)
  - Duration (price age) hazard: probability of adjustment as a function of time elapsed since the last change; constant in Calvo (1983), upward-sloping in state-dependent models
Proxy for price-gap: distance from competitors’ reset price

- Take sales-filtered prices $p_{pst}^f$
Proxy for price-gap: distance from competitors’ reset price

- Take sales-filtered prices $p_{pst}^f$

- Calculate gap as

$$x_{pst} = p_{pst}^f - \bar{p}_{pt}^* - \hat{\alpha}_s,$$

where

- $\bar{p}_{pt}^*$ is the average (reference) reset price of competitors that changed their prices at $t$
- $\hat{\alpha}_s$ is the store-FE in $p_{pst}^f - \bar{p}_{pt}^* = \alpha_s$. 
Proxy for price-gap: distance from competitors’ reset price

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- Valid proxy

  - FE control for permanent differences across stores (amenities, geography)
  - $\bar{p}_{pt}^*$ is ‘optimal’ as far as competitors reset to optimal prices
Estimating duration hazard

\[ y_{pst,t+1} = \sum_{j=1}^{J} \beta_{y}^{j} I_{pst-1}^{[x_{j-1},x_{j})} + \alpha_{ps} + \alpha_{t} + \varepsilon_{pst} \]

- An empirical challenge is to control for unobserved heterogeneity across products, stores, time
  - We run panel regressions with item (product-store) and time fixed effects
  - Fixed effects eliminate variation coming from permanent differences between items; variation coming from aggregate shocks with uniform impact
Estimating duration hazard

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  - We run panel regressions with item (product-store) and time fixed effects
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- Another challenge is to pick the right functional forms
  - We sidestep the issue by running non-parametric regressions by allocating products into \( J \) bins and estimating average effects within each bin
Estimated generalized hazard functions

- State-dependence: Adjustment probability increasing with gap
- Flat: probability stays moderate even for large gaps
- Asymmetric: higher chance of adjustment at negative gaps
- Slope not too dissimilar across US and EA4
Estimated duration hazard

\[ I_{pst,t+1} = \sum_{j=1}^{J} \beta^j I_{pst-1}^j + \alpha_{ps} + \alpha_t + \varepsilon_{pst}, \]

- Not downward sloping (important to control for heterogeneity and exclude sales)
- Initially strongly upward sloping
- Mildly upward sloping in EA; close to constant in US
Strength of state dependence

- Generalized hazard and density can quantify state dependence (Caballero and Engel, 2007)
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- Inflation

\[ \pi = \int -x \Lambda(x) f(x) dx, \]

where \( x \) gap, \( f(x) \) density, \( \Lambda(x) \) hazard
Strength of state dependence

- Generalized hazard and density can quantify state dependence (Caballero and Engel, 2007)

- Inflation

\[ \pi = \int -x\Lambda(x)f(x)\,dx, \]

where \( x \) gap, \( f(x) \) density, \( \Lambda(x) \) hazard

- Impact effect of permanent shock \( m \)

\[ \frac{\partial \pi}{\partial m} = \int \Lambda(x)f(x)\,dx + \int x\Lambda'(x)f(x)\,dx, \]

intensive  extensive
Strength of state dependence, cont.

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<thead>
<tr>
<th>Margins</th>
<th>EA4</th>
<th>US</th>
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<td>Overall impact effect</td>
<td>11.5%</td>
<td>17.2%</td>
</tr>
<tr>
<td>Intensive (relative)</td>
<td>74.6%</td>
<td>75.1%</td>
</tr>
<tr>
<td>Extensive (relative)</td>
<td>25.4%</td>
<td>25.0%</td>
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- State-dependence (extensive margin)
  - Matters
    - Affects price flexibility proportionally in US and euro area
    - Driven by more dispersed gap distribution in the US
Matching a state-of-the-art price-setting model (Woodford, 2009)

