

# Price Setting in Online and Offline Markets

## Evidence from Korea

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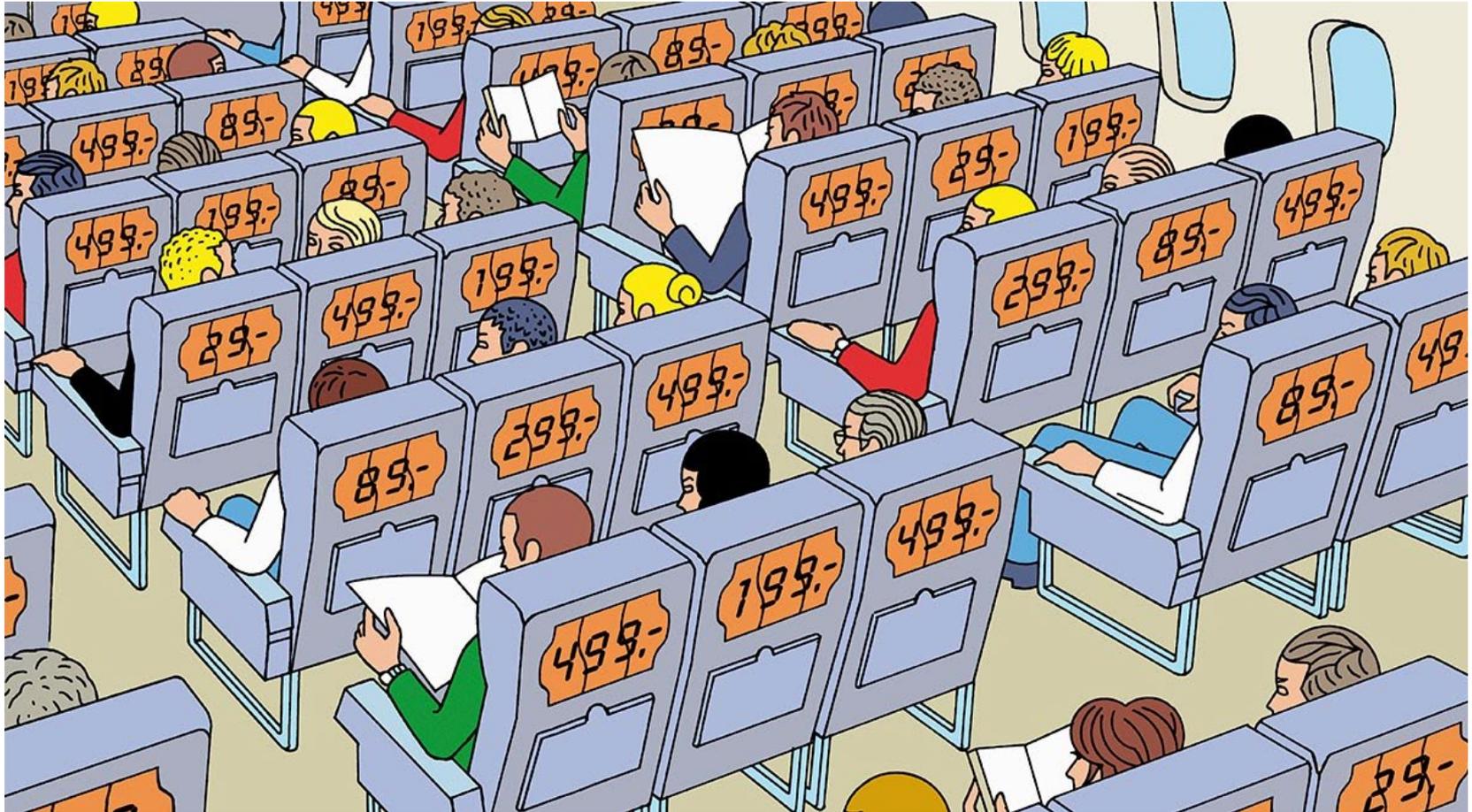
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# What we do in this paper

