Surveillance & Society

Price Monitoring, or Where Surveillance Studies Meets the Sociology of Price Formation

Aaron Shapiro

Volume 22, Number 3, 2024

Open Issue

URI: https://id.erudit.org/iderudit/1113681ar
DOI: https://doi.org/10.24908/ss.v22i3.16940

See table of contents

Publisher(s)

Surveillance Studies Network

ISSN

1477-7487 (digital)

Explore this journal

Cite this article

Shapiro, A. (2024). Price Monitoring, or Where Surveillance Studies Meets the Sociology of Price Formation. *Surveillance & Society*, *22*(3), 248–262. https://doi.org/10.24908/ss.v22i3.16940

Article abstract

This essay stages an encounter between surveillance studies and the sociology of price and price formation. I argue that surveillance is integral to the calculative operations of retail price strategies, especially during periods of high inflation, and that these calculative operations hinge on the human infrastructure of a precarious data-collecting workforce. I present my argument through a case study of competitor price monitoring, a corporate surveillance practice in which commercial actors record, process, and transmit information on competitors' pricing, inventory, and display strategies. While pricing intelligence services like web-scraping and dynamic pricing algorithms are typically applied in e-commerce settings, I focus here on a firm that specializes in the collection of brick-and-mortar retail price data, with special attention to the labor practices involved in the manual (in-person, device-aided) production of retail price information at the national-industrial scale. Building on auto-ethnographic observations as a price data collector as well as analysis of employee reviews of the firm on sites like Indeed and Glassdoor, I argue that surveillance studies can contribute in significant ways to our understanding of the material practices, and politics, of price and price formation.

Surveillance & Society

Article

Price Monitoring, or Where Surveillance Studies Meets the Sociology of Price Formation

Aaron Shapiro

University of North Carolina at Chapel Hill, USA
aaron.shapiro@unc.edu

Abstract

This essay stages an encounter between surveillance studies and the sociology of price and price formation. I argue that surveillance is integral to the calculative operations of retail price strategies, especially during periods of high inflation, and that these calculative operations hinge on the human infrastructure of a precarious data-collecting workforce. I present my argument through a case study of competitor price monitoring, a corporate surveillance practice in which commercial actors record, process, and transmit information on competitors' pricing, inventory, and display strategies. While pricing intelligence services like web-scraping and dynamic pricing algorithms are typically applied in e-commerce settings, I focus here on a firm that specializes in the collection of brick-and-mortar retail price data, with special attention to the labor practices involved in the manual (in-person, device-aided) production of retail price information at the national-industrial scale. Building on auto-ethnographic observations as a price data collector as well as analysis of employee reviews of the firm on sites like Indeed and Glassdoor, I argue that surveillance studies can contribute in significant ways to our understanding of the material practices, and politics, of price and price formation.

Introduction

In September 2023, the United States Department of Justice (DOJ) filed a lawsuit against Agri Stats, Inc., a secretive information broker for the meat processing industry. The DOJ alleged that Agri Stats violated the Sherman Antitrust Act (and had been doing so for decades) by selling "competitively sensitive information" to meat processors, including retail sales prices, labor and production costs, and operational profits of clients' competitors—who were also Agri Stats clients. These informational practices are consequential because meat processors occupy a strategic middle in the supply chain, a choke point between farmers and retailers. Together, Agri Stats' clients processed more than 80% of pork and 90% of all poultry sold in the United States. And while the processors could have used the information from Agri Stats competitively, making meat more affordable for consumers, the DOJ complaint reveals that executives at the company routinely encouraged clients to raise prices, even when supply chain costs dropped (Dayen 2023). None of the information in Agri Stats' reports was available to other market stakeholders, such as farmers, workers, and retailers, creating what the DOJ called "an information asymmetry that further exacerbates the competitive harm of Agri Stats' information exchanges" (US Department of Justice 2023).

Agri Stats' alleged anti-competitive information practices are egregious but not uncommon. In this essay, I discuss preliminary research on a firm similar to Agri Stats—what I will call PricePoint Retail, Inc.—in order to stage a dialogue between surveillance studies and the sociology of price and price formation. The sociology of price formation rejects the orthodox economic assumption that prices are neutral reflections of exchange or use value (Beckert 2011; Callon 2016). Sociological approaches, and particularly those influenced by science and technology studies (STS), understand prices to be one of any number of *market*

Shapiro, Aaron. 2024. Price Monitoring, or Where Surveillance Studies Meets the Sociology of Price Formation. *Surveillance & Society* 22 (3): 248-262.
https://ojs.library.queensu.ca/index.php/surveillance-and-society/index | ISSN: 1477-7487

devices, or "material and discursive assemblages" (Callon, Millo, and Muniesa 2007: 2) from which markets are constructed as active sites of economic, or economizable, activity (see also Caliskan 2007; Caliskan and Callon 2009, 2010). Like other market devices, such as display technologies and scoring tools (Cochoy, Hagberg, and Kjellberg 2018; Poon 2007), prices both express and enact disparities in market power (Bååth 2023). They are the outcomes of, and participants in, struggles between differentially equipped market actors operating within stratified fields of calculation (Beckert 2011; Callon and Muniesa 2005; Callon 2016).

Such struggles occur at every point along the supply chain, from upstream production and distribution to downstream retailing (Berndt and Boeckler 2011). I focus in this essay on the downstream end of the supply chain, where retail firms selling identical products compete on price advantages rather than qualitative differences in product offerings. In this context, retail pricing strategies are "optimized" to satisfy two competing demands. On one hand, retailers sell at competitive (i.e., lower) prices to attract customers and increase their market share; on the other hand, retailers sell at supra-competitive (i.e., higher) prices to boost profit margins. Achieving the right balance between these imperatives is an intricate calculative feat. For example, retailers may opt to lose money on products in one category (so-called "loss leaders") in order to induce spending in another where profit margins are higher. Figuring out the right formula for this cross-subsidization requires not only an intimate knowledge of consumer spending habits and purchase histories, a process to which scholars of commercial surveillance have long attended (Gandy 1993; Turow 2005), but also gathering and processing information on competitors' pricing strategies, a process that has received considerably less attention. I argue that this latter practice, known as *competitor price monitoring* or *pricing intelligence*, is a consequential case study for understanding surveillance's role in the calculative operations we call "prices," especially during inflationary periods when pricing is most politicized.

