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Inflation measurement with high frequency data

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UKRI Economic and Social Research Council

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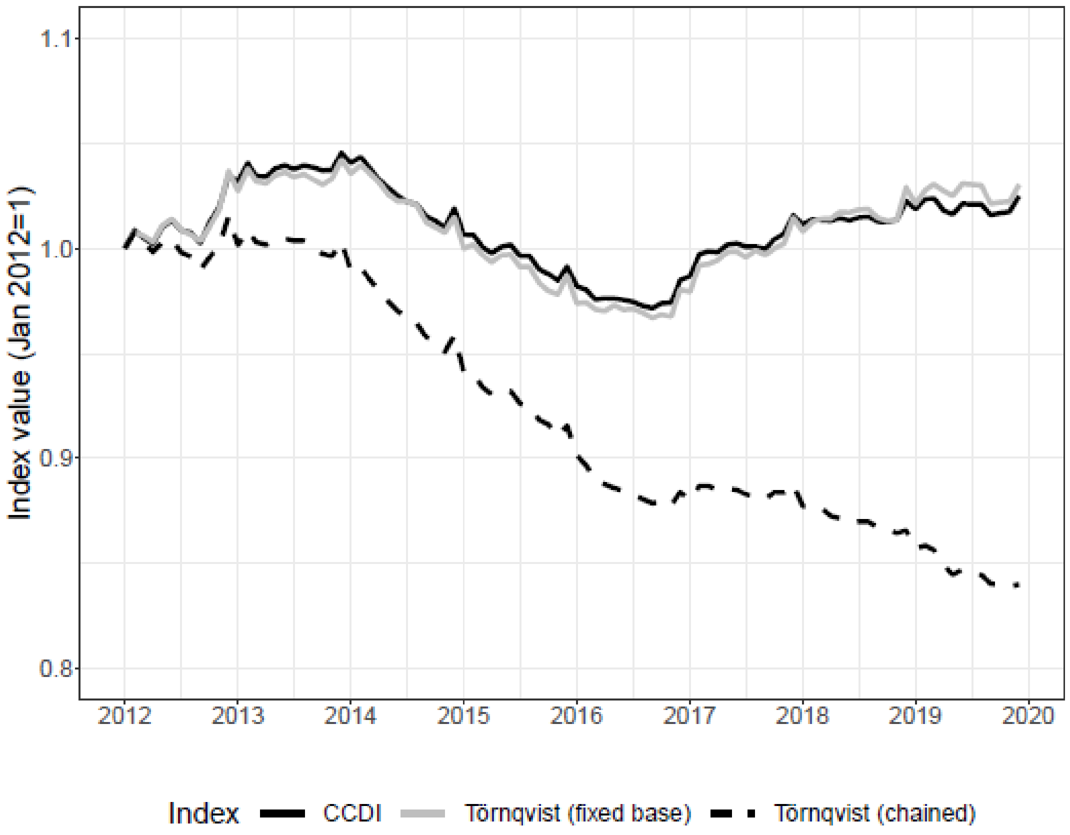
Background

- Growing interest by NSIs in using transactions level (“scanner”) data for price measurement
  - EPOS data from retailers have much larger **sample sizes** all production of index numbers at **greater frequency** than traditional price surveys
- Production of higher frequency indices (e.g. month to month price changes) creates new challenges
  - Traditional (“bilateral”) index number methods can exhibit worryingly large “chain drift”
- Engaged by ONS through ESCoE to review ONS plans for using ***multilateral index number methods*** in the CPI
  - Report: ESCoE Discussion Paper No. 2022-08 April 2022

Why multilateral index numbers

- Chaining indexes is desirable because we want accurate measures of inflation between consecutive periods and we have product churn – don't want the basket to get out of date
- But chaining month-to-month with transaction level data can lead to massive chain drift



Why multilateral index numbers

- Multilateral indexes introduced to this context for the purpose of controlling chain drift by Ivancic, Diewert and Fox (2009, 2011)

- The CCDI index in the previous figure is a multilateral method calculated over the full sample
  - By definition does not suffer from chain drift bias – uses all periods of data

- With non-revisable CPIs, need a method for ***extending*** the series when new data is released
  - Simply expanding the window for multilateral indexes can result in a re-writing of history.
  - Extend series by splicing “windows” together so that old price comparisons are unaffected

- Extending the series reintroduces chain drift to some degree
  - Empirical question how much

This paper

- Empirically assess different **multilateral index number methods, window lengths and extension methods** using a wide variety of goods (N=178) over a long period of time (2012-2019)
  - Draw on household scanner data from the UK
  - Use IndexNumR package in R written by Graham White

- Previous work has tended to look at smaller numbers of products over short time periods (e.g. Ivancic et al. 2009, 2011, de Haan and van der Grient (2011), Lamboray 2017, Chessa 2021, Diewert 2022)