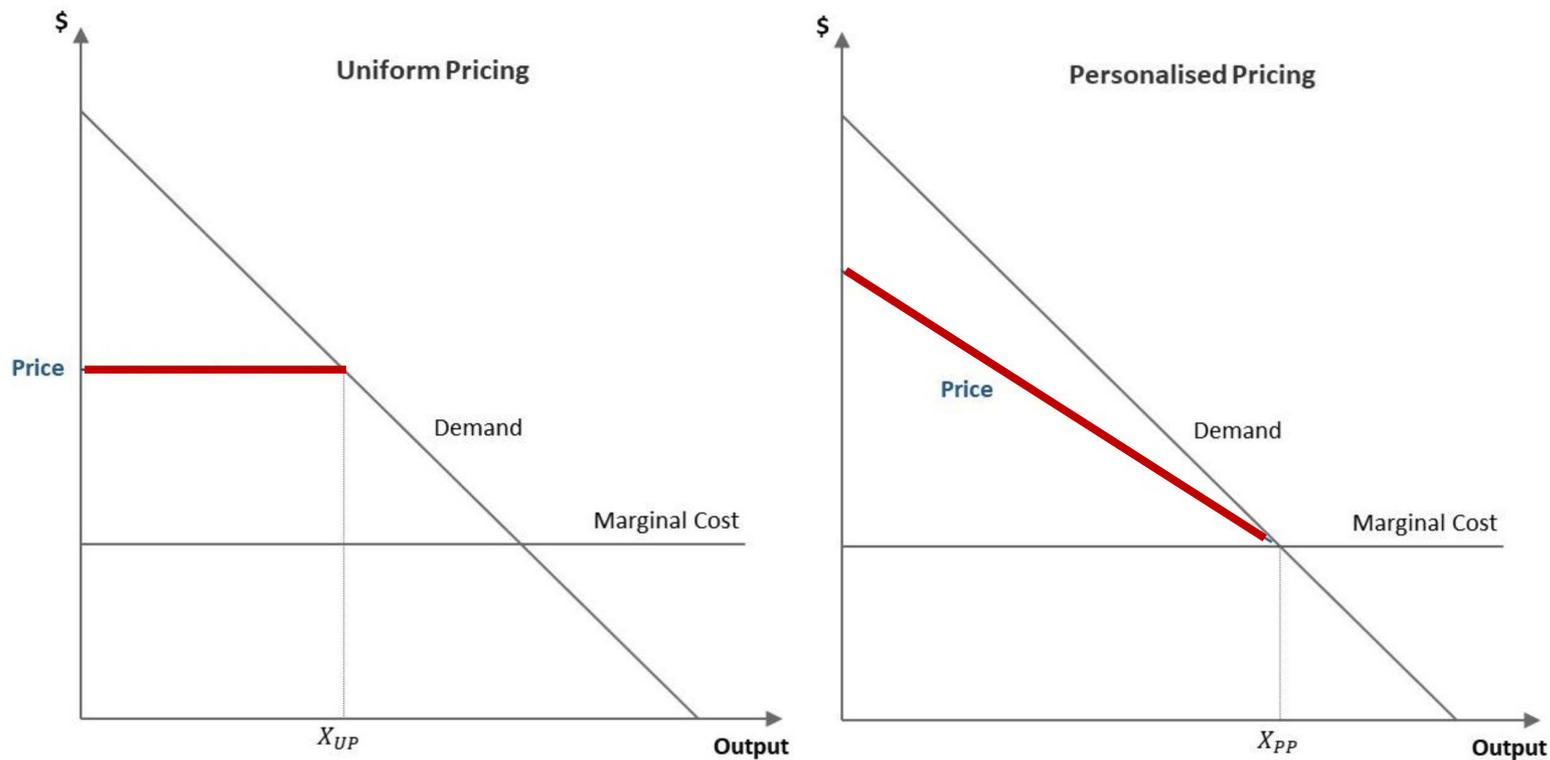
- We compare:

- ① Online prices vs. Offline prices
- ② List prices vs. Transaction prices

# Personalized Pricing



<https://hbr.org/2017/10/how-retailers-use-personalized-prices-to-test-what-youre-willing-to-pay>



With **uniform pricing** (on the left), each consumer pays the same price for each unit. With **personalised pricing** (on the right), each consumer pays a different price for each unit, as a linear function of the willingness to pay.