My argument is based on two sources of data: preliminary auto-ethnographic observations recorded while working as a PricePoint data collector for two weeks in December 2022 and a qualitative analysis of employee reviews of PricePoint on job sites Indeed, Glassdoor, and InHerSight. In the next section, I provide a high-level overview of the pricing intelligence industry, highlighting how price monitoring and price setting in online markets can facilitate tacit collusion between dominant retailers. In the following, I introduce PricePoint Retail, Inc., and discuss the methodologies I used to investigate the firm as well as my findings. The ethnographic portion of the research included a three-day online and in-person training period, as well as eight days in the field gathering price information at retail locations of PricePoint clients' competitors in central North Carolina. At the end of each shift, I took fieldnotes on my experiences to reflect on what was expected of me as a data collector and what challenges I faced on the job. The qualitative content analysis involved scraping and coding PricePoint employee ratings and reviews of the company. I present my findings by toggling between ethnographic observations and the content analysis of employee reviews. The paper concludes by discussing how price monitoring plays a significant but under-appreciated role in the politics of retail price inflation, with attention to how dialogue between surveillance studies and the sociology of price formation can open new lines of inquiry.

Price Monitoring

The sociology of price formation insists that prices are social rather than purely "economic" constructs (Beckert 2011). But prices are also political: firms' power to set prices reflects and enacts disparities in market influence (Nitzan and Bichler 2009). In theory, companies are constrained in the exercise of price-setting power by competition with their rivals; in practice, firms exploit loopholes to coordinate pricing strategies with their competitors—what is often called "anticompetitive" behavior—through both overt and covert information exchanges (Harrington 2022). As the DOJ's case against Agri Stats shows, the production and collation of competitively sensitive pricing information can facilitate oligopolistic or cartel-like behavior among a handful of well positioned firms, generating consumer harms in the form of supra-competitive prices. But Agri Stats' very existence as an information intermediary also insulates the company's clients from allegations of outright collusion. With weekly and monthly reports from Agri Stats, meat processors never had to communicate with one another to coordinate prices: they sent information and payments to the intermediary and received information in exchange. This is why the DOJ brought its suit against Agri Stats rather than the meat processors.

Competitor price monitoring serves a function similar to Agri Stats for retail firms, with the added protection that retail prices are considered publicly available information. Competitor price monitoring refers to the collection, processing, and transmission of retail price data and other merchandising and promotional strategies. In the United States, the production and collation of retail pricing and marketing information cannot constitute collusive behavior in violation of antitrust law because anyone can walk into a store, or search on Google, to see what competitors are charging (see Ballou 2021; Harrington 2022; Vaska 1985). Still, price monitoring raises several issues that critical scholarship ought to address, including the use of covert and often labor-intensive forms of surveillance as a material input in the calculative operations of retail price formation.

Competitor price monitoring is especially common in e-commerce settings, where retail prices are not only broadcast on the internet but also easily scraped by software. However, even with sales prices available in machine-readable formats, the tracking and monitoring of online retail prices in real-time is a massive endeavor. E-commerce giants delegate pricing decisions to algorithmic systems that update rapidly, across hundreds of thousands of items, and autonomously, without day-to-day human input (MacKay and Weinstein 2022). For instance, Amazon's dynamic pricing system is purported to monitor the prices set by third-party sellers on its own marketplace as well as on competitor sites and is believed to make up to 2.5 million price changes per day with a variance as high as 20% (Huzenkova 2023). This allows Amazon to identify and punish third-party sellers offering lower prices on other sites by downranking or removing their products from display on Amazon's marketplace (Tkacik 2023). The online marketplaces of Amazon's rivals in the United States—namely, Walmart and Target—likely work similarly (MacKay and Weinstein 2022).

But while mega-corporations have the resources and capacity to build automated pricing systems in-house, many smaller firms do not. Smaller e-commerce sites outsource price monitoring to third-party services that specialize in dragnet price surveillance. This is evident when conducting web searches for terms related to "competitor price monitoring" or "pricing intelligence," with results yielding a litany of companies peddling web-scraping and data-collection tools as business-to-business (B2B) software-as-a-service (SaaS) applications. These tools, often sold alongside inventory management and algorithmic pricing systems, promise clients "insight[s] into [competitors'] prices, products, strategies, marketing gimmicks and promotions" (WebDataGuru 2022). Retailers then leverage those "insights" into their pricing strategies by "pricing down" on popular items in a bid to undercut rivals and expand market share, or conversely, by "pricing up" to capitalize on demand spikes or competitors' low inventory (see Aryan 2020). Competitor price monitoring, in short, highlights the informational entanglements of supply-side actors using prices as a wedge, or cudgel, to gain market advantages over competing firms. As a recent essay in the *Harvard Business Review* puts it, "the ability to revise prices swiftly and on a large scale has emerged as a decisive differentiator—especially during periods of inflation, when prices fluctuate more frequently" (Fisher, Gallino, and Li 2023).

If pricing practices are decisive, they have also alarmed antitrust scholars, who warn that algorithmic pricing can facilitate tacit forms of collusion, enabling effective cartels to evade regulatory enforcement (Calvano et al. 2020; Ezrachi and Stucke 2020; Lamontanaro 2021; Stucke and Ezrachi 2016).[1] Competitor price

[1] MacKay and Weinstein (2022) also show that algorithmic pricing may lead to supra-competitive pricing even without price coordination because not all pricing algorithms are equally sophisticated. Firms with pricing algorithms that update more frequently than competitors', or that use machine learning algorithms to automatically adjust pricing strategies in response to competitors', have asymmetrical market advantages. Competitors anticipate these advantages and, in response, charge higher prices to make up the difference in market share. This allows the algorithmically advantaged firms to form a price floor of their choosing, undercutting rivals while charging supra-competitive prices and ultimately pushing up prices across the board. Others note the relationship between these effects and price instability. For example, in a report for the National Bureau of Economic Research, Calvallo (2018) found evidence

monitoring, in this sense, exemplifies what Hartzog and Selinger (2015) call "surveillance as the loss of obscurity." Although prices were always nominally public bits of information, they were historically rather difficult to access, record, process, and transmit at the scale and speed necessary for retailers to incorporate competitors' pricing strategies into their own decision making. How information is collected through "pricing intelligence," and how corporations leverage that information, represent differences not only in degree but also in kind from how pricing information has been treated by the law, with consequences for how we understand collusion and anti-competitive behavior. Like automated license plate readers' mass scanning and tracking capabilities, price monitoring lowers the transaction costs of finding, collating, and activating information that was available but not accessible at a volume large enough to be meaningful or "actionable." It is about eroding the obscurity that had functionally prohibited corporations from granular knowledge of their competitors' pricing and promotional strategies, or which had at least made such practices too difficult and expensive to be a viable advantage.[2]

Such issues raise a set of concerns different from what we in surveillance studies usually consider. Price monitoring redirects critical attention from the more-familiar scenes of consumer sorting, discrimination, and valuation—what Fourcade and Healy (2013) call "classification situations," in which prices are "personalized" to extract as much consumer surplus as possible (Gandy 1993; Moor and Lury 2018)—to the largely "im-personalized" and highly secretive practices of corporate surveillance, through which prices become artillery in battles for market dominance and differential profit margins (Nitzan and Bichler 2009). This is not to say that consumer surveillance no longer matters in shaping how markets impact individuals' life chances (Fourcade and Healy 2017; Gandy 1993), only that we need to consider techniques of "consumer intelligence" and "pricing intelligence" *together* if we are to fully appreciate surveillance as a material practice integral to, perhaps even constitutive of, prices.