- Show how our moments can be used for model selection and calibration
- Take Woodford (2009) model off-the-shelf
  - Microfoundation of ‘random menu cost’ models (Dotsey et al., 1999; Alvarez et al., 2020, implies a particular functional form)
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- Calibrate (i) review cost ($\kappa$), (ii) standard deviation of idiosyncratic shocks ($\sigma_A$), (iii) information cost ($\theta$) to match
  - Generalized hazard function, frequency, size of reference price changes
  - Check how it matches price-change distribution, age hazard
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- Translate differences in moments into differences in parameters
Targeted moments

EA4

Generalized hazard

Model
Data

US

Generalized hazard

Model
Data

Price gap density

Model
Data

Price gap density

Model
Data
Untargeted moments

EA4

US

Duration hazard

Duration hazard

Standardized price-change distribution

Standardized price-change distribution
Implications for EA4 vs. US heterogeneity (Woodford, 2009)

- Calibrated parameters

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<td>Review cost ($\kappa$)</td>
<td>9.0%</td>
<td>9.2%</td>
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<td>Stdev. of idiosyncratic shocks ($\sigma_A$)</td>
<td>3.3%</td>
<td>5.5%</td>
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- Implications
  - State dependence is present but mild in both countries (information frictions are high)
  - Higher idiosyncratic-shock variation in US plays a prominent role in explaining higher frequency of price changes
Covid-19 shock in Germany and Italy

▶ What can the 2020 Covid shock in supermarkets can teach us about price setting?
Covid-19 shock in Germany and Italy

- What can the 2020 Covid shock in supermarkets can teach us about price setting?

- Large and persistent demand shock Germany and Italian in supermarkets

  - Real Expenditure Growth

    - Restricted access to food-away-from-home
    - Limited cost shock: essential sector, sheltered from lockdown
Covid-19 shock in Germany and Italy

- What can the 2020 Covid shock in supermarkets can teach us about price setting?

- Large and persistent demand shock Germany and Italian in supermarkets

  - Restricted access to food-away-from-home
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- Sizable supermarket inflation in Germany and Italy:

  - Have supermarket adjusted their temporary discounts?
  - What explains cross-country differences in inflation?
Result #1: Yes: significant adjustment through temporary discounts

- Fewer and smaller discounts in both Germany and Italy

- Change in sales frequency/size

- Formulas
Result #1: Yes: significant adjustment through temporary discounts

- Fewer and smaller discounts in both Germany and Italy
  - Can be justified by
    - Less competition for bargain hunters and product/store switching
    - Inventory management
**Result #2: Heterogeneous response in Germany versus Italy**

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<td>Overall impact effect</td>
<td>8.5%</td>
<td>12.4%</td>
</tr>
<tr>
<td>Intensive (relative)</td>
<td>58.9%</td>
<td>72.8%</td>
</tr>
<tr>
<td>Extensive (relative)</td>
<td>41.1%</td>
<td>27.2%</td>
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- Italian prices more flexible than German prices
  - Different market structure: DE: 16 chains; IT: 466 chains
Result #2: Heterogeneous response in Germany versus Italy

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  - Different market structure: DE: 16 chains; IT: 466 chains

- Larger increase reference-price inflation in Italy (DE: +0.3%, IT: +1.2%)
Conclusion

- Conclusions
  - Supermarket prices change more frequently and by larger amounts in the US than in the EA4
  - State-dependence raises price flexibility more in the US
  - Both factors are driven by higher product-level volatility in the US; confirmed by a structural model
Conclusion

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▶ Supermarket prices change more frequently and by larger amounts in the US than in the EA4

▶ State-dependence raises price flexibility more in the US

▶ Both factors are driven by higher product-level volatility in the US; confirmed by a structural model

▶ Implications

▶ State dependence means that higher trend inflation and large shocks will make prices endogenously more flexible

▶ Further research is necessary to understand the source and the role of product-level shocks


References II


References IV


References


Gautier, Erwan, Magali Marx, and Paul Vertier (2022b) “The Transmission of Nominal Shocks when Prices are Sticky,” unpublished manuscript.