Source: OECD, "Personalised Pricing in the Digital Era," Background Note by the Secretariat, 28 November 2018

# Distinction between list prices and transaction prices



*How would the spread of personalized discounts in online markets affect Index Theory and CPI Practices?*

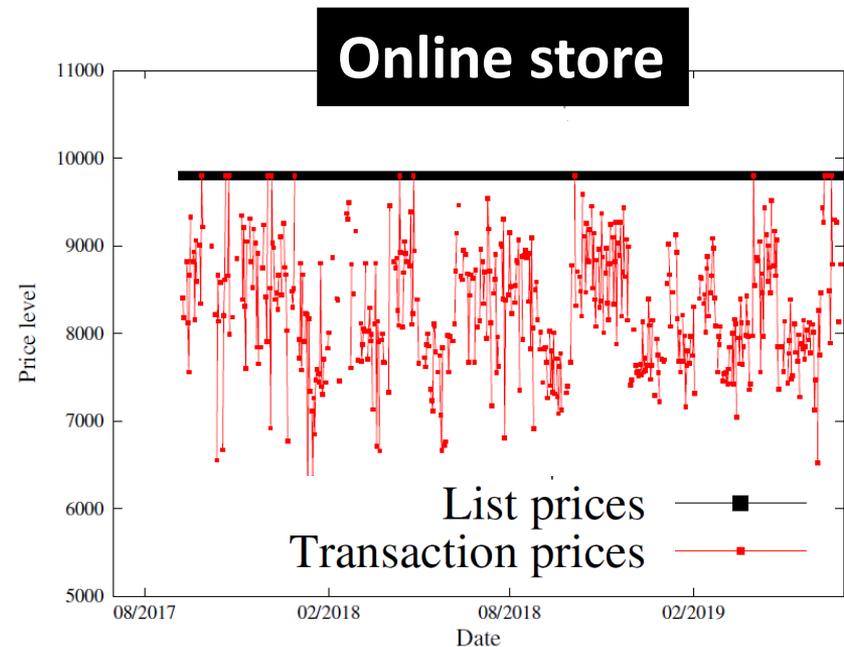
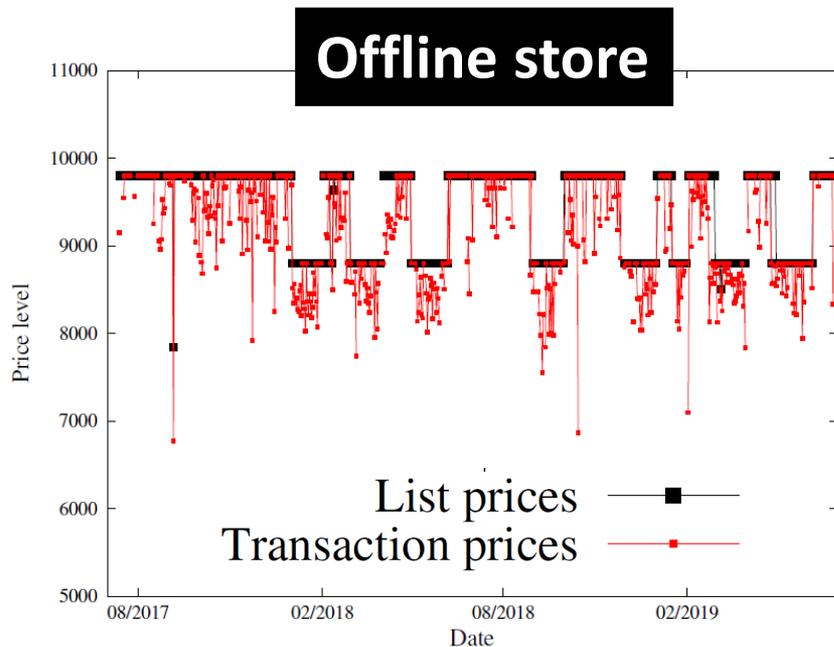
# Scanner Data from South Korea

- Provided by a South Korea's leading multinational conglomerate corporation (Let's call it "Company K"), with department stores, supermarkets, drugstores, electronics stores, convenience stores, etc., under its umbrella.
- The dataset contains both **list and transaction prices**. The difference between the two is customer/transaction-specific price discounts, which we refer to as "**personalized discounts**."
  - Previous studies on online markets typically use list prices rather than transaction prices, thus ignoring price fluctuations stemming from personalized discounts.
- Subsidiary companies sell their products through both offline and online channels, which allows us to compare **the offline and online prices for the same product sold by the same company**.
  - Previous studies compared online and offline prices for a particular product, but the companies offering the two prices were typically different. The difference between offline and online prices detected in such datasets may stem from differences in the two companies' attributes.