Going Offline

Antitrust scholars warn that algorithmic pricing generates consumer harms by allowing market leaders to raise prices without consequence. The ambient tracking and monitoring of competitors' online prices by retail giants or information intermediaries is the baseline input for these systems: without the rote monitoring and tracking of online prices, there would be no collusive tendencies or harms. This much already warrants consideration from surveillance studies scholars. But it is also important to note that e-commerce remains a minority of retail sales. The vast majority—85%—of retail spending in the United States still occurs in brick-and-mortar settings (Statista.com 2023). And given how much money is on the metaphorical table, retail corporations are unlikely to leave their in-store pricing strategies to chance.

The trouble for retailers is that collecting pricing information on competitors' in-store inventory is much more challenging and expensive than getting that data online. Brick-and-mortar prices cannot be scraped by software (at least without access to competitors' real-time, in-store pricing and inventory databases). Moreover, even when retailers pursue "omnichannel" sales strategies—selling products both online and off—they typically charge different rates for the same products depending on the purchase context. Online prices for, say, power tools on homedepot.com are not a reliable proxy for what Home Depot charges for the same goods in the store (see, e.g., Mohammed 2017). Rather than price "blindly," retailers invest in the costly operations of manual data collection at competitors' brick-and-mortar locations.

The existence, and profitability, of PricePoint Retail, Inc., is evidence that retailers are willing to pay handsomely for in-store pricing intelligence.[3] Founded in the 1980s and headquartered in the suburbs of a mid-sized US city, PricePoint specializes in producing reports on pricing, promotions, and inventory for

---

that Amazon's dynamic pricing affects retail pricing strategies sectorally, making prices more sensitive to the kind of demand shocks and inflationary pressures that occurred during the first months and years of the COVID-19 pandemic.

[2] I am grateful to Jathan Sadowski for reminding me of the connection to Hartzog and Selinger's (2015) argument and for the helpful framing.

[3] PricePoint is a pseudonym.

supermarket chains and other large retailers, such as Walmart and Target.[4] The company describes itself as "the industry leader in competitive retail intelligence." Its "core service" is "collecting pricing information at the competitor's store, as well as letting [clients] know which items are carried or not carried at that competitor."[5]

PricePoint's in-store retail monitoring services predate online price tracking and intelligence. When PricePoint launched its e-commerce division in the early 2010s, it had already been selling pricing data in the supermarket sector for more than two decades. Today the company boasts of an extensive reach, with over 1,500 "research associates," "field representatives," and "scanning specialists" on payroll in the US and Canada.[6] More than 80% of all store locations for firms listed on SuperMarket News' Top 75 are PricePoint clients, meaning that PricePoint employs at least one data collector within sixty miles of nearly every supermarket in the majority of North America. It also means that the largest grocery-selling firms in the US by revenue and market share—Walmart, Kroger, Costco, Albertsons, Publix, and Ahold Delhaize (owner of Food Lion, Giant, and Stop and Shop, among others)—are likely using PricePoint's services to track and monitor competitors' in-store pricing, inventory, and display strategies.

PricePoint is, however, a highly secretive company. Little information is available publicly about the firm or its operations. The majority of web-search results for PricePoint's de-anonymized name direct the searcher to job advertisements for data collector positions. At the time of writing, there are more than 1,900 openings listed on PricePoint's website across every region of the US and most provinces of Canada. If these positions were all filled, PricePoint's workforce would more than double in size, indicating either significant growth or high rates of turnover.

Covert Methods for a Covert Industry

To learn about the labor involved in pricing intelligence at the national-industrial scale, I drew on two sources of data. First, I conducted auto-ethnographic research as a data collector for PricePoint. I had used a similar method to prepare for research on platform labor in the on-demand service economy (Shapiro 2020: 101–109). By spending several months as a bike courier for an app-based food-delivery service, I learned first-hand how platform operators squeezed and manipulated gig workers, and this understanding guided the research design I later used to interview delivery riders. The covert work of participant-observation was necessary in this context because of the corporate secrecy I encountered at the platforms. And like on-demand services, the details of pricing intelligence operations are tightly guarded trade secrets. Furthermore, as I explain below, identifying PricePoint employees in the field for interviews is made difficult by the fact that data collectors are typically required to work covertly in retail settings. After several failed attempts to recruit data collectors for interviews through professional social networks like LinkedIn, I applied to work as a data collector myself. And after two perfunctory interviews, I received an offer.

There are valid ethical concerns about conducting covert auto-ethnographic research in institutional settings, despite the fact that many influential texts in the social sciences are based on covertly collected ethnographic data, such as Goffman's (1961) book on mental institutions and, more recently, Scheper-Hughes' (2007) research on the organ trade. Dominant regulatory approaches to research ethics generally assume that covert ethnography is harmful for those subject to it. However, according to Marzano (2018), because institutionalized ethics guidelines are as much about liability as research guidance, they tend to ignore disparities in social power and therefore preemptively prohibit researchers from "studying up" (Nader 1969). Most guidelines also conflate covertness with deceitfulness, assuming that failure to disclose one's identity as a researcher is tantamount to intentionally misleading participants or misrepresenting the research to them (see Spicker 2011). So, while attending to these as ethical risks is necessary for conducting covert

[4] Walmart and Target are identified as PricePoint clients in publicly available sources.

[5] These and other quotes are taken from public sources or training materials. I do not cite the sources in order to maintain the company's anonymity.

[6] Job descriptions for these roles are identical or nearly identical.

research responsibly, the risks should not disqualify the method wholesale. As Marzano (2018: 411) concludes:

> As there are clearly instances in which the prohibition of covert research is advantageous to those who would prefer that the truth of what they are doing is not told, we must challenge assumptions regarding the presumed unethicality of covert research or risk becoming complicit in the murky business of powerful elites and the organisational and institutional interests they serve.

Given these more nuanced considerations about covert auto-ethnographic research, I felt it appropriate to proceed. I did not inform the hiring staff at PricePoint that I was a researcher, but I also did not lie about it. The hiring staff saw my resumé, which showed my university affiliation. During the interview process, they were more interested to know if I had a valid driver's license and vehicle, and that I was comfortable with having to lift heavy objects, than determining my motivations for taking the job. Finally, because I did not interview anyone or even observe human interactions as part of this pilot study (I only observed the labor process as I experienced it), the project would not be subject to institutional human subjects research review.