- Examine sources of chain drift bias
  - We believe novel to the literature

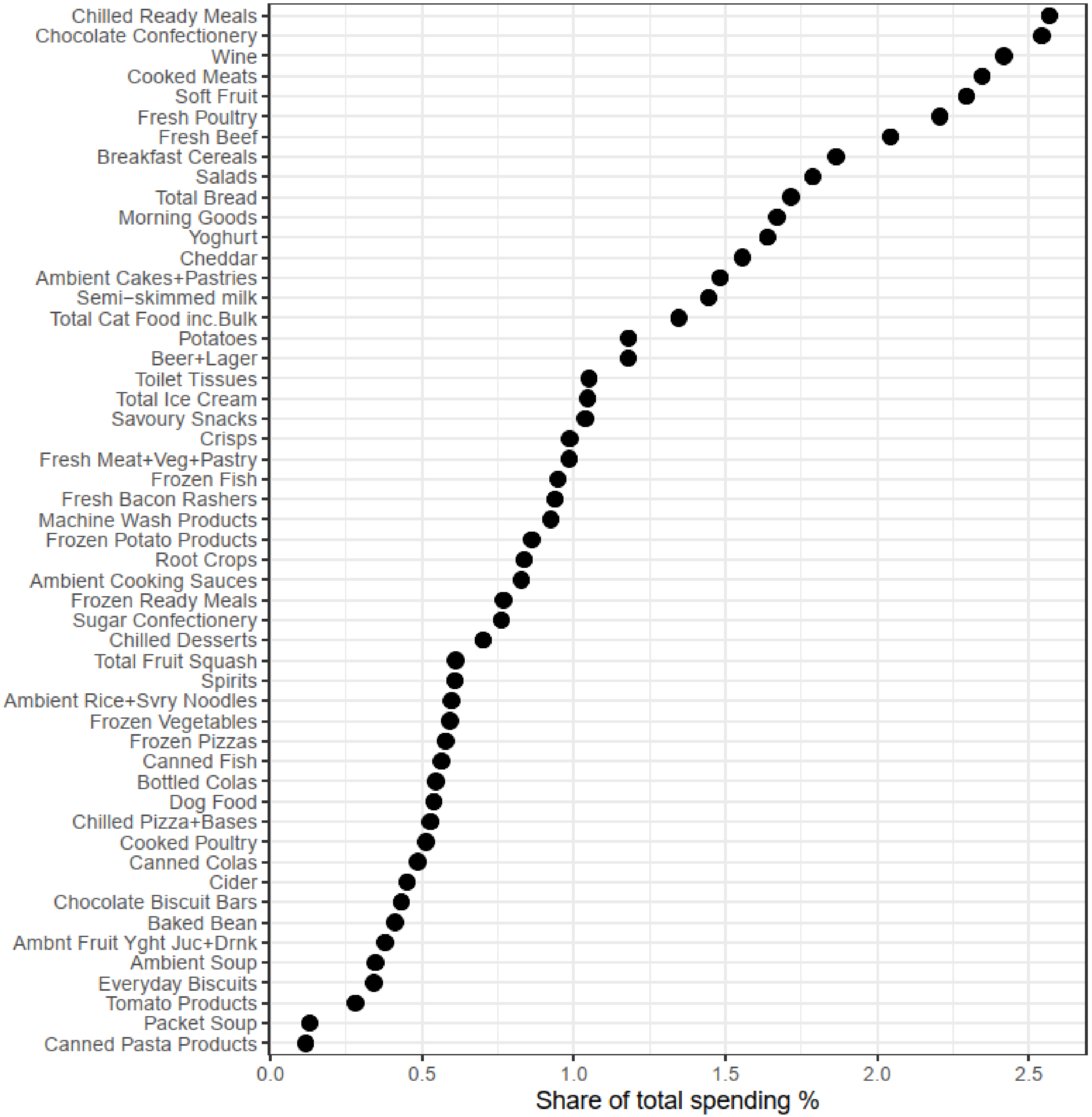
This paper

The next two slides show some characteristics of the data:

- Product coverage: 178 product categories comprising all fast-moving consumer goods over 8 years

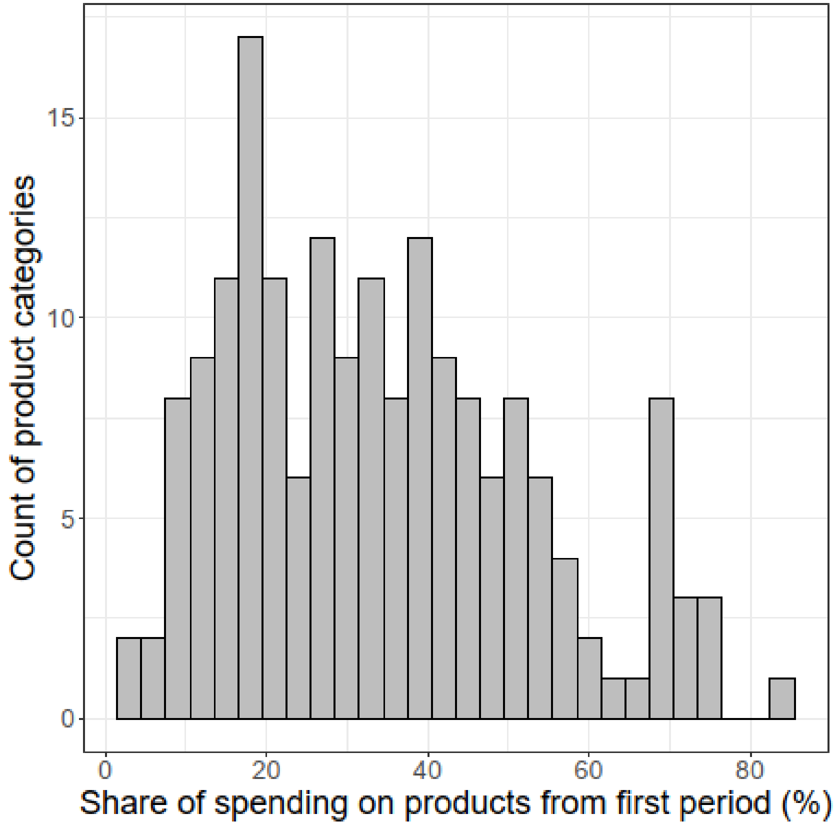
- There is significant product churn. For the median product category, 32% of spending in December 2019 went on items that had positive spending associated with them in January 2012. Product churn on this measure is highest for
  - moist wipes,
  - machine wash products,
  - cat food and
  - fresh bacon joints.

Figure 3.1: *Share of total spending on product groups*



Product Churn

Figure 4.2: *Share of final period spending on products available in first period*



Note: Figure shows the distribution of the share of spending in the final period (December 2019) that goes on products that were purchased in the first period (January 2012) across product categories.

Findings

- Confirm that bilateral indices suffer serious chain drift and that fixed base indices tend to become unrepresentative
- GEKS-Fisher and GEKS-Walsh indices largely similar to CCDI (GEKS-Tornqvist) with occasional outliers. Differences with the Geary Khamis (GK) index more substantial.
- Different extension methods associated with similar chain drift biases. GK more sensitive to choice of extension method.
- Can't do price imputation with GK
- 25-month window when extending indices substantially reduces chain drift
- **Recommendation:** CCDI index extended using mean splice and at least a 25-month window

Findings

- Product churn is strongly correlated with rates of chain drift bias
- High frequency (monthly) churn a problem when window lengths are short, low frequency (annual) churn still an issue for longer window lengths

Multilateral indices

- Various options – GEKS

$$\mathbb{P}^{\tau}_{GEKS-F} = \prod_t \left[P_F^{\tau,t}\right]^{1/T} \quad \text{where } P_F^{\tau,t} \text{ is a Fisher index}$$

$$\mathbb{P}^{\tau}_{CCDI} = \prod_t \left[P_{Tq}^{\tau,t}\right]^{1/T} \quad \text{where } P_{Tq}^{\tau,t} \text{ is a Törnqvist index}$$

$$\mathbb{P}^{\tau}_{GEKS-W} = \prod_t \left[P_W^{\tau,t}\right]^{1/T} \quad \text{where } P_W^{\tau,t} \text{ is a Walsh index}$$