Table 1: Overview of the Dataset

Offline				
	Sample period	No. of stores	No. of products	No. of records
Supermarket	Jan 2014-Jun 2019	733	103,258	1,694,428,735
Drugstore	Feb 2015-Jun 2019	138	30,972	33,461,045
Electronics store	Jun 2016-Jun 2019	494	48,335	13,075,131
Convenience store	Jan 2014-Jun 2019	12,799	—	223,496,284
Online				
	Sample period	No. of stores	No. of products	No. of records
Supermarket	Jun 2016-Jun 2019	1	27,896	47,655,404
Drugstore	Jun 2017-Jun 2019	1	10,042	577,090
Electronics store	Jun 2016-Jun 2019	1	25,692	227,399
Convenience store	—	0	0	0

# Offline and online prices of a particular skincare product



- ✓ Large fluctuations in offline list prices are due to temporary sales (i.e., price reductions applied to all customers). There is no temporary sales in online list prices.
- ✓ Transaction prices are much lower than the corresponding list prices in most periods, both in offline and online markets, suggesting that the extent of personalized discounts is non-negligible.

# Personalized discount rates

Figure 2: Personalized Discount Rates of a Skincare Product

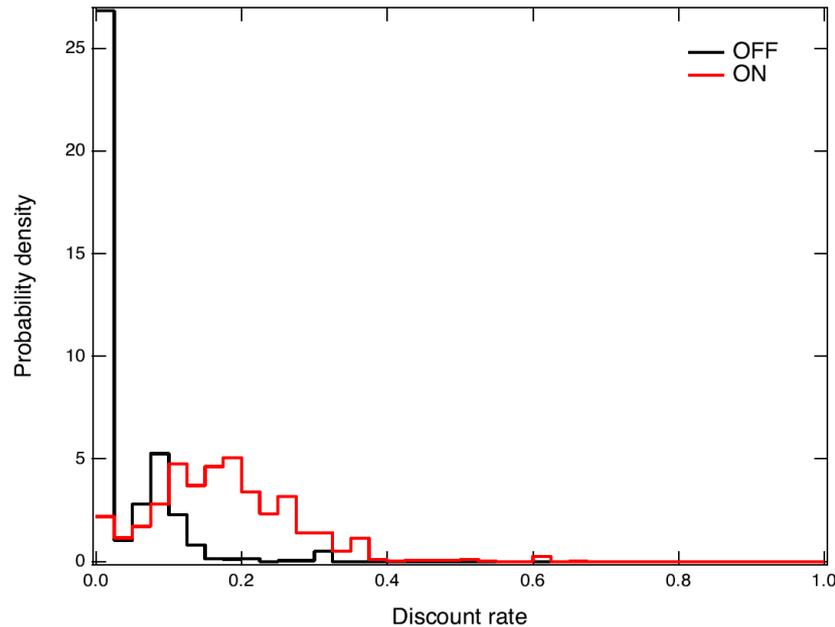


Table 3: Personalized Discount Rates

	Offline		Online	
	Mean	Std Dev	Mean	Std Dev
Supermarket	0.0227	0.0346	0.0639	0.0412
Drugstore	0.0764	0.0489	0.3341	0.1473

- ✓ Personalized discount rates are, on average, greater in online markets
- ✓ The dispersion of personalized discount rates across customers is also greater in online markets.

Note: The black line shows the histogram of personalized discount rates of a particular skincare product at a particular offline shop over the entire sample period. The red line shows the corresponding histogram at an online shop.