But while the ethnographic research yielded important insights, it was also limited by personal and professional time constraints and by my identity as a white, cis-gendered man working as a data collector in supermarkets in the US South.[7] To validate and expand the analysis beyond rudimentary observations, I analyzed employee ratings and reviews of PricePoint on three job websites: Indeed.com, Glassdoor.com, and InHerSight.com. These reviews are publicly available and anonymized by default, although the majority of reviewers chose to disclose their location by state, province, or city.

I started the analysis by compiling sample sets of reviews from Indeed and Glassdoor, as these sites host several hundred more reviews than InHerSight. The samples were constructed in proportion to PricePoint's ratings distributions. Ratings distributions decompose a firm's average ratings to their component scores. Replicating these distributions allowed me to construct representative samples. Table 1 below shows the ratings distributions for PricePoint on Indeed and Glassdoor. I manually scraped one-hundred reviews from each site, using the percentages as a reference. For instance, my sample contained thirty-four five-star reviews from Indeed and thirty from Glassdoor; twenty-eight four-star reviews from Indeed and twenty-five from Glassdoor; and so on. I populated each of the ratings grades randomly by recording the date, location, and comments from every fourth review, thus ensuring that the average rating for the sample matched PricePoint's average global ratings.[8]

InHerSight is similar to Indeed or Glassdoor but caters specifically to women. In addition to criteria typical of other job sites (salary satisfaction, learning opportunities, employer responsiveness), InHerSight also surveys reviewers on dimensions that reflect women's workplace priorities, such as maternity and adoptive leave, mentorship programs, family growth support, and so on. At the time of writing, InHerSight has 108 ratings for PricePoint, with an average rating of 1.9, but it only displays four reviews. I included these in the sample to complement the data from Indeed and Glassdoor.

[7] I conducted the auto-ethnographic portion of research during the winter break of my university's academic calendar. When the spring semester started, it was no longer feasible to continue working as a data collector while attending to my normal faculty responsibilities and family obligations.

[8] Some reviewers allege that PricePoint pays formers workers to review the company favorably on job sites as part of the exit survey. While I cannot verify this, I tried to account for the issue by removing four- and five-star reviews with identical or nearly identical language. I also excluded from the sample reviews posted by corporate employees, such as computer programmers and logistics managers, who work at corporate headquarters rather than in the field as data collectors.

Table 1: *PricePoint Ratings Distributions for Indeed and Glassdoor*

	Indeed.com	Glassdoor.com
Total # of ratings	446	652
Rating average	3.65 stars	3.43 stars
5 stars	34% (152)	30% (196)
4 stars	28% (126)	25% (163)
3 stars	17% (78)	16% (104)
2 stars	11% (47)	11% (72)
1 star	10% (43)	18% (117)

When the sample set was compiled (n = 204), it reflected a wide range of tenure, spanning a couple of weeks on the job to twelve years of experience, as well as considerable geographic diversity. The corpus includes reviews from workers or former workers from thirty-eight US states (including Hawaii and Alaska), Puerto Rico, and three Canadian provinces (Ontario, Quebec, and New Brunswick). To analyze the data, I developed a preliminary coding frame drawing on my auto-ethnographic observations that I refined iteratively by hand throughout the coding process (Luker 2008). While analysis revealed several interesting themes, the final framework consisted of four primary topics: flexibility (77.5%); pay (41%); training, skill, and embodied knowledge (41%); and the work of working undercover (24%). The significance of these reflects both qualitative and quantitative considerations: although flexibility was the only theme to recur throughout the majority of reviews, the other themes are important because they reveal disparities in PricePoint data collectors' on-the-job experiences.

Working the Store

Research corroborated my intuition that in-store price monitoring is similar to other kinds of data labor, such as gig work, content moderation, and "click-work" (Gray and Suri 2019; Irani 2015; Roberts 2019; van Doorn 2017). Like these other "humans-as-a-service" jobs, the primary appeal of working for PricePoint is scheduling flexibility—work when you want, without direct managerial supervision (Griesbach et al. 2019; Milkman et al. 2021; Stark and Pais 2020; Vallas and Schor 2019). Indeed, flexibility and independence were some of the most prominent themes in my qualitative analysis of PricePoint reviews. Nearly four of every five reviewers in my sample—including those who rated PricePoint poorly (one–two stars)—cited self-scheduling and independence as the most important benefits of working as a PricePoint data collector. Posts with titles like "work when you want," "be your own boss," or even just "flexible," were common. Flexibility was particularly appealing for people who needed part-time or secondary work, and reviewers noted the job's compatibility with the unpredictable and varied schedules of college students, parents, and people caring for elders. However, even some of the most favorable reviews of PricePoint (four–five stars) acknowledged that the benefits of flexibility were matched by substantial downsides, including low pay, extensive driving requirements, tedium, and the physically demanding nature of the work. These reviewers conceded that while the job was good for them because of personal circumstances, it may not be as appealing to others. Many of the lowest rated reviews (one–two stars) also cited flexibility as an upside but argued that the benefits of self-scheduling did not offset the job's challenges and low pay.

The reviews showed as well that some data collectors viewed the job's flexibility as contingent upon several factors. One constraint is retail locations' hours. The supermarkets and mega-stores where data collectors record pricing information often closed earlier or opened later than workers preferred. Another constraint is variation in the busy-ness of assigned retail locations (for example, on weekends versus weekdays). The most significant constraints, however, were imposed by PricePoint. Nearly two dozen reviewers (11%) complained that the job could be stressful due to its unpredictability and strict deadlines. Typically, workers are assigned tasks due two to four days later, but they also reported receiving short-turnaround jobs with strict deadlines. This could happen if they were audited and missed accuracy thresholds. As one former worker explained, "if they're not happy with a job you've already finished, they might randomly message you and say you need to redo it all within 24 hours."[9] Other reviewers (2%) reported receiving assignments with little to no notice because data collectors in the district missed deadlines or quit entirely. In five reviews (2.5%), former employees complained that attrition was rampant, straining current workers' scheduling. When someone else walks off the job, PricePoint re-assigns their tasks without extending the deadline.

The parallels between pricing intelligence and gig work were not lost on data collectors. One reviewer called working for PricePoint "glorified gig work." Another lamented that gig workers actually have it better. Being a data collector is "basically a gig job but you can't really pick and choose what you do. They treat you like a gig worker, but you don't get the full flexibility."

This is consistent with my auto-ethnographic observations both as a data collector with PricePoint and, in previous research, as a gig worker for a food-delivery platform. The first thing I learned about working for PricePoint was that the job is remarkably taxing. Despite having indicated only ten to fifteen hours of availability per week, I was immediately assigned a series of jobs that took, at minimum, twenty-five to thirty hours, plus driving time. I worked alongside a field supervisor on my first day as part of the company's training, but I was never supervised or instructed afterwards. And although I worked as quickly as I could manage, the jobs I was assigned took much longer than expected based on PricePoint's allotments. On other occasions, the job was so quick to complete that it was difficult to justify the amount of driving involved. As one former data collector recalled, "you'll wind up having to drive 40 minutes to a store for a job that takes literally ten minutes." This is where working for PricePoint differed from gig work. Gig work platforms like Uber and Doordash nominally allow their contractors to reject undesirable assignments, but because PricePoint workers are employees, they have to take whatever "bullshit" jobs get assigned to them.