HICP vs IRi expenditure shares by category
## Overview table

<table>
<thead>
<tr>
<th></th>
<th>DE</th>
<th>FR</th>
<th>IT</th>
<th>NL</th>
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<tbody>
<tr>
<td><strong>Time series</strong></td>
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<td></td>
<td></td>
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<tr>
<td># 2-digit ZIPs</td>
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<td># stores</td>
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<td>5851</td>
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<td># chains</td>
<td>16</td>
<td>43</td>
<td>466</td>
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<tr>
<td>% in HICP/CPI</td>
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<td>1662</td>
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<td>24.09</td>
<td>56.19</td>
<td>31.22</td>
<td>30.01</td>
<td>6.2</td>
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<tr>
<td># observations (bn)</td>
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<td>11.92</td>
<td>11.3</td>
<td>7.66</td>
<td>2.7</td>
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Food and non-alcoholic beverage inflation in the US and euro area

[Chart showing inflation rates from 2003 to 2021 for the euro area and United States.]
## Overview table, posted-price filter

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<th>US</th>
</tr>
</thead>
<tbody>
<tr>
<td>% same-direction changes</td>
<td>2.15</td>
<td>5.39</td>
<td>8.1</td>
<td>3.58</td>
<td>6.03</td>
</tr>
<tr>
<td>% also fractional</td>
<td>1.66</td>
<td>3.71</td>
<td>5.36</td>
<td>1.65</td>
<td>3.31</td>
</tr>
<tr>
<td>% fractional price</td>
<td>7.6</td>
<td>8.05</td>
<td>11.66</td>
<td>5.91</td>
<td>6.96</td>
</tr>
<tr>
<td>% below closest integer</td>
<td>68.93</td>
<td>53.83</td>
<td>59.48</td>
<td>62.33</td>
<td>58.95</td>
</tr>
</tbody>
</table>
Duration hazard functions (posted prices)
Duration hazard functions (with heterogeneity/no FE)
Price setting with information frictions (Woodford, 2009)

- Starting point: a standard menu-cost model (Golosov and Lucas, 2007)
  - Monopolistic competition with differentiated goods ($\varepsilon$: elasticity of substitution)
  - Idiosyncratic cost shocks $A_t(i) = A_{t-1}(i) + \nu_t, \nu \sim N(0, \sigma_A^2)$
  - Price gap $(x_t(i) = p_t(i) - p^*(i))$ determines profit
  - Fixed (menu) cost of a price review $\kappa$
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- Timing of price review: rational inattention
  - Costly signal $f(x)$ about the state (cost ↑ w/ informativeness: $\theta I = -\theta E [\log f(x)]$)
  - Result #1: optimal policy described by a hazard function (adjustment (signal) probability as a function of current gap $\Lambda(x)$)
  - Result #2: Functional form of hazard function is well defined, depends on $\theta$ ($\theta = \infty$: constant hazard, calvo; $\theta = 0$: step function, (S,s)).
Heterogeneity across EA4 countries

- Large cross-country heterogeneity across EA countries (particularly low in Germany - fewest chains, large in France - much more chains)

<table>
<thead>
<tr>
<th>Frequency (monthly, mean)</th>
<th>DE</th>
<th>FR</th>
<th>IT</th>
<th>NL</th>
<th>US</th>
</tr>
</thead>
<tbody>
<tr>
<td>Posted</td>
<td>12.41</td>
<td>42.23</td>
<td>27.56</td>
<td>24.77</td>
<td>39.35</td>
</tr>
<tr>
<td>Reference</td>
<td>4.53</td>
<td>12.78</td>
<td>9.04</td>
<td>10.06</td>
<td>13.34</td>
</tr>
<tr>
<td>Ratio</td>
<td>2.74</td>
<td>3.31</td>
<td>3.05</td>
<td>2.46</td>
<td>2.95</td>
</tr>
</tbody>
</table>
HICP vs IRi expenditure shares by category

