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Identifying Algorithmic Pricing Technology Adoption in Retail Gasoline Markets†

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Although firms have made use of pricing software for decades, recent technological advancements created a shift from mechanically set prices to artificial intelligence (AI)/machine learning (ML)–powered algorithms that can incorporate large quantities of data, learn, and autonomously make decisions. This new algorithmic pricing (AP) software has raised concerns about potential impacts on firm behavior and competition. A recent theoretical literature has shown that sophisticated pricing algorithms can increase retail prices either by facilitating/learning collusive behavior or by changing the nature of the game firms play (Calvano et al. 2020; Asker, Fershtman, and Pakes 2021, Miklós-Thal and Tucker 2019; Brown and MacKay, forthcoming). However, there has been no evidence of markets transitioning from one pricing technology to another to test theoretical predictions. This paper investigates pricing technology in the German retail gasoline market. In this market, according to trade publications and other sources, AP software became widely available beginning in 2017.[1] However, despite the availability of comprehensive station-level pricing data, there is no direct information on which stations adopted the new technology. In this paper, we describe how we overcome this challenge and identify changes in pricing technology.

I. Background: Algorithmic Pricing in Retail Gasoline

Fuel retailers are typically secretive about their pricing technology. The use of AP software in European fuel retail markets began in the early 2010s. However, the main penetration of AI/ML-based AP software appears to have happened in the mid-2010s (WSJ.com, CSPDailyNews.com). In Germany, the December 2017 issue of *Tankstop*, a trade publication for gas station operators, carried ads for an AP software, noting that it has been available since that summer (see Assad et al. 2022 for more details). Other companies active in Germany also began explicitly distinguishing between rule-based pricing and AP in mid-2017 (Kalibrate 2016, Kalibrate 2017).

Promotional materials by AP software providers describe tools that can help station owners "master market volatility with AI-powered precision pricing" and "respond rapidly to market events and competitor changes" (Kalibrate 2021). Additional promoted benefits include optimizing for long-term revenues and avoiding price wars (Kantify). Most software providers reveal few details about AP technology, but they stress the ability of their algorithms to incorporate market conditions and variables such as own and competitor prices, sales volumes, costs, weather, and traffic events into their decision-making. Providers who do give more details (i.e., the Brazillian start-up Aprix in towardsdatascience.com) describe a three-stage process: First, the algorithms gather information about the market. Then, they model the relationship between the inputs (the state) and desired outputs such as margins, profits, or market shares. Finally, they set optimal prices to maximize outputs conditional on the state. The

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[1] Legal disclaimer: This paper analyzes the impact of the adoption of AP on competition strictly from an economic point of view. To our knowledge, there is no direct evidence of anticompetitive behavior on the part of any algorithmic software firms or gasoline brands mentioned in this paper.

algorithm repeats the stages with new information, adapting and learning. The described algorithms are not explicitly strategic but include competitors' prices as inputs.[2] A simple interpretation of the effects of AP software adoption is that it gives stations more information about the state of the market and makes them substantially more sensitive to the state. This is especially true in markets with near-perfect information due to mandated price transparency, such as the German retail gasoline market.

II. Identifying Algorithmic Pricing Adoption

The main dataset comes from the German Market Transparency Unit for Fuels through the website https://www.tankerkoenig.de/. It includes all price changes for E5 fuel for over 16,000 German gas stations from January 2016 to December 2018. For each station, raw data include location information (five-digit zip code, latitude and longitude coordinates) as well as an associated brand. We merge in annual regional demographics from Eurostat. We incorporate weather information from the German Meteorological Service (dwd.de) and oil price data from FirstRate Data (FirstRateData.com). In Assad et al. (2022), we also use regional wholesale fuel prices from Oil Market Report, a private independent German gasoline information provider.