These discrepancies reflect some of the core contradictions of flexibilized work, as documented in the gig economy and beyond (see Chung 2022). At PricePoint, flexibility hinges on a meticulously devised piece-rate payment system—what the company calls a "progressive productivity rate" (see Figure 1). The progressive productivity rate is a pay schedule that decreases per-item compensations over time as data collectors become more adept at gathering price data. The system is integral to worker flexibility and independence because tying wages to the entry of individual data points frees PricePoint from having to employ field supervisors.

Platform-mediated gig work has brought renewed attention to piecemeal payment systems in recent years (e.g., Shaikh, Lampinen, and Brown 2023), but the tactic is as old as industrial capitalism. Piece-rate wages, Marx (1867) once wrote, are "the form of wages most in harmony with the capitalist mode of production" because they provide "a lever for [both] the lengthening of the working-day, and the lowering of wages." The techniques of Taylorist "scientific management" also relied on piece-rate wages to manipulate productivity standards and extract more surplus from workers (Braverman 1974). PricePoint's training materials inherit this wisdom, depicting the piece-rate system not only as necessary for workers to enjoy the benefits of scheduling flexibility but also as a benefit in and of itself. For example, as PricePoint's representatives repeated in boilerplate responses to negative reviews on Indeed and Glassdoor, the "productivity-based compensation… allows [data collectors] to increase their hourly rate as they gain speed and efficiency." In other words, it is not management but workers who "have control of their pay rate," since workers can always "increas[e] [their] speed/efficiency to earn more."

[9] I modified the text of the reviews without changing the meaning so that PricePoint would not be identifiable by web search.

Pay Type	Rate Table				Training Tier 1				Training Tier 2				Training Tier 3			
Access Type	Non Scanned		Scanned		Non Scanned		Scanned		Non Scanned		Scanned		Non Scanned		Scanned	
Check Type	Primary	Secondary	Primary	Secondary	Primary	Secondary	Primary	Secondary	Primary	Secondary	Primary	Secondary	Primary	Secondary	Primary	Secondary
BASE11																
Hard Lapel																
Directed	$0.0790	$ 0.0395	$0.0790	$ 0.0395	$0.1067	$ 0.0533	$0.1067	$ 0.0533	$ 0.0960	$ 0.0480	$ 0.0960	$ 0.0480	$ 0.0864	$ 0.0432	$ 0.0864	$ 0.0432
Undirected	$0.0930	$ 0.0465	$0.0300	$ 0.0150	$0.1349	$ 0.0674	$0.0435	$ 0.0218	$ 0.1214	$ 0.0607	$ 0.0392	$ 0.0196	$ 0.1092	$ 0.0546	$ 0.0352	$ 0.0176
Lapel																
Directed	$0.0750	$ 0.0375	$0.0750	$ 0.0375	$0.1013	$ 0.0506	$0.1013	$ 0.0506	$ 0.0911	$ 0.0456	$ 0.0911	$ 0.0456	$ 0.0820	$ 0.0410	$ 0.0820	$ 0.0410
Target List	$0.1000	$ 0.0500	$0.1000	$ 0.0500	$0.1350	$ 0.0675	$0.1350	$ 0.0675	$ 0.1215	$ 0.0608	$ 0.1215	$ 0.0608	$ 0.1094	$ 0.0547	$ 0.1094	$ 0.0547
Undirected	$0.0640	$ 0.0320	$0.0300	$ 0.0150	$0.0928	$ 0.0464	$0.0435	$ 0.0218	$ 0.0835	$ 0.0418	$ 0.0392	$ 0.0196	$ 0.0752	$ 0.0376	$ 0.0352	$ 0.0176
Open																
Directed	$0.0510	$ 0.0255	$0.0510	$ 0.0255	$0.0689	$ 0.0344	$0.0689	$ 0.0344	$ 0.0620	$ 0.0310	$ 0.0620	$ 0.0310	$ 0.0558	$ 0.0279	$ 0.0558	$ 0.0279
Undirected	$0.0150	$ 0.0075	$0.0150	$ 0.0075	$0.0218	$ 0.0109	$0.0218	$ 0.0109	$ 0.0196	$ 0.0098	$ 0.0196	$ 0.0098	$ 0.0176	$ 0.0088	$ 0.0176	$ 0.0088
Restricted																
Directed	$0.0590	$ 0.0295	$0.0590	$ 0.0295	$0.0797	$ 0.0398	$0.0797	$ 0.0398	$ 0.0717	$ 0.0358	$ 0.0717	$ 0.0358	$ 0.0645	$ 0.0323	$ 0.0645	$ 0.0323
Undirected	$0.0640	$ 0.0320	$0.0150	$ 0.0075	$0.0928	$ 0.0464	$0.0218	$ 0.0109	$ 0.0835	$ 0.0418	$ 0.0196	$ 0.0098	$ 0.0752	$ 0.0376	$ 0.0176	$ 0.0088

Figure 1: *PricePoint's progressive productivity rate chart*

This company line is reinforced through what can only be described as propagandistic videos posted to PricePoint's social media feeds. In one video, a current employee testifies (from what appears to be a script) to the benefits of the piece-rate system:

> My favorite aspect of my job is how we get paid. I love getting paid per piece. It means that every item I collect, I get paid. So, I get to control how much money per hour that I want to make by how fast and efficiently I work. If I take breaks or slow down, I don't get paid quite as much per hour. I like the fact that I get to control it. And at the end of the day, I don't have to work a set amount of hours per day. When my job is done, I just get to be done. I can still make the same amount of money as if I had worked the entire day.

The testimony contrasts sharply with the experiences of several workers in my sample (6%) who claimed that meeting PricePoint's productivity targets yielded hourly earnings significantly lower than the advertised $16 per hour. A small minority (2.5%) reported that they brought home less than state-mandated minimum wages, a claim that PricePoint representatives vehemently denied. But even if PricePoint uses wage floors to prevent violating state laws, achieving the requisite proficiency for workers to make a decent hourly wage and satisfy quality-control audits requires hundreds if not thousands of hours of experience. The employee in the video states that she has worked for PricePoint for thirteen years and "done just about every type of job they have to offer."