- DE
- FR
- IT
- NL
- US

Alcoholic beverages
Goods for routine HH maintenance
Meat, fish and seafood
Milk, cheese, eggs, oils and fat
Non-alcoholic beverages
Personal care
Sugar, jam, honey, chocolate, confectionery

Covid-19
Reference-price vs sales inflation (year-on-year)
Examples of price spells

DE

EAN 5000112552218
Store ID 18417689

FR

EAN 5000112609684
Store ID 576612

US

EAN 0049000012521
Store ID 262860

- Posted price
- Reference price
Frequency of reference-price changes, EA4 vs US
Absolute reference-price-change distribution

- **Euro Area**
  - mean = 0.14
  - med. = 0.09
  - 10% = 0.02
  - 25% = 0.04
  - 75% = 0.19
  - 90% = 0.34

- **United States**
  - mean = 0.10
  - med. = 0.05
  - 10% = 0.01
  - 25% = 0.03
  - 75% = 0.11
  - 90% = 0.22
Standardized posted- and reference-price-change distribution

- Euro Area: kurt.: 2.54, skew.: -0.05
- United States: kurt.: 2.32, skew.: -0.08
Size of price changes as a function of the price-gaps (reference prices)
Store-level scanner data from IRi

- Germany and Italy; Large brick-and-mortar supermarkets; All products in these supermarkets

- From mid-February to mid-May in 2019 and 2020; 2013-2017

- 20 two-digit ZIP area in both countries (population share: DE: 16%, IT: 42%; expenditure share: DE: 8%, IT: 40%)

- To minimize composition change
  - Stores that are available throughout 2013-2020 (DE: 668/815, IT: 1486/2387)
  - ‘Established’ products available throughout 2013-2020 (DE: 57.000/266.000, IT: 83.800/535.500)
Price setting

- Cleaning weekly unit-value prices: posted-price ($P_{psw}^p$) filter
  - Mid-week price changes: consecutive same-direction weekly price change
  - Rounding upwards fractional prices

- Sales filtering:
  - Distinguish high-frequency vs persistent price adjustment
  - Approach: reference-price ($P_{psw}^f$) filter: 5-week modal price
  - Iteratively updated to align its change with posted-price change as in Kehoe and Midrigan (2015)

- Decomposition: ‘Reference-price’ and ‘sales’ inflation
  \[ \pi_w^p = \pi_w^f + \pi_w^s. \]
Change in sales

Change in frequency and size of sales (current-weight)

\[ \Delta \xi^s_w = \xi^s_w - \xi^s_{w-52}, \quad \xi^s_w = \sum_{psw} \gamma_{psw} I^s_{psw}, \quad \xi^s_{w-52} = \sum_{psw} \gamma_{psw} I^s_{psw-52} \]

\[ \Delta \psi^s_w = \psi^s_w - \psi^s_{w-52}, \quad \psi^s_w = \frac{\sum_{ps} \gamma_{psw} I^s_{psw} \left( \log P^s_{psw} - \log P^p_{psw} \right)}{\sum_{ps} \gamma_{psw} I^s_{psw}}, \]

\[ \psi^s_{w-52} = \frac{\sum_{ps} \gamma_{psw} I^s_{psw-52} \left( \log P^s_{psw-52} - \log P^p_{psw-52} \right)}{\sum_{ps} \gamma_{psw} I^s_{psw-52}} \]

where \( I^s_{psw} \) is an indicator function that takes the value 1 if product \( p \) in store \( s \) is on sale.
Real expenditure growth, y-o-y, 2020
Inflation, y-o-y, 2020
Reference-price inflation, y-o-y, 2020
HICP (food and beverage) and IRi supermarket indexes

[Graph showing HICP and IRi indices for Germany and Italy from January 2014 to January 2021]
Change in the frequency and size of sales, y-o-y, 2020
Frequency and size of reference-price changes, y-o-y, 2020

![Graph showing frequency and size of reference-price changes in Germany and Italy, with data points from 17 Feb to 11 May 2020.](image-url)
Frequency and size of reference-price decreases, y-o-y, 2020
Frequency and size of reference-price increases, y-o-y, 2020