- Or Geary-Khamis

$$b_n = \sum_t \left(\frac{q_n^t}{q_n}\right)\left(\frac{p_n^t}{\mathbb{P}^t_{GK}}\right) \quad \text{for } n = 1, \ldots, N$$

$$\mathbb{P}^t_{GK} = \frac{\mathbf{p}^{t\prime}\mathbf{q}^t}{\mathbf{b}'\mathbf{q}^t} \quad \text{for } t = 1, \ldots, T.$$

The linking problem

- The indices satisfy the multiperiod identity test ($P^{1,2}P^{2,3}P^{3,1} = 1$)
- But.. when new months are included in the index, past prices will need to be revised
- One set of solutions is *rolling window* to link indices calculated in different windows (1,…,T) and (2,..,T)
  - “roll forward” index P by one period to get $\tilde{P}$
  - Use an overlapping period *s* to extend the index

$$\rho^{T+1}(s) = \frac{\mathbb{P}_s}{\mathbb{P}_1}\frac{\widetilde{\mathbb{P}}^{T+1}}{\widetilde{\mathbb{P}}^{s}}$$

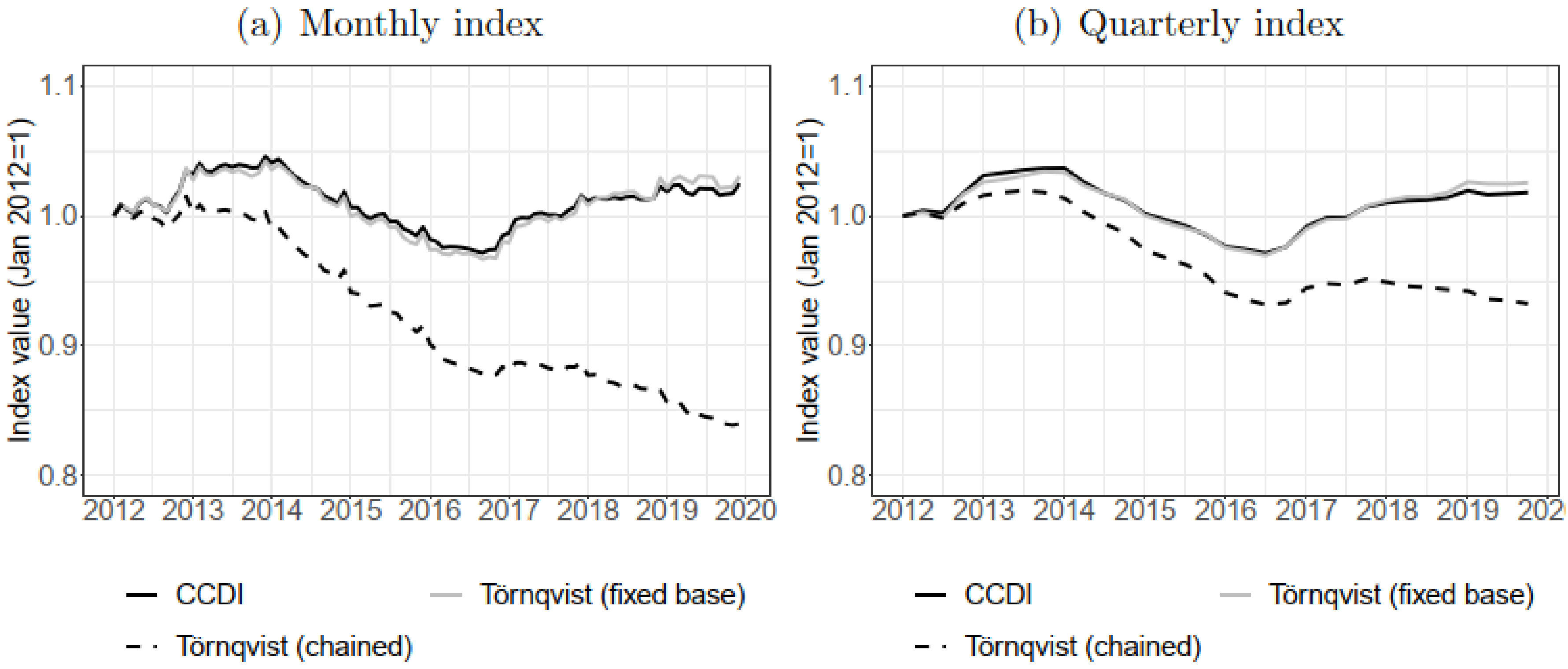
- Rolling window approaches use different splice periods, *s* (window, half, movement etc.)
  - Mean splice takes geometric average using all possible splicing periods
- Other extension methods are possible (and we include)

Chain drift

- Splicing allows the index to be updated without altering the series that has been published
- But reintroduces chain drift
- We assess chain drift bias across different indices, window lengths and extension methods
- Bias defined as difference between index calculated over the whole period and spliced index