A key challenge is that we do not observe AP adoption decisions. To overcome this challenge, we use a data-driven approach to identify changes in station pricing technology. As described in Section I, algorithms continuously observe the state by scraping information on competitors' prices, weather conditions, and traffic from the internet and other sources. Once the state changes, the algorithms reoptimize prices. Human- or rule-based price setting would operate in a similar manner but would be worse at observing and conditioning on state variables. Therefore, changes in a station's responsiveness to the state should capture the adoption of AP software. We consider the following four variables for describing a station's responsiveness to the state, which also represent the promises of AP software providers: (i) the number of price changes made in a day, (ii) the average response time to a rival's price change (in minutes), (iii) the average responsiveness of a station's prices to large shocks in crude oil prices, and (iv) the average responsiveness of a station's prices to local weather shocks. Similar measures have been previously used to measure pricing technology heterogeneity (Brown and MacKay, forthcoming; Aparicio, Metzman, and Rigobon 2021).

We look for structural breaks in these measures using Quandt likelihood ratio (QLR) tests for each measure and station. The tests recover the date of the best-candidate break (if one exists). Figure 1 shows the distribution of best-candidate structural breaks for each measure. We find a number of statistically significant breaks in the data. Many of these occur in the middle of 2017, when we believe that AP technology became available to stations. Nearly 50 percent of best-candidate breaks in the number of price changes are in the spring of 2017. Similarly, 40 percent of best-candidate breaks in the responsiveness to local weather shocks, 20 percent of best-candidate breaks in rival response time, and nearly 20 percent of breaks in responsiveness to oil price shocks happen around that time as well.[3]

These structural breaks also capture quantitatively important changes in pricing behavior, with large differences in all four measures between stations with and without breaks in the sample period. On average, stations without structural breaks in the number of price changes adjust their prices approximately five times per day during the sample period, roughly once every three hours. Stations with structural breaks change their prices approximately eight times per day during the sample period, or once every hour and a half. We also find that stations with structural breaks respond to rivals within 50 minutes of a price change, while the average response time for stations without structural breaks is over 84 minutes. These changes in frequency of price adjustments and responsiveness are similar to those identified by Brown and MacKay (forthcoming) and Aparicio, Metzman, and

[2] Many questions remain about how this algorithm or other algorithms of this type operate in practice—the type of learning (passive versus reinforcement), the length of memory, etc.

[3] Since variation in responsiveness to oil price shocks appears to be less clear-cut in the data as compared to the other three measures, we also test a definition of adoption that excludes it. Our main results hold.