# Regression of transaction prices on list prices

	Supermarket		Drugstore	
	Offline	Online	Offline	Online
Coefficient on list prices	0.989	0.999	0.942	0.614
	(0.000)	(0.000)	(0.001)	(0.088)
Constant term	-0.001	0.000	0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)
No. of Observations	169,939.504	3,248.357	2,880.081	81.401
Adjusted R2	0.741	0.868	0.146	0.001

- ✓ The coefficients on the list price is very close to 1 except in online drugstores. This means that 1 percent change in the list price of a particular product, on average, leads about 1 percent change in the corresponding transaction price.
- ✓ However, adjusted R2 is low, especially so in drugstores, indicating that a non-negligible portion of time series variation in transaction prices comes from changes in personalized discounts over time.

# Comparison of Online and Offline Prices

**Question #1:** Are prices lower in online markets than in offline markets?

**Question #2:** Are prices less sticky in online markets than in offline markets?

**Question #3:** Are prices closer to the law-of-one-price in online markets than in offline markets?

# Question #1: Are prices lower in online markets than in offline markets?

## List Prices

	Identical	Higher online	Lower online	Online markup	Online difference
Supermarket	0.715	0.077	0.208	-0.094	-0.027
Drugstore	0.314	0.686	0.000	0.412	0.283

## Transaction prices

	Identical	Higher online	Lower online	Online markup	Online difference
Supermarket	0.594	0.145	0.261	-0.035	-0.014
Drugstore	0.066	0.089	0.845	-0.217	-0.203
Electronics store	0.189	0.096	0.715	-0.090	-0.073

- ✓ The probability that list prices are identical between offline and online is high, which is consistent with the findings reported in previous studies based on list prices, such as Cavallo (2017).
- ✓ The probability that transaction prices are identical between online and offline is not that high. Transaction prices tend to be lower in online markets than in offline markets.

## Question #2: Are prices less sticky in online markets than in offline markets?

Table 7: Frequency of Price Changes: Goods Available both Online and Offline

	List prices			
	Offline		Online	
	Increase	Decrease	Increase	Decrease
Supermarket	0.049	0.050	0.107	0.100
Drugstore	0.010	0.010	0.000	0.003
	Transaction prices			
	Offline		Online	
	Increase	Decrease	Increase	Decrease
Supermarket	0.109	0.112	0.150	0.142
Drugstore	0.233	0.233	0.482	0.470
Electronics store	0.097	0.114	0.249	0.258

### Question #3: Are prices closer to the law-of-one-price in online markets than in offline markets?

Table 10: Price dispersion across customers

	List price		Transaction price	
	Offline	Online	Offline	Online
Supermarket	0.144	0.085	0.171	0.096
Drugstore	0.033	0.001	0.111	0.271
Electronics store	—	—	0.085	0.035

- ✓ The dispersion of list prices in online markets, while not zero, is much smaller than the corresponding price dispersion in offline markets. This is consistent with the idea of faster convergence in online markets.
- ✓ However, the dispersion of transaction prices in online markets is greater than the corresponding dispersion of list prices. In online markets, sellers can easily collect information about consumer attributes and past purchase history and use it to offer a different discount to each consumer. This may impede the law-of-one-price in online markets.

# Amazon Effect: Prices offered at various offline stores would converge to online prices, thus reducing the price dispersion across offline stores.

**Green line: Offline price dispersion for products sold only offline**  
**Orange line: Offline price dispersion for products sold both offline and online**



- We calculate the extent to which the list prices of any two offline stores operating in different regions differ for a given product and repeat this for all offline store combinations. Those values are then averaged to obtain an indicator of offline price dispersion for that product.
- We classify products into those sold only offline and those sold both offline and online.

✓ Prices at various offline shops of a particular product tend to converge to the corresponding online price only when the product is available online.