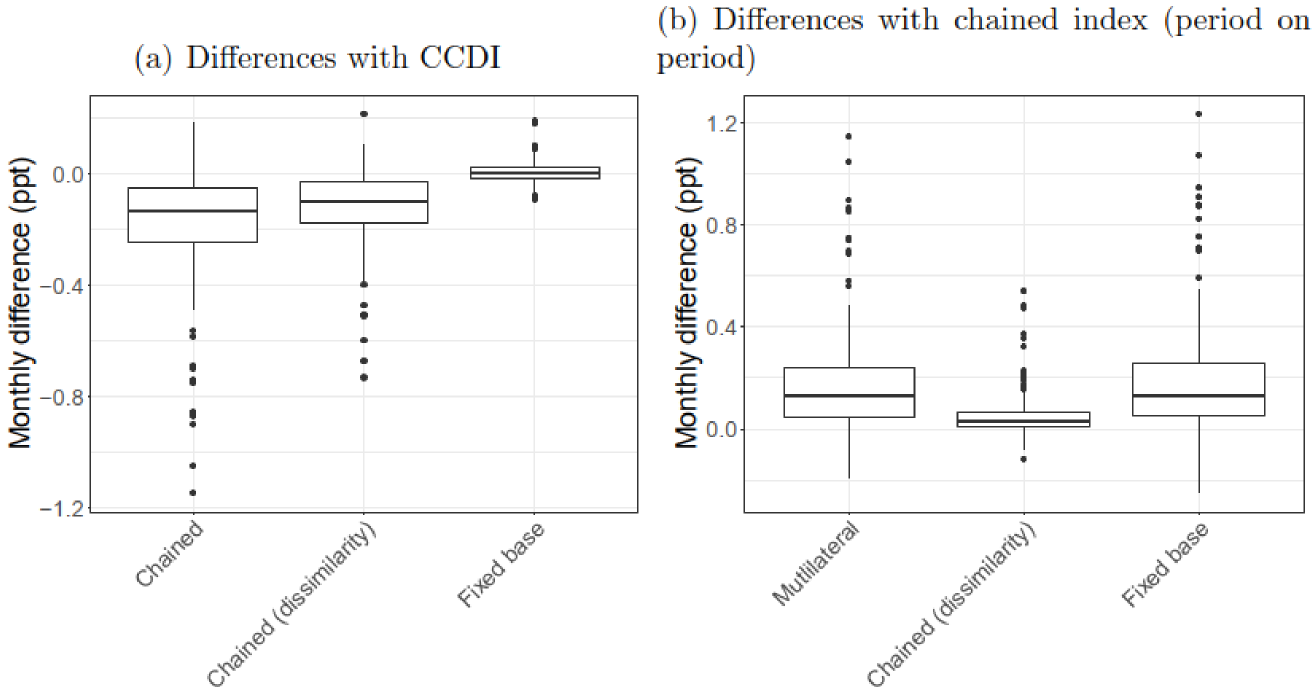
Chain drift

Figure 4.3: *Chain drift bias: CCDI vs bilateral Törnqvists*



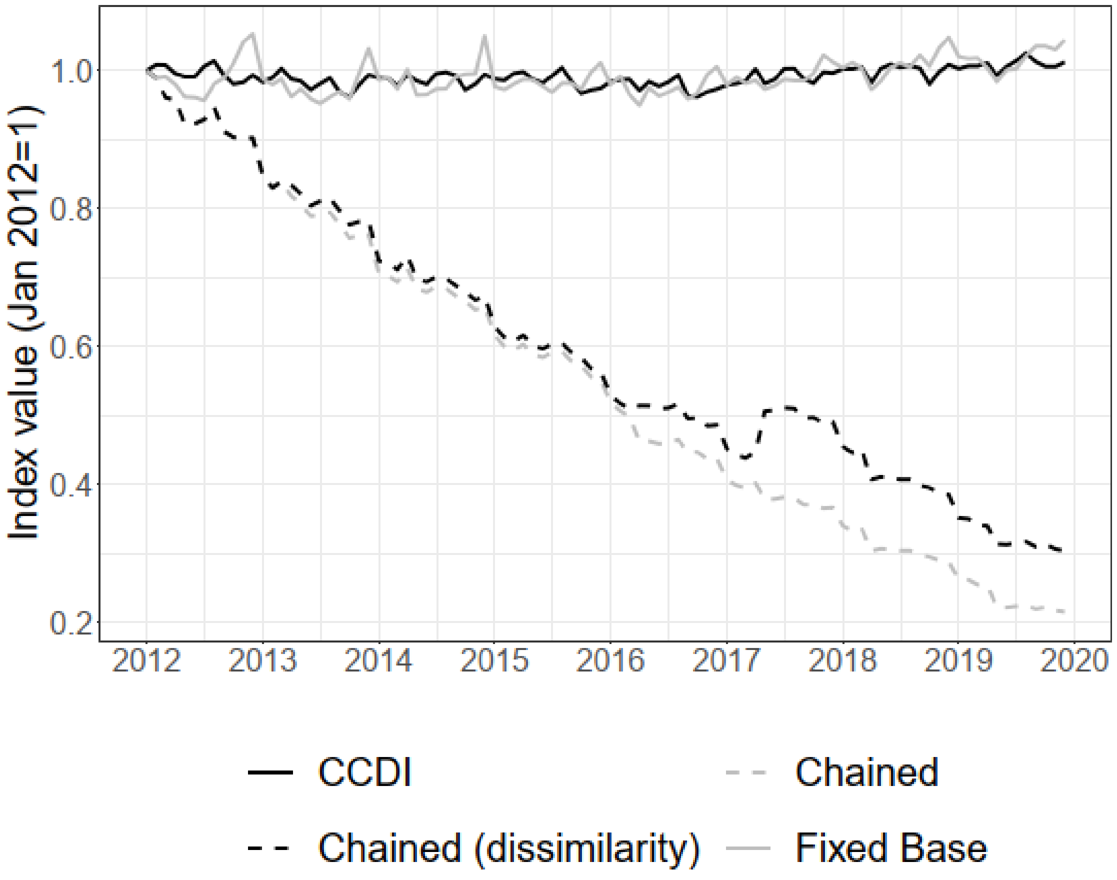
Note: Figures show index number values for the CCDI multilateral index, the Törnqvist fixed base index and a monthly chained Törnqvist index. The indexes are calculated across all fast-moving consumer goods.

Figure 4.4: *Average monthly difference between CCDI and bilateral Törnqvist indexes by product*