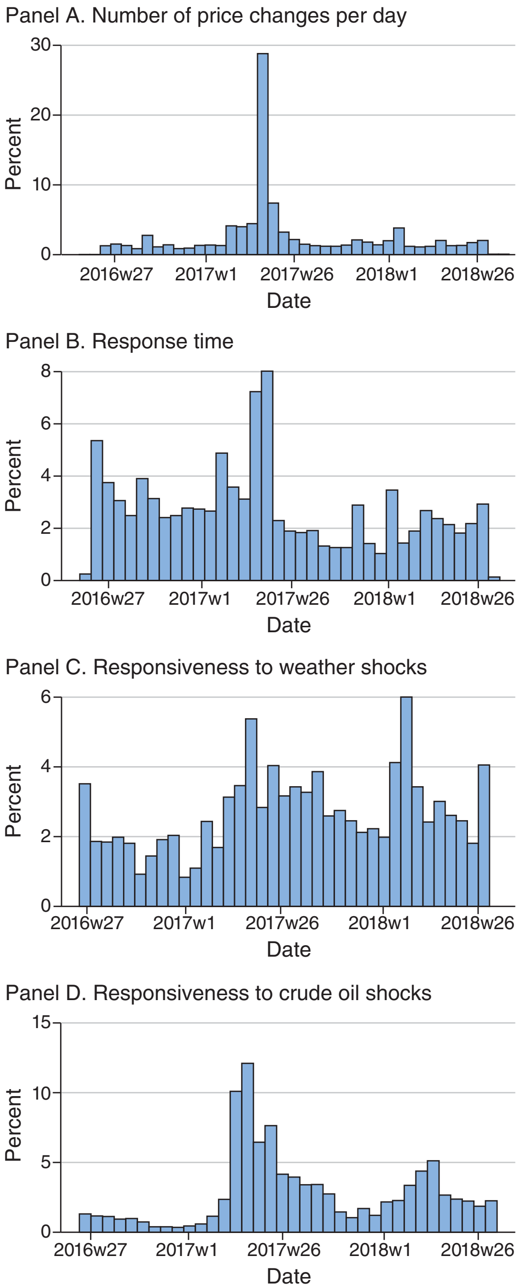

FIGURE 1. DISTRIBUTION OF BREAK DATES FOR EACH MEASURE

Note: Each panel shows a histogram of QLR best-break dates for a given measure.

Rigobon (2021) following the introduction of online AP technologies. We also find substantial differences in the other measures—for example, there are 3.7 weather shocks per week, and stations with structural breaks in weather responsiveness respond 25 percent of the time after their break. By comparison, stations without structural breaks respond only 12 percent of the time. In Assad et al. (2022), we show that changes between stations with and without breaks appear very rapidly around the middle of 2017. Overall, our structural break measures are picking up rapid and substantial changes in pricing technology.

Many factors may influence a single measure of pricing behavior on its own, but breaking in multiple markers in close proximity should provide a strong indication of an actual change in pricing technology, which in our case is the adoption of AP pricing. We label a station as an adopter of AP software if it experiences best-candidate structural breaks in any combination of at least two measures of pricing behavior within four weeks. Our results are robust to stricter alternative definitions of adoption. Using this approach, we classify 2,728 stations (20 percent) as adopters. Figure 2 shows the distribution of adoption dates for all adopters, defined as the average year-week between best-candidate break dates of the measures in which a station experiences a significant break. Over 50 percent of these average break dates occur in the middle of 2017, consistent with the supposed increased availability of AP software in the middle of 2017 in Germany. Stations classified as adopters show meaningful differences in their pricing behavior compared to stations without best-candidate structural breaks and stations with best-candidate structural breaks that are not classified as adopters.

III. Impact on Pricing and Competition, Policy Discussion, and Conclusions

Having identified AP adoption, we examine its impact on retail prices and margins in a companion paper, Assad et al. (2022). Due to the potential endogeneity of station-level adoption decisions, we use an IV approach, instrumenting for station i's adoption using the share of stations in i's brand that have adopted. We show that adoption increases station-level margins by about \$0.013 per liter, or 15 percent. We isolate the effects of adoption on competition by comparing effects in monopoly and nonmonopoly markets. We find that average

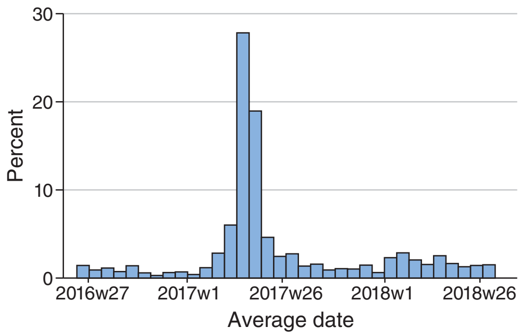

Figure 2. Frequency of Average Break Date for Measures Breaking within 4 Weeks (2,728 Stations)

Notes: This histogram shows the distribution of dates at which stations are labeled as adopters. We define an adoption date as the average best-candidate break date among at least two best-candidate break dates for the four measures.

effects are driven by nonmonopoly markets. We also show that in two-thirds of station markets, margins increase only following market-wide adoption, and resulting firm strategies are consistent with softening competition.

Overall, our findings suggest that although AP may yield potential efficiency benefits, regulators should be wary of mass adoption of AP software. We focus on retail gasoline, but "off-the-shelf" AP software is widely available in many other markets, online and offline. Assad et al. (2021) discuss potential policy implications, and Johnson, Rhodes and Wildenbeest (2021) offer market design features that limit supracompetitive prices by algorithms.

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