# Takeaways

- 1. Personalized discounts is an important source of variations of transaction prices. This is especially so for online markets.**
  - It is an important source of **cross sectional variation** in transaction prices across customers.
  - It is an important source of **time-series variation** in transaction prices.
- 2. Online prices tend to be lower and more flexible than offline prices. However, online prices may not necessarily be less dispersed than offline prices.**
- 3. Offline prices are less dispersed across physical stores for those products available both offline and online than for those products available only offline.**

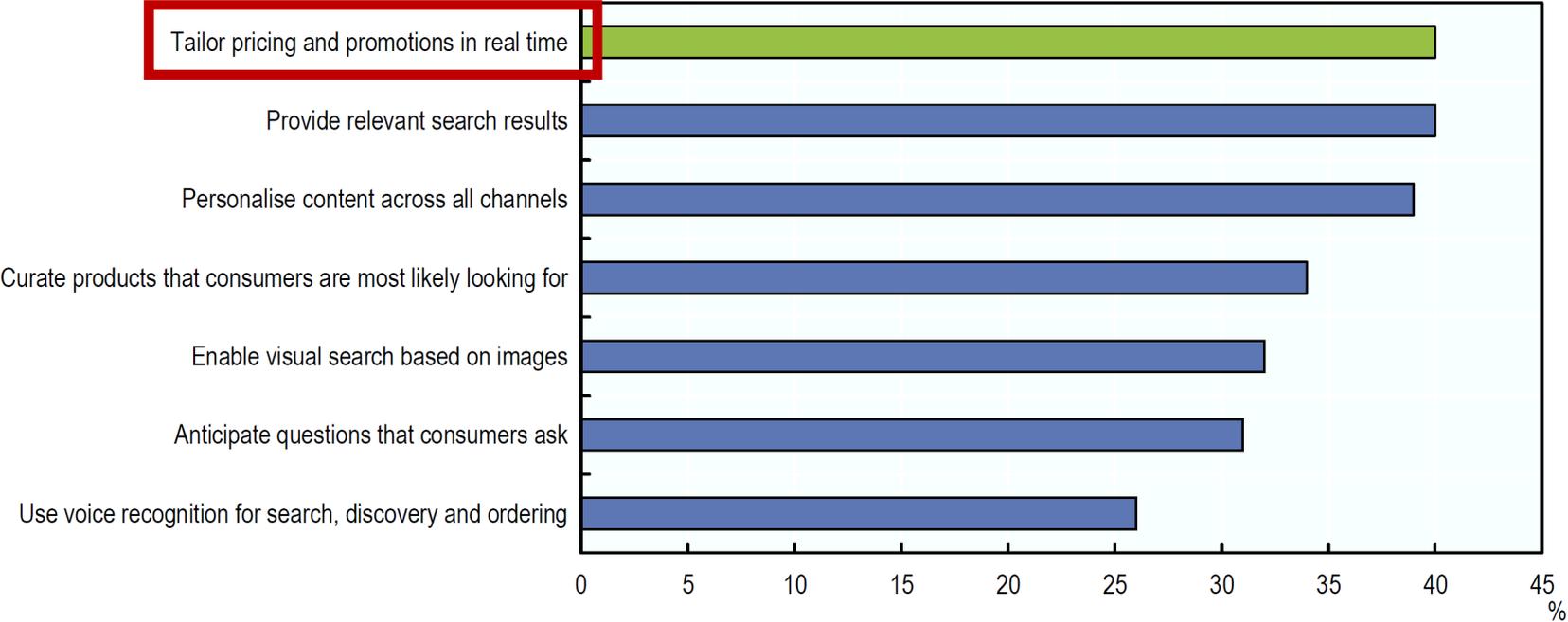
## Questions to OG members

# How should we cope with personalized pricing in CPI construction?

- The index theory with many consumers each of whom faces a different price vector is discussed in Chapter 18 of CPI Manual (2004).
- However, “standard” index theory we usually rely on is based on the assumption that the prices of a particular product at a particular store on a particular day are identical across customers. However, this assumption is no longer valid due to the rapid spread of personalized pricing.
- Specifically, we can no longer use the expenditure share of a particular product as weight in aggregation.
- However, we can still construct something like a **Personalized CPI** (i.e., different CPIs for different persons) using “standard” methodology.
- Then, one of the new issues that come to my mind is how to aggregate personalized CPIs across individuals. Should we go to **Democratic CPI** (i.e. equal weight to individuals) or to **Plutocratic CPI** (i.e., individual’s expenditure share as weight)?
- Any more issues we should care about?

