Algorithmic Pricing Facilitates Tacit Collusion: Evidence from E-Commerce

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As the economy digitizes, menu costs fall, and firms can more easily monitor prices. These trends have led to the rise of automatic pricing tools. We employ a novel e-commerce dataset to examine the potential implications of these developments on price competition. We provide evidence from an RDD that the immediate impact of automatic pricing is a significant decline in prices. However, repricers have developed strategies to avoid the stark competitive realities of Bertrand-Nash competition. By employing plausibly exogenous variation in the execution of repricing strategies, we find that "resetting" strategies (which regularly raise prices, e.g., at night) effectively coax competitors to raise their prices. While the resulting patterns of cycling prices are reminiscent of Maskin-Tirole's Edgeworth cycles, a model of equilibrium in delegated strategies fits the data better. This model suggests that if the available repricing technology remains fixed, cycling will increase, and prices could rise significantly in the future.

CCS Concepts: • **Applied computing** → **Electronic commerce**; **Economics**; • **Theory of computation** → *Computational pricing and auctions*; *Market equilibria.*

Additional Key Words and Phrases: algorithmic pricing, tacit collusion, dynamic games, Edgeworth cycles

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With the advent of the digital age, menu costs have been falling, yet little is known about how the ability to frequently update prices affects price competition. While the Folk Theorem warns us that the predictive power of equilibrium reasoning is limited in dynamic environments with brief periods, simulation studies raise concerns about potential algorithmic collusion [2]. Hence, empirical research into the issue of repricing is necessary.

This paper employs extensive data on the pricing decisions made by third-party sellers on a well-known e-commerce platform to empirically assess and expand the theoretical predictions of the literature on dynamic pricing. Like [1], we find that delegation of pricing to simple algorithms can facilitate tacit collusion by reducing the set of available strategies. Furthermore, the algorithms currently employed are more straightforward than the Markov-perfect strategies of Maskin and Tirole [3] and emerge naturally as the result of a best-response process.

Our setting, Amazon Marketplace, is organized around the concept of a (narrowly-defined) product: sellers do not create separate listings for the same product (as they would on, e.g., eBay). Instead, different offers for a product are pooled together on a unique product page. As far as customers are concerned, the multiplicity of offers often is ignored: about 80% of purchases go through the 'Buybox,' i.e., the 'Buy Now' and 'Add To Cart' buttons on the product page. Amazon selects which merchant 'owns' this button using a (partially randomized) proprietary algorithm

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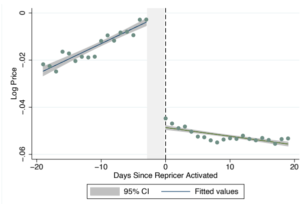

Fig. 1. Price Response.

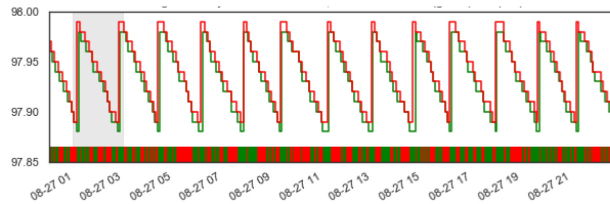

Fig. 2. A Typical Pricing Cycle.

that loads heavily on which offer is the cheapest; in our model in the paper, we assume that all sales go to the cheapest offer for tractability.

From a seller's perspective, the pooling of offers on product pages and the 'Buybox' mechanism create strong incentives to undercut competitors' prices. Together with the ease of monitoring and updating prices using Amazon's MWS API, these features have created conditions conducive to the rise of a plethora of 'repricing' tools. These tools enable sellers to specify simple algorithmic pricing rules (e.g., 'always undercut my competitor by one cent') that are executed whenever a competitor changes prices.

Exploiting repricing company data and seeing offers' prices before and after merchants activate their (individually chosen) algorithmic pricing strategies, Figure 1 uses a regression discontinuity design to establish that algorithmic pricing lowers prices on average by 4%. We also find (not depicted in the graph) that in the short-run this decline in prices is associated with a 20% increase in Buybox share and a 40% increase in profits. Consistent with this, there is no accompanying decline in (undepicted) 'Buybox' prices on impact, i.e., the algorithms seem to initially lower prices just enough to ensure exposure to demand but no further.

Over time, however, the Buybox price also declines. This points to what the repricing world calls the problem of 'price wars': if multiple merchants use repricing rules that lead to automatic undercutting of their opponents' price, prices can drop precipitously. To avoid this, several companies offer 'price bump' or 'resetting' strategies: the algorithm will automatically raise price back to a pre-specified maximum either at a regular interval or when a specific price is reached. These strategies create the cycling pattern depicted in Figure 2 where we graph the prices of two offers (green and red) on a particular running shoe over time; the color strip at the bottom of the graph indicates which offer 'owns' the Buybox at any given time.

Intuitively, resetting should raise prices as opponents follow the price increase and the cycle is reset. In the full paper, we show that this intuition can be formalized in a game-theoretic model that predicts cycling around monopoly price. Furthermore, we exploit plausibly exogenous variation in the execution of price resets to show that an automatic price increase raises own price by an average of 7.74% and competitor price by an average of 1.23%. Thus, resets effectively coax competitors to raise their prices. Finally, these resets occur most frequently at night when the cost from exceeding a competitors' price is lowest (as there is only limited arrival of customers.)

The full paper is available at https://lmusolff.github.io/papers/Algorithmic_Pricing.pdf.

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