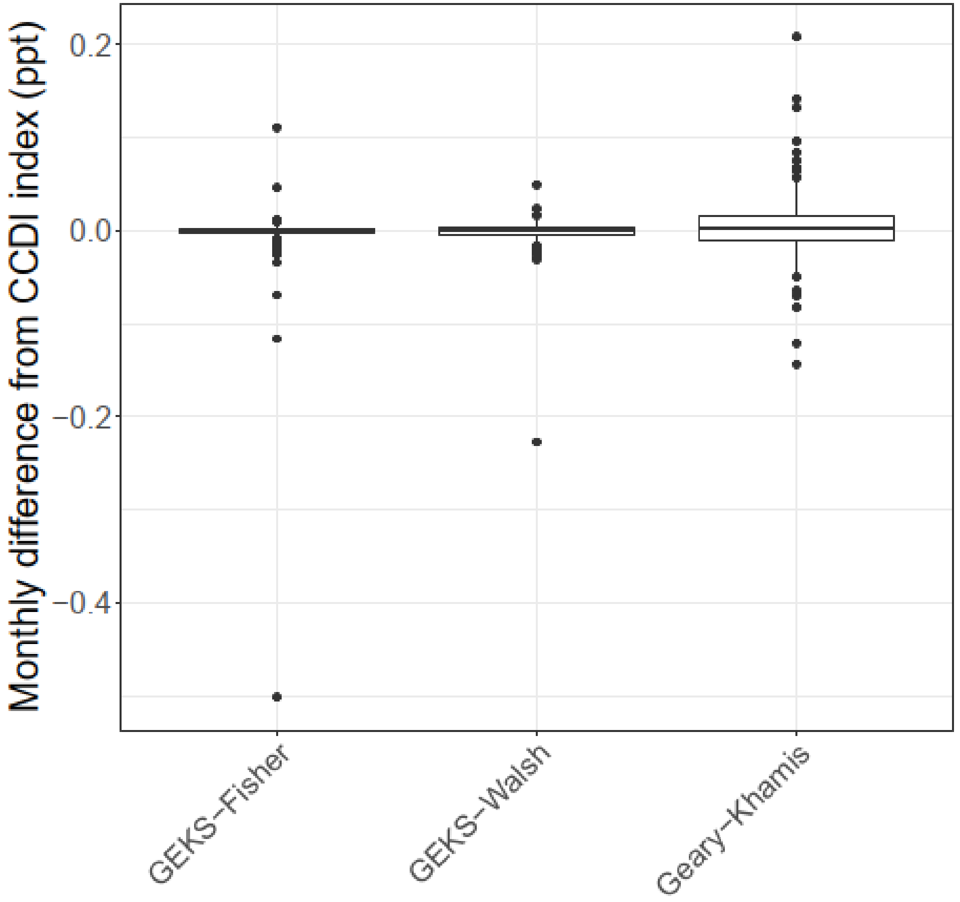
Note: In panel (a), each box plot summarizes the distribution (across product categories) of differences in average monthly inflation rates between the CCDI index calculated over the whole period and i) a bilateral Törnqvist chained period-on-period ii) a bilateral Törnqvist chained with using the predicted share dissimilarity approach and iii) a fixed-base Törnqvist. In panel (b), each box plot summarizes the distribution of differences in average monthly inflation rates between the period-on-period chained index bilateral Törnqvist, and i) a CCDI index calculated over the whole period ii) a bilateral Törnqvist chained with using the predicted share dissimilarity approach and iii) a fixed-base Törnqvist. We exclude outliers (the three products with the largest positive and three largest negative amounts of chain drift bias) from each plot.

Figure 4.5: *Monthly CCDI and bilateral Törnqvist indexes for Chocolate and confectionery*



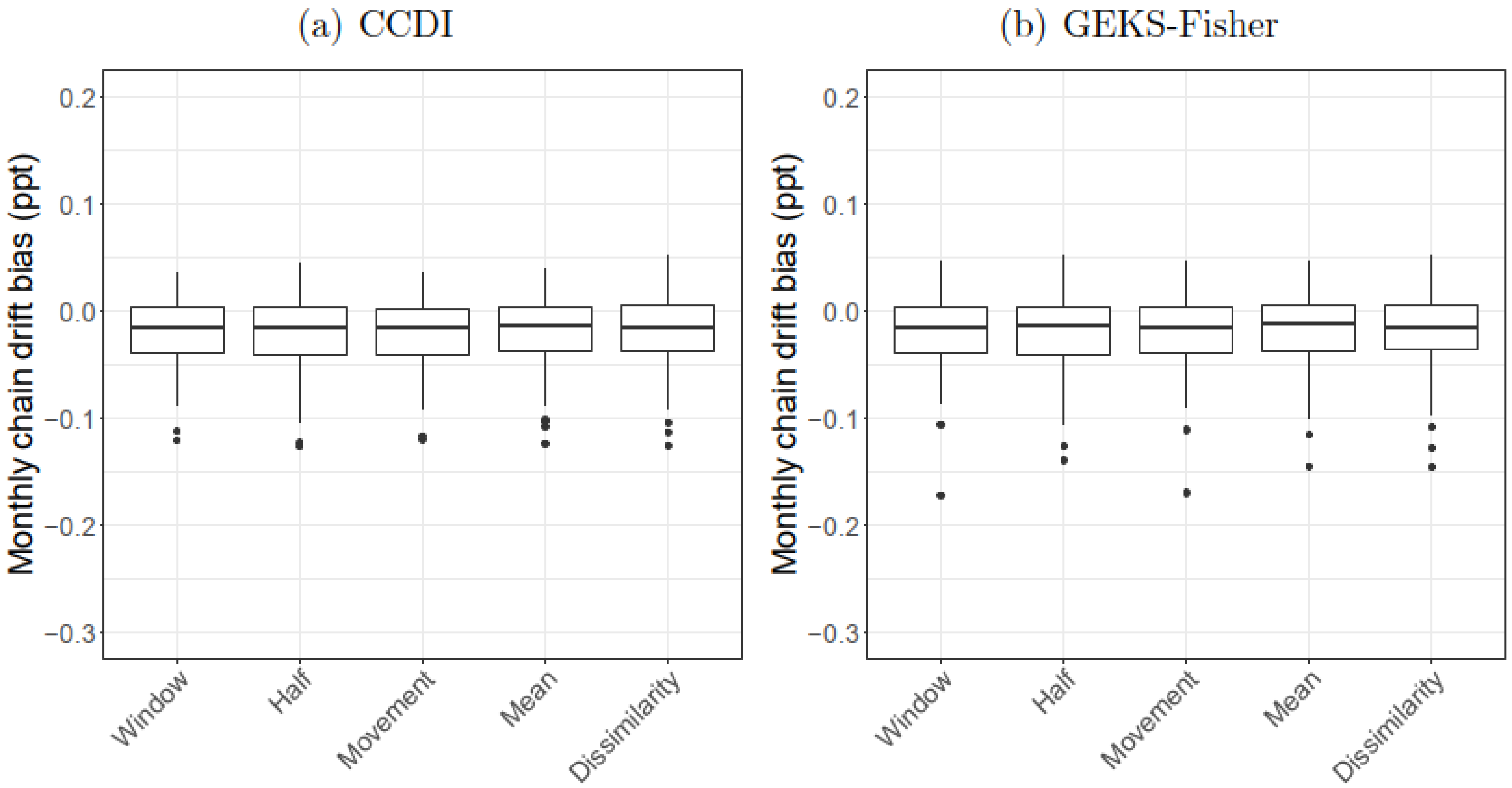
Note: Figure shows index number values for the CCDI multilateral index calculated over the whole period, the Törnqvist fixed base index, a monthly chained Törnqvist index chained period-on-period, and a Törnqvist index chained using the dissimilarity approach for the product Chocolate and Confectionary.