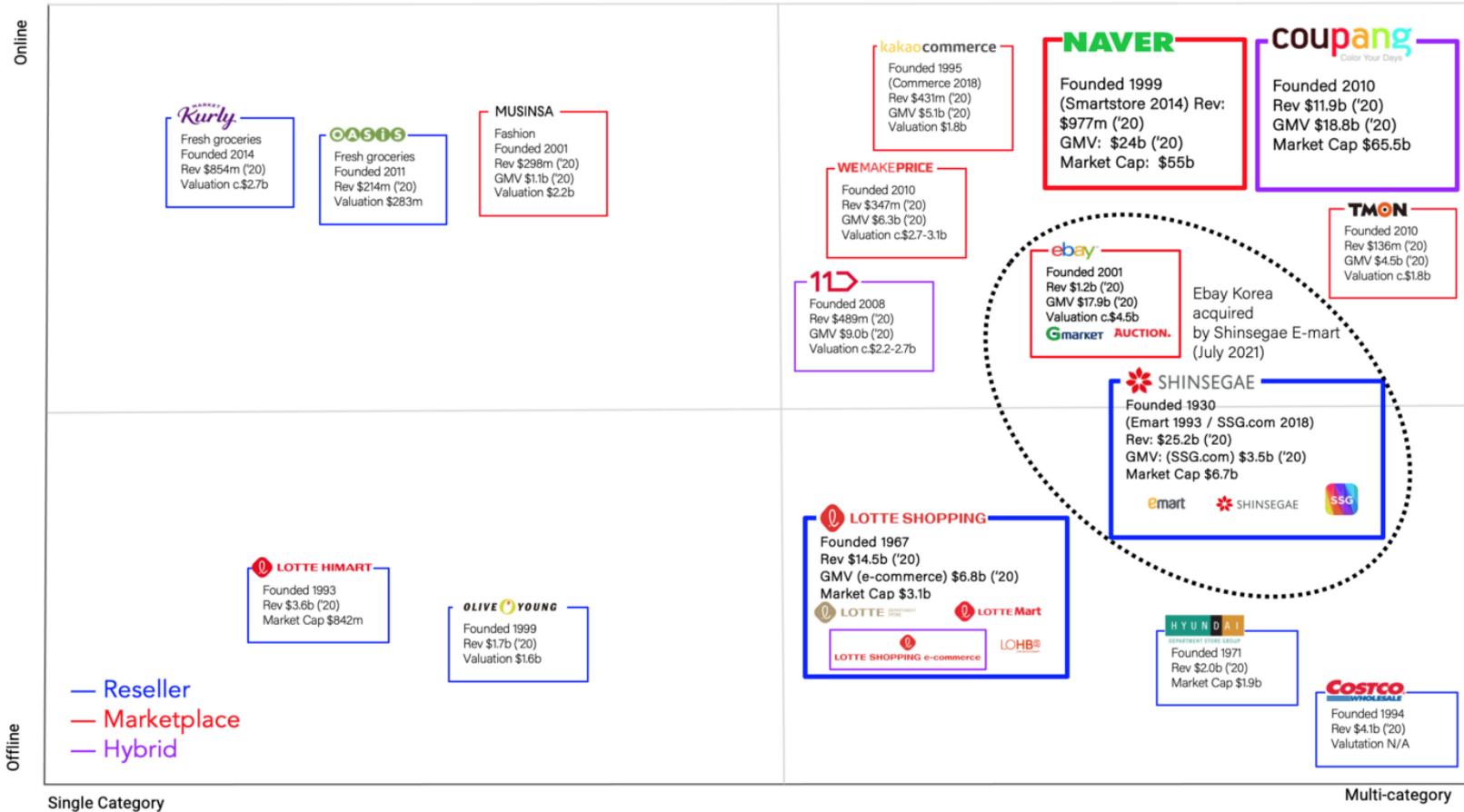
### Figure 3. How brands use artificial intelligence (AI) to personalise the consumer experience

(Among retailers that have adopted AI for at least one application)



Source: OECD, “Personalised Pricing in the Digital Era,” Background Note by the Secretariat, 28 November 2018

# Some major players of the Korean retail industry



<https://medium.com/korelya-capital/the-battle-for-koreas-e-commerce-leadership-229b5e47d6f>