Data collectors' jobs seem simple, then, but they are deceptively complex. Data collectors travel to the retail locations of PricePoint clients' competitors (often in distant locales) and work their way through store aisles using handheld scanning devices or smartphones to collect pricing, inventory, and display information on a wide range of inventory selected by the client. Some of the inventory lists remain the same week-to-week; others change more frequently. The data collection process involves scanning products' UPC codes and manually keying in pricing data as well as numerically coded notations. The notations augment pricing details with information on promotions and inventory levels—for instance, that an item is on sale, out of stock, not sold at that location, sold by weight rather than unit, and so on. But the codes for these auxiliary notations are not necessarily intuitive, and they differ by client. One client might use 04, 09, 02, and 05, respectively, to code those bits of information, while another might use 10, 40, 70, and 30 (Fieldnotes, December 10, 2022). It is the data collector's responsibility to memorize these codes. When an item is on sale, the data collector has to record the original price, the sale price, and whether the sale applies only to loyalty card members or to all shoppers (Fieldnotes, November 26, 2022).

Recording data fast enough to keep up with PricePoint's efficiency standards therefore requires a high level of embodied knowledge, a fair bit of craftiness, and lots of in-store experience. When working at a Walmart Supercenter, for instance, I was instructed by a more seasoned data collector to familiarize myself with the entire footprint of the store and to keep the Walmart app open on my phone so I could double-check the UPC code on in-store products—in his experience, the Walmart app was much more reliable than the scanner provided by PricePoint (Fieldnotes, December 17, 2022). At a supermarket chain, I found that I needed to learn how every supermarket in the area color-codes the Styrofoam on its meat packaging to indicate quality and grade, and to memorize the hierarchy of private-label brands so I could translate by eye between the client's private labels and those of the client's competitors (Fieldnotes, November 29, 2022). Toy aisles at mega-stores like Walmart and Target are notoriously difficult because children are wont to leave items out of place. When working cosmetics sections, data collectors might need to identify, differentiate, and locate a couple dozen shades of lipstick out of several hundred, often in the midst of paying customers (Fieldnotes, December 10, 2022). (Retrieving lipstick data was one of the more humbling of my on-the-job experiences. At a Walmart on a Saturday between Thanksgiving and Christmas—retail's busiest season—it took me an hour to record cosmetics information in what should have taken me under fifteen minutes. In fairness, two employee reviews vindicated my frustrations by lamenting the difficulty of working cosmetics sections.) The work of retail price monitoring is, in short, skilled work (Cooper, Bridges, and Ticona 2021), and data collectors who fail to meet the standards of quality control audits are sanctioned, re-trained, and with too many red flags, fired.

PricePoint also expects its data collectors to work covertly in many, if not most, cases. In this sense, retail price monitoring looks a lot like "mystery shopping," only the target of the information-gathering is not employees' behavior or demeanor but competitors' pricing strategies (Robert 2021). PricePoint's training materials distinguish between "open" and "lapel" jobs. On open jobs, the data collector is supposed to check in at the customer service desk and wear a PricePoint lanyard to identify themselves; on lapel jobs, data collectors are expected to conduct their work discreetly, to "act like shoppers," and contact a PricePoint supervisor if store management confronts them. On "hard lapel" jobs, workers are expected to exercise increased caution and maximal discretion, and they are compensated with a bonus per-item rate (but only by fractions of a cent).

In my two weeks working at PricePoint, all of the jobs I was assigned were lapel jobs, but I did not find collecting price data covertly to be terribly difficult, especially if the retail location was busy. At most stores, clerks are used to seeing customers compare in-store prices on their smartphones (so-called "showrooming"), and the physical motions of this activity look nearly identical to those of data collection. During my training, I was advised that confrontations with store management are rare—that workers had only been asked to leave stores on a handful of occasions in recent years. Nowadays, reasoned one of PricePoint's district managers during my training, floor managers at supermarkets are paid so little that they do not have time or energy to enforce anti-espionage policies. Besides, in-store price monitoring is kind of an open secret in the industry. All the big players do it: Target might be watching Walmart's egg and produce prices, Walmart Kroger's meat and dry goods sections, Kroger Target's dairy promotions, and so on (in a hypothetical loop). Based on my experiences, PricePoint data collectors can find themselves spying on retailers that share a parking lot with the client—and, indeed, spying on one client for another (Fieldnotes, November 26 and 29, 2022).

Other PricePoint data collectors' experiences differed from mine, though. Twenty-five reviews in my sample (12.5%) cited working "undercover" or "incognito" as a source of job-related stress and anxiety, or otherwise found it "insulting" given the pay. Others called the practice "unethical," a form of "stealing," and claimed that PricePoint requires its fieldworkers to adopt a "flexible moral code." And because workers also shop at the retail locations they are assigned, the looming prospect of getting banned from the store exposes them to personal risk. One of the reviews posted to InHerSight documents a startling encounter with the Asset Management team at a Walmart:

> They told me that because my assignment was "undercover," I had to go unnoticed and blend in with my surroundings. But they didn't train us for this! After fifteen minutes of following these exact orders, I was surrounded by Asset Management. Four of them, objectively intimidating men, one on each side of the aisle. You can tell by how they dress and the way they watch your every move. When I reported the harassment to the [district manager], she was "shocked," as if she didn't believe me! She NEVER gave

> me any tips on how to work without being stalked or how to "blend in." And when I reported [the incident], she just said "get out of there." Well, when working under time constraints and with these lists that have to be completed by a certain time on a specific day, just leaving doesn't work. It makes it impossible for this to be a part-time, "work at your own pace and on your schedule" kind of job. I had to work around the store staff as if I was a criminal and this was NOT what I signed up for at MINIMUM WAGE. I understand that PricePoint can't control the store staff. But equipping their employees with the tools and skills on how to work would have been greatly appreciated. It's to the point now that when I go to Walmart for my own shopping I'm followed around, even when I'm not scanning or doing anything but my normal civilian shopping!

That this review was posted to a website where women employees, specifically, evaluate their employers on quality of work, reveals the uneven gendered dynamics of flexibilized labor and gig work in general (see e.g., Milkman et al. 2021) as well as the complex interplay of surveillance practices in retail settings. But the account also gestures, implicitly, toward the racialized dynamics of retail data collection. For while I do not know the racial identity of the review's author, the well-documented persistence of racial profiling in commercial settings in the US is likely to make "shopping while Black" a significant liability for African American and other racial-minority data collectors at PricePoint and companies offering similar services (Gabbidon and Higgins 2020; Schreer, Smith, and Thomas 2009). Not only are black data collectors more likely to be singled out and harassed by both shoppers and store security than their white counterparts (and therefore more likely to be kicked out of a store), they may also experience increased financial strain, since PricePoint's policy is to *not* compensate workers for time spent and earning opportunities lost after getting kicked out of a store. And on top of that, black data collectors could face dangerous encounters with law enforcement as well as criminal charges: when workers are *reassigned* to locations from which they were previously ejected (a practice that appears to occur regularly, according to the reviews), store managers may consider their presence trespassing, call the police, and file a criminal report.