Figure 4.6: *Average monthly inflation rates relative to CCDI index*

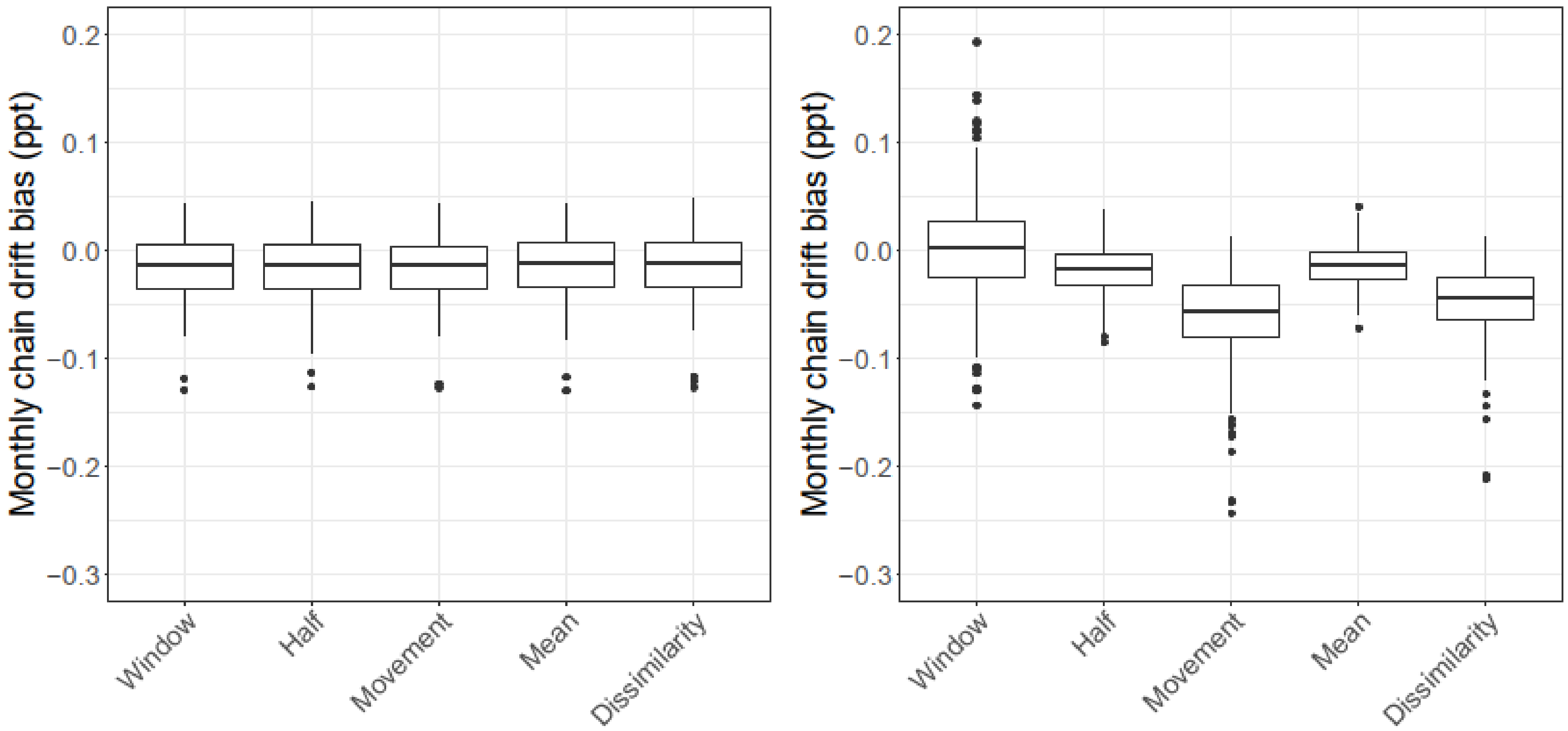


Note: Each box plot summarizes the distribution (across product categories) of differences in average monthly inflation rates between the index named in the horizontal axis and the CCDI index. Indexes are calculated using all 96 year-months of data.

