Discussion on "Digital Pricing and Algorithms" by Mike Walker Competition and Markets Authority

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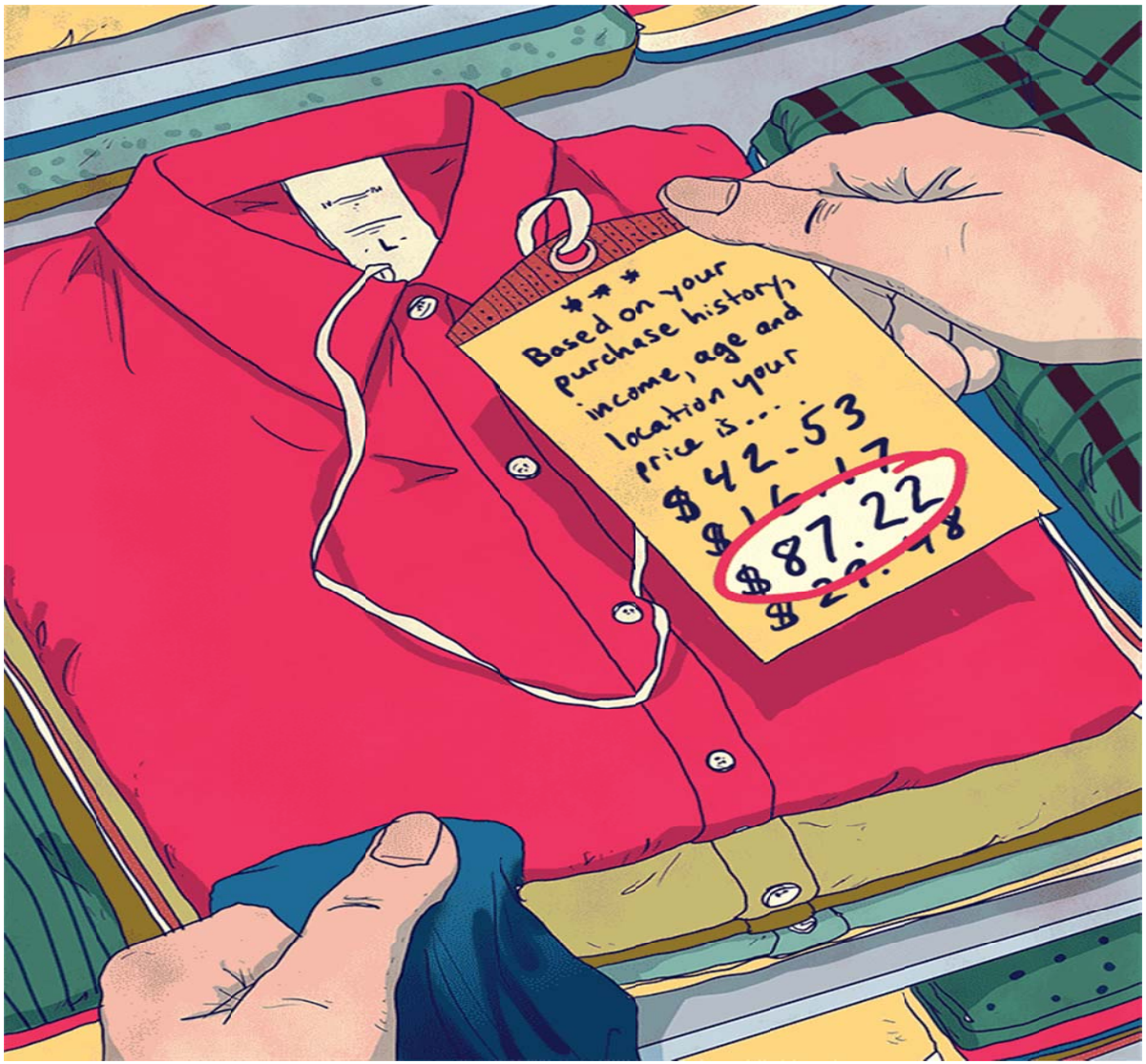
Structure of the Discussion

1. Personalized Pricing/Behavior-Based Price Discrimination
2. Tacit Collusion
3. Combination of Personalized Pricing and Tacit Collusion

Digital Pricing



Personalized Pricing

- Tool to allow fine-tuned price discrimination.
  Extreme case: First-degree price discrimination (every consumer gets her own price).
- It's true that this improves efficiency.
- However: Gains are foremost on the firms' side whereas consumers usually lose.
- Competitive evaluation depends on the standard: consumer welfare versus total welfare

Importance of Competition

- Loosely speaking, personalized pricing exacerbates the effects of monopoly and of competition
- With a dominant firm (monopolist), greater extraction of consumer surplus through personalized pricing (Varian, 1992).
  Consumer welfare falls.
- With competition between firms, firms compete on multiple fronts, which drives prices down (Thisse and Vives, 1988).
  Consumer welfare often rises.

Policy Intervention on Personalized Pricing?

- Perhaps not needed.
- Firms often abstain from it, fearing repercussion of consumers.
- Firms traditionally practice price discrimination in many different variants.
  Digital pricing mainly allows to do so in a better way.

Tacit Collusion

- As the pricing algorithm allows to condition on competitors' prices, collusion can be achieved.
- Algorithmic pricing may facilitate collusion because of very frequent interaction and faster responses than with human behavior (Ezrachi and Stucke, 2017).
- In addition, firms using digital pricing often sell multiple products.
  Multi-market contact makes collusion easier due to harsher punishment possibilities (Bernheim and Whinston, 1990).
- Does this facilitate tacit collusion?

'Adaptive Algorithms'

- Algorithm based on a market model, estimates behavior, and bases optimal prices, for example, on rival prices.
- Adaptive algorithms can only collude if instructed by the programmers to do so.
  For example, present price conditions on past rival behavior etc.
- Therefore, algorithmic pricing collusion very likely easier to detect than human collusion (Calvano et al., 2018).
- Still, question arises on what is the right punishment for the programmer and the manager.
  Collusion now involves different layers within the organization.

'Machine Learning Algorithms'

- Algorithm experiments with different prices and learns from experience.
- It is not based on a model, sacrifices short-term gains to learn more, and prices optimally given what it has learned.
- Programmer just chooses frequency of experimentation, weights on variables, etc.
- State of the art: difficult to achieve collusion with learning algorithms (Harrington, 2017).
- However: This algorithm poses a challenge for competition policy.
  Collusion can be achieved even if the program was designed innocently. ('Meeting of the minds' cannot be proven.)

Combination of Personalized Pricing and Collusion

- Much of our knowledge about tacit collusion is based on uniform pricing models.
- Does the possibility to charge personalized pricing change the scope for collusion?
- Example: Firms compete in various prices for many different types
  $\Rightarrow$ Punishment can be executed on multiple fronts, which may facilitates collusion dramatically.
- Learning algorithm may achieve collusive pricing in a faster way as more data is available.

Combination of Personalized Pricing and Collusion

Possible implications for competition policy:

- Learning algorithms, which can condition on the rivals' prices, can be problematic.
- On the other hand, forbidding the program to react to rival prices is much too strong.
- Giving a clear-cut policy implication is difficult here.
- General Conclusion: Tacit collusion perhaps not a big problem at the moment, but this could change in the near future.