Such qualifications are important reminders that racialized, gendered, and other forms of discrimination creep into the retail and service sectors laterally through "refractive" dynamics of surveillance (Levy and Barocas 2017; Rosenblat et al. 2017). They also underscore the limitations of my observations as a white, cis-gendered man working as a data collector in supermarkets in the US South. For whom is price monitoring a viable "gig"? For whom are the vaunted benefits of flexibility a reality? What costs must PricePoint's workforce pay for the clients' pricing intelligence?

Price as a Surveillant Informational Practice

Data collectors' experiences show that price monitoring is an intensive and highly uneven "informational practice," an "activity that materializes information in everyday contexts" and must therefore "be actively cultivated and nurtured by people, organizations, and their socio-technical actor-networks" (French 2014: 232). At scale, it is also, accordingly, a surveillant practice, a "form of systematic monitoring that exerts an influence or has a tangible outcome" (Monahan and Murakami Wood 2018: xx; see Newell 2023). In this essay, I have sketched a preliminary picture of how the surveillant informational practices of competitor price monitoring form a human-powered infrastructure for retail pricing strategies. Foregrounding such practices reveals that prices matter not only during transactional encounters between consumers and corporations but also as communicative instruments that *must be made to signal something*, at great cost and effort, about competing firms' marketing strategies. In short, turning retail prices into market devices requires the mobilization of a vast workforce of precariously positioned data collectors.

Such mobilizations make price monitoring a matter of concern: they represent a difference not just in degree but in kind from how the law treats pricing information. In theory, price monitoring could benefit consumers if retailers used pricing intelligence data to lower in-store sales tags. But lower prices are by no means a guaranteed outcome of price monitoring. As the recent rounds of inflation have shown, price "competition" does not always exert a downward pressure on prices. Firms compete not only for market share but also for increased profit margins. The goal is never simply to meet the average rate of accumulation but to beat it (Nitzan and Bichler 2009). And to accomplish this, corporations need to know what the competition is charging.

Weber and Wasner's (2023) recent work on "sellers' inflation" documents how the post-COVID surge in price inflation was accompanied by markups and corporate profits not seen in the US since the 1950s (see Konczal and Lusiani 2022). While their model does not include data for companies in the supermarket sector,[10] the analysis shows that dominant firms across industries have a tendency under "normal" circumstances to establish price floors and, acting as a cartel, punish rivals who charge less. By contrast, oligopolistic market leaders typically only raise prices when they expect their direct competitors to do the same. Sellers' inflation occurs when market leaders act on this latter expectation. According to Weber and Wasner (2023), this is precisely what happened in the first months and years of the COVID-19 pandemic, as sectoral supply chain shocks created an opportunity for firms to coordinate price hikes without explicitly colluding. With bottlenecks upstream raising distribution and warehousing costs, retail firms responded by hiking prices downstream to protect their profit margins. And because they could count on competitors doing the same—and because they could *verify* that competitors were in fact doing the same through price monitoring—they had both an *alibi* and a *motive* for charging more: an alibi because the price floors were going up across the board, and a motive because "if firms deviate[d] from this price hike strategy, the threat of share sell-offs by financial investors [would] enforce compliance with such implicit agreements" (Weber and Wasner 2023: 2). The combination of financial pressure and market conditions created a "temporary monopoly power" that allowed market-leading firms to "not only protect but to increase profits" (Weber and Wasner 2023: 2).

It is generally understood that price tracking facilitates what antitrust scholars call "conscious parallelism," or the intentional coordination of prices without explicit collusion (Blechman 1979; Vaska 1985). At scale, this process plays an integral role in pushing up prices globally. But just as significantly, price monitoring increases the *granularity* of competitively sensitive information. For instance, PricePoint's clients can see not only that competitors raised prices on certain items but also that they used promotions and discounts to cover their tracks—for instance, by charging more for bread but offering a temporary buy-one-get-one-free deal to make the price hike less detectable to consumers. Sociologists of price formation have attended to these encounters as "calculative asymmetries" between differentially equipped market actors—in this case, consumers and retailers (Callon and Muniesa 2005). Price monitoring, by contrast, directs us to the calculative *symmetries* that allow market-leading firms in concentrated sectors to have it both ways—to charge supra-competitive prices without sacrificing market share. This, I would submit, is as valid a definition for sellers' inflation as any other.

By zooming in on competitor price monitoring, we see how the macro-dynamics of price inflation are based, at least in part, on the vast, intricate, and rote work of price surveillance—the recording, processing, and transmitting of pricing information by a workforce of poorly paid data collectors. Surveillance studies can contribute to the sociology of price formation by bringing its ethical critique of power asymmetries to bear on our understanding of prices, not only as market devices but also as practices requiring sustained attention and investment (Bååth 2023; French 2014). A surveillance studies perspective is needed, in other words, to understand the labor and exploitation involved in activating and reproducing prices as both reflections and enactments of market power. Like other forms of "flexibilized" work that surveillance scholars have attended to, price surveillance is organized by gendered, classed, and racialized divisions in labor markets, and is subject to varied forms of workplace surveillance (Anderson 2016; Sewell and Wilkinson 1992; van Doorn 2017). Conversely, by attending to the sociomaterial practices of markets, scholars can expand the purview of surveillance studies to include informational practices used by corporations to establish and maintain market power—at the expense of both their own precarious workforces and consumers at large.

[10] While Weber and Wasner's (2023) analysis uses data from manufacturing firms, consumers viewed supermarkets as one of the major culprits of "greedflation": opinion polls showed public perceptions of the grocery sector dropped by fourteen points between 2021 and 2022—the most of any US business sector (Brenan 2022).

For while prices may always be social and political, understanding *prices as surveillance* opens up a new "hidden abode" of information and labor practices that relies on a human infrastructure of disposable workers and which is now critical to intra-capitalist competition.

My hope in reporting on this preliminary research is that it inspires others to bring perspectives from surveillance studies to bear on the material practices of pricing intelligence, the social and economic conditions of the data producing workforce, and the reproductive infrastructures that data collectors rely on to eke out a living amid deteriorating labor conditions (Gray and Suri 2019; Irani 2019; Shaikh, Lampinen, and Brown; van Doorn and Shapiro 2023). For while price monitoring is not as *prima facie* invasive or "creepy" as consumer surveillance (Ruckenstein and Granroth 2020), it is rampant and, as I have tried to show here, consequential. Perhaps most importantly, it is a timely reminder for our age of economic insecurity that "surveillance capitalism" is an entirely redundant concept (Lauer and Lipartito 2021; Igo 2021).

References

Anderson, Donald Nathan. 2016. Wheels in the Head: Ridesharing as Monitored Performance. *Surveillance & Society* 14 (2): 240–258.

Aryan, Lokesh. 2020. Three Ways Competitor Price Tracking Can Make Your Brand Profitable. YourStory.Com, June 4. https://yourstory.com/2020/05/three-ways-competitor-price-tracking-brand-profitable [accessed March 3, 2024].