Figure 5.1: *Chain drift bias with different splicing methods (25 month window)*



(c) GEKS-Walsh (d) GK

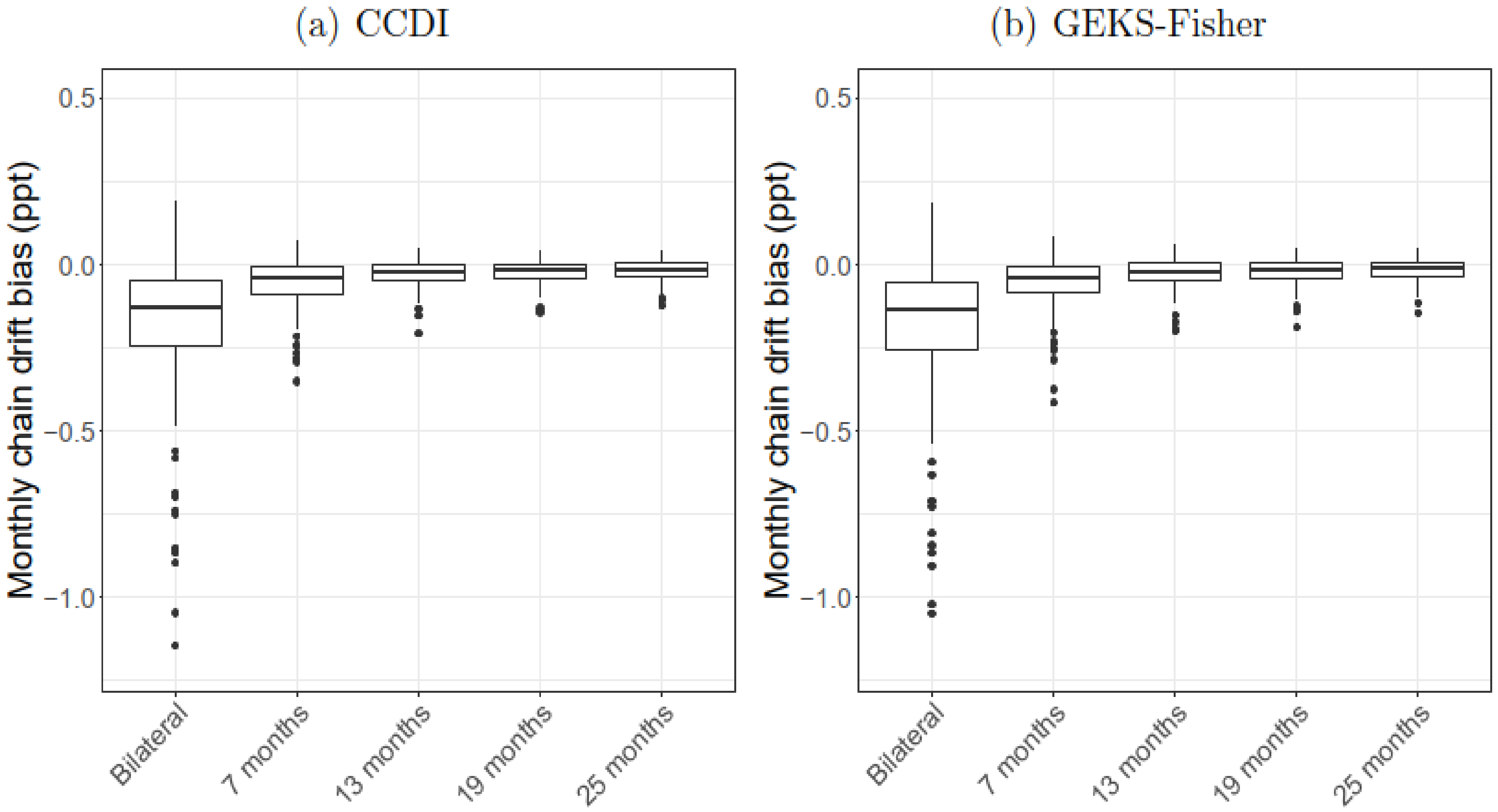


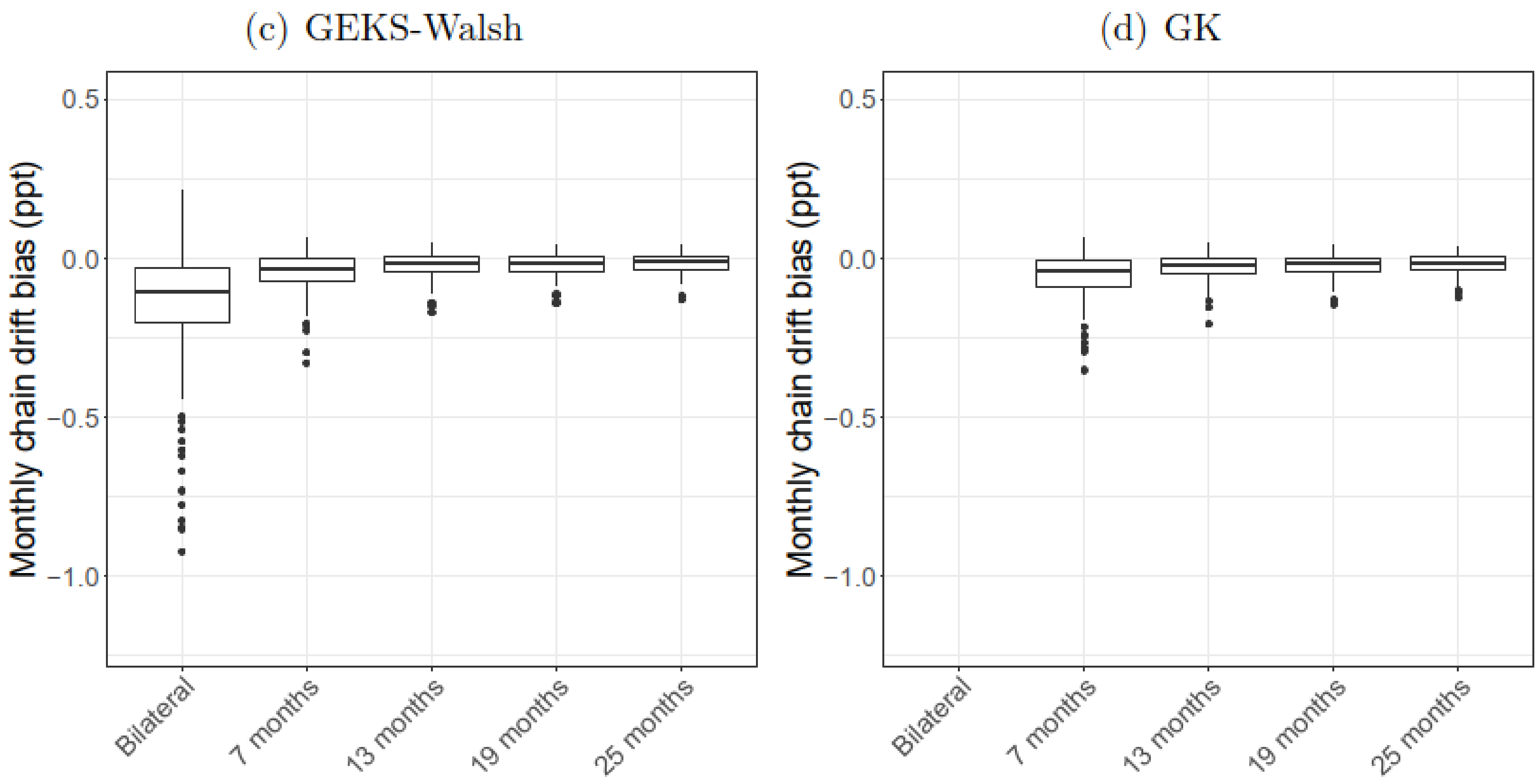
Note: Each box plot summarizes the distribution (across product categories) of differences in average monthly inflation between the spliced index (over a 25 month window) using the linking method named in the horizontal axis and the corresponding non-spliced index. We exclude the products with the three largest positive and negative values for chain drift in each plot.

