Discussion of Household Inventory, Temporary Sales, and Price Indices by Ueda, Watanabe and Watanabe

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What the paper does

- Construct model of household inventory decisions
 - differentiate household purchasing and consumption decisions
- Use model & scanner (purchasing) data to estimate consumption quantities and prices under temporary sales
 - induce consumers to purchase more than they consume initially \rightarrow stockpiling
- Main application to intertemporal bias in chained superlative price indices
 - Result with estimated consumption data the chain bias is lower, even at low frequencies
- Other applications: price elasticity, inference on stockpiling behaviors

Intuition



Figure 1: Pattern of Price and Quantity Changes during a Sales Event

Note: The solid dots represent observable posted prices (top) and quantities purchased (bottom). The circles represent unobservable consumption prices (top) and quantities consumed (bottom).

Application: Intertemporal bias in chained superlative indices

- Price indices constructed as weighted average of price relatives
- Chain drift occurs whenever prices bounce around and quantities adjust (temporary sales, seasonal products, product turnover with clearance sales)





Hypothetical 3-period example

		Period			
			1	2	3
product1	period				
	Price	1	0	5	10
	Quantity	1	0	20	0
	delta p logs			0.69897	1.430677
Product2					
	Price	1	0	10	10
	Quantity	1	0	10	10
	delta p logs			1	1
Total Quantiy		2	0	30	10



Example with Alternative Price Indexes

- CPIs tend to use fixed weights = average quantities
 - \rightarrow similar to what the stockpiling model is doing in practice
 - \rightarrow chain bias should tend to disappear at lower frequencies (eg. if temporary sales last few days, and data is monthly)

Measuring Chain drift

 Ivancic, Diewert, and Fox (2011) → chained price index should take same value if prices and quantities for all products are equal at the beginning (0) and the end (tau)

$$d_{0,\tau,dt}^X = \sum_{s=1}^{(\tau-1)/dt} \pi_{(s-1)dt,sdt}^X - \pi_{0,\tau-1}^X,$$

- Difference between calculating chained vs directly is the chain bias
- As dt increases, chain bias tends to 0
- If you have the P and Q at all time periods, then why use a chained index at all?
 → chaining has many practical advantages, including the ability to account for changes in product mix

In Japan, the chain bias is still significant at monthly frequency



	Price indices					
dt	Törnqvist (purchase-weighted)	$\begin{array}{c} {\rm T\ddot{o}rnqvist} \\ {\rm (consumption-weighted)} \end{array}$	Order r superlative (consumption-weighted)			
		Annual chain drift				
1	-40.44***	-5.69***	-1.20			
7	-7.24^{***}	-2.28^{***}	-1.23^{***}			
14	-2.43^{***}	-1.10***	-0.59^{***}			
28	-0.97^{***}	-0.46^{***}	-0.04			
52	-0.66^{***}	-0.20^{**}	0.23			
91	-0.61^{***}	0.06	0.17			
182	-0.49^{***}	0.01	0.14			
		Annualized inflation rat	e			
1	-46.34	-13.06	-10.71			

Table 1: Chain Drift and Inflation Rate

But the importance of stockpiling around sales fell dramatically over time

Figure 3: Asymmetry in the Quantity Purchased When the Price Increases and When It Decreases



 The numbers in the previous slide are an average for the chain drift over the 1990-2020 period

• What is the chain drift at monthly frequency if we only look at the recent period?

Comments

- What is driving the decrease in stockpiling over time?
 - Predictability or size of sales?
 - Increase in cost of stockpiling?
 - Lower inflation?
- Is Japan the best environment to look at this?
 - Yes: detailed and long data, change over time
 - But low inflation & low panic/volatility

Covid stockouts (shortages) were relatively low in Japan

• Cavallo & Kryvtsov (2021) What can stockouts tell us about Inflation?



Figure 1: Identifying Stockouts on a Retailer's Website

Covid stockouts (shortages) were relatively low in Japan

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More connected to "Stockpiling" behaviors

Net discontinued goods More connected to supply disruptions

In the US, temporary sales were countercyclical during Covid



Clothing: back to normal

USA Furniture Items on Sale by Year (%)

0 Jan 1

Mar 1

May



Jul 1

Jan 1

Furniture: low sales

Electronics: low sales

In Japan, some evidence of large price discounts when Covid hit



Summary

- Great paper \rightarrow simple method, great data, important applications
- Suggestions:
 - What drives changes over time in the degree of stockpiling?
 - Event studies around big shocks (earthquake, covid)
- Extensions: results may be even larger in countries with volatile sales and higher inflation