Some observations

- The GK index is more sensitive to the linking method than the CCDI or GEKS indexes
- The most extreme outliers (not shown in the plots) are much higher for the GK index than for the other indexes.
- The figures provide the first empirical evidence on the use of the **predicted share dissimilarity method for splicing rolling window multilateral indexes**.
    - Except for the case of the GK index, the performance is very similar to the other methods. These results are more encouraging than for its use in chaining bilateral indexes

Figure 5.2: *Chain drift bias using different window lengths (using mean splice)*





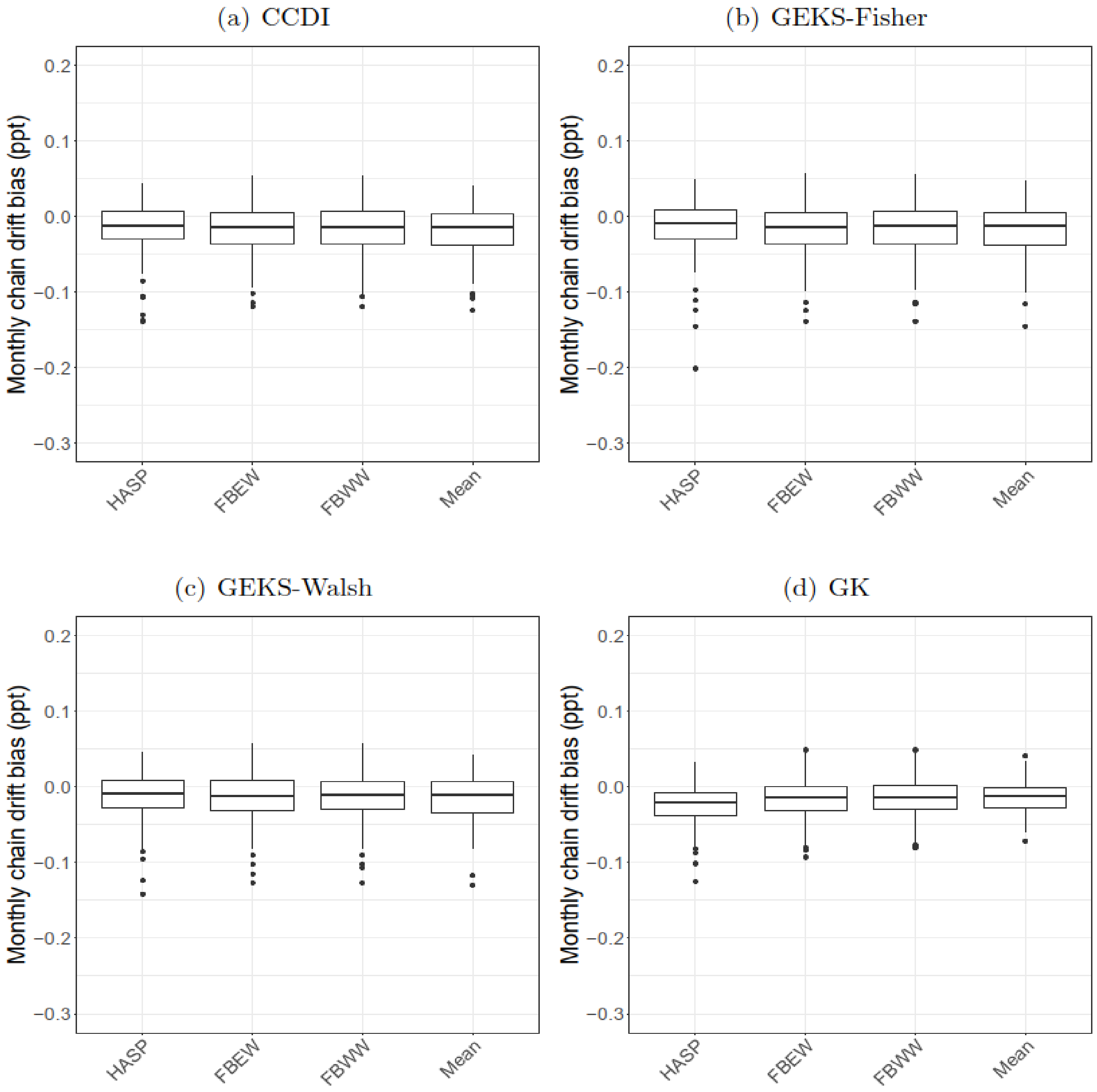
Note: Each box plot summarizes the distribution (across product categories) of differences in average monthly inflation between the spliced index (using the mean spliced) computed over the window length named in the horizontal axis and the corresponding non-spliced index. We exclude the products with the three largest positive and negative values for chain drift in each plot. In the case of the CCDI, GEKS-Fisher and GEKS-Walsh, we also include the chain drift bias associated with their corresponding bilateral indexes (equivalent to using a window length of one month). The GK index does not have a corresponding bilateral index.

Possible determinants of chain drift bias

- For all index numbers, longer windows lengths lead to considerably less chain drift bias

- While spliced indexes can exhibit chain drift bias, even short window lengths perform considerably better than bilateral indexes.
    - The median average monthly chain drift bias for the bilateral Törnqvist is -0.13 ppt, around 10 times greater than the bias with a 25-month window length.

Figure A1: *Chain drift bias with different splicing methods (25 month window)*



Some observations

- Of the additional methods considered in the preceding figure, HASP performs the worst in terms of introducing more extreme cases of chain drift bias across all the indexes.

Possible determinants of chain drift bias

Table 5.3: *Determinants of chain drift bias (25 month window length)*

	CCDI (1)	GEKS-Fisher (2)	GEKS-Walsh (3)	GK (4)
Monthly churn	0.074	0.076	0.021	0.139*
	(0.108)	(0.122)	(0.103)	(0.074)
Annual churn	0.149***	0.154***	0.129***	0.061*
	(0.046)	(0.052)	(0.044)	(0.033)
Pricing seasonality	0.001	0.023	0.001	−0.028
	(0.048)	(0.053)	(0.045)	(0.033)
Price promotions	−0.009	−0.021	−0.006	−0.023
	(0.027)	(0.030)	(0.026)	(0.018)
Quantity promotions	−0.024	−0.038*	−0.031*	−0.001
	(0.019)	(0.021)	(0.018)	(0.012)
Observations	175	175	175	175
R^2	0.110	0.100	0.085	0.073

Note: All indexes are extended using the mean splice. *$p<0.1$; **$p<0.05$; ***$p<0.01$.

Possible determinants of chain drift bias

Summary of findings from regression analysis:

- Higher rates of product churn are the main determinant of chain drift bias
- Each percentage point increase in annual churn is associated with between a 0.13 and 0.15 ppt increase in chain drift for the CCDI, GEKS-Fisher and GEKS-Walsh indexes.
- Monthly and annual churn contribute to 88% of the total explained variance in chain drift in the 25-month spliced CCDI index.
- High-frequency (monthly) churn appears to be a particular problem for the GK index.

Conclusions and directions for future research

- Recommend the use of the CCDI index with mean splice and 25-month window
  - GEKS-Fisher appears to be sensitive to occasional outliers
  - Can use (hedonic) imputation for missing prices (which is not possible using GK)

Future research:

- When does product missingness become a problem?
- Does the timing of product entry and exit affect the optimal splicing period/method?

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