Bååth, Jonas. 2023. Towards a Unified Theory of Market Prices: Turning to Pricing in Practice. *Socio-Economic Review* 21 (1): 5–23.

Ballou, Brendan. 2021. The "No Collusion" Rule." *Stanford Law & Policy Review* 32 (2): 213–252.

Beckert, Jens. 2011. "Where Do Prices Come from? Sociological Approaches to Price Formation." Socio-Economic Review 9 (4): 757–86.

Berndt, Christian, and Marc Boeckler. 2011. Geographies of Markets: Materials, Morals and Monsters in Motion. *Progress in Human Geography* 35 (4): 559–567.

Blechman, Michael D. 1978. Conscious Parallelism, Signalling and Facilitating Devices: The Problem of Tacit Collusion under the Antitrust Laws. *New York Law School Law Review* 24 (4): 881–906.

Braverman, Harry. 1974. *Labor and Monopoly Capital: The Degradation of Work in the Twentieth Century*. New York: Monthly Review Press.

Brenan, Megan. 2022. U.S. Business Sector Average Rating Worst Since 2008. Gallup, September 9. https://news.gallup.com/poll/400835/business-sector-average-rating-worst-2008.aspx [accessed March 3, 2024].

Caliskan, Koray. 2007. Price as a Market Device: Cotton Trading in Izmir Mercantile Exchange. *The Sociological Review* 55 (2_suppl): 241–260.

Çalışkan, Koray, and Michel Callon. 2009. Economization, Part 1: Shifting Attention from the Economy towards Processes of Economization. *Economy and Society* 38 (3): 369–398.

———. 2010. Economization, Part 2: A Research Programme for the Study of Markets. *Economy and Society* 39 (1): 1–32.

Callon, Michel. 2016. Revisiting Marketization: From Interface-Markets to Market-Agencements. C*onsumption Markets & Culture* 19 (1): 17–37.

Callon, Michel, Yuval Millo, and Fabian Muniesa, eds. 2007. *Market Devices*. Oxford, UK: Blackwell.

Callon, Michel, and Fabian Muniesa. 2005. Peripheral Vision: Economic Markets as Calculative Collective Devices. *Organization Studies* 26 (8): 1229–1250.

Cavallo, Alberto. 2018. More Amazon Effects: Online Competition and Pricing Behaviors. Working Paper, National Bureau of Economic Research. https://doi.org/10.3386/w25138.

Calvano, Emilio, Giacomo Calzolari, Vincenzo Denicolò, and Sergio Pastorello. 2020. Artificial Intelligence, Algorithmic Pricing, and Collusion. *American Economic Review* 110 (10): 3267–3297.

Chung, Heejung. 2022. *The Flexibility Paradox: Why Flexible Working Leads to (Self-) Exploitation*. Bristol, UK: Policy Press.

Cochoy, Franck, Johan Hagberg, and Hans Kjellberg. 2018. The Technologies of Price Display: Mundane Retail Price Governance in the Early Twentieth Century. *Economy and Society* 47 (4): 572–606.

Cooper, Zane, Lauren E. Bridges, and Julia Ticona. 2021. Constructing the Digital Skills Crisis: A Critical Conceptual History of "Skill." Presented at *The 22nd Annual Conference of Internet Researches, Virtual Event, October 13–16*. https://doi.org/10.5210/spir.v2021i0.12154.

Dayen, David. 2023. Lawsuit Highlights Why Meat Has Been Overpriced for 40 Years. *American Prospect*, October 3. https://prospect.org/power/2023-10-03-lawsuit-highlights-why-meat-overpriced/ [accessed March 3, 2024].

Doorn, Niels van. 2017. Platform Labor: On the Gendered and Racialized Exploitation of Low-Income Service Work in the 'on-Demand' Economy. *Information, Communication & Society* 20 (6): 898–914.

Doorn, Niels van, and Aaron Shapiro. 2023. Studying the Gig Economy "Beyond the Gig": A Research Agenda. SSRN, October 9. https://ssrn.com/abstract=4583329.

Fisher, Marshall, Santiago Gallino, and Jun Li. 2023. A Step-by-Step Guide to Real-Time Pricing. *Harvard Business Review*, November 1. https://hbr.org/2023/11/a-step-by-step-guide-to-real-time-pricing [accessed March 3, 2024].

Fourcade, Marion, and Kieran Healy. 2013. Classification Situations: Life-Chances in the Neoliberal Era. *Accounting, Organizations and Society* 38 (8): 559–572.

———. 2017. Seeing like a Market. *Socio-Economic Review* 15 (1): 9–29.

French, Martin. 2014. Gaps in the Gaze: Informatic Practice and the Work of Public Health Surveillance. *Surveillance & Society* 12 (2): 226–242.

Ezrachi, Ariel, and Maurice E. Stucke. 2020. Sustainable and Unchallenged Algorithmic Tacit Collusion. *Northwestern Journal of Technology and Intellectual Property* 17 (2): 217–260.

Gabbidon, Shaun L., and George E. Higgins. 2020. *Shopping While Black: Consumer Racial Profiling in America*. New York: Routledge.

Gandy, Oscar. 1993. *The Panoptic Sort: A Political Economy of Personal Information*. Boulder, CO: Westview Press.

Goffman, Erving. 1961. *Asylums: Essays on the Social Situation of Mental Patients and Other Inmates*. Piscataway, NJ: AldineTransaction.

Gray, Mary L., and Siddharth Suri. 2019. *Ghost Work: How to Stop Silicon Valley from Building a New Global Underclass*. Boston, MA: Houghton Mifflin Harcourt.

Griesbach, Kathleen, Adam Reich, Luke Elliott-Negri, and Ruth Milkman. 2019. Algorithmic Control in Platform Food Delivery Work. *Socius* 5 (January): 1–15.

Harrington, Joseph E. 2022. The Anticompetitiveness of a Private Information Exchange of Prices. *International Journal of Industrial Organization* 85 (December): https://doi.org/10.1016/j.ijindorg.2021.102793.

Hartzog, Woodrow, and Evan Selinger. 2015. Surveillance as Loss of Obscurity. *Washington & Lee Law Review* 72 (3): 1343–1387.

Huzenkova, Yulia. 2023. Amazon Pricing Strategy: Ultimate Guide. Sellbery, February 28. https://sellbery.com/blog/amazon-pricing-strategy-ultimate-guide/ [accessed March 3, 2024].

Igo, Sarah. 2021. Afterword. In *Surveillance Capitalism in America*, edited by Josh Lauer and Kenneth Lipartito, 203–210. Philadelphia, PA: University of Pennsylvania Press.

Irani, Lilly. 2015. Difference and Dependence among Digital Workers: The Case of Amazon Mechanical Turk. *South Atlantic Quarterly* 114 (1): 225–223.

———. 2019. Justice for Data Janitors. In *Justice for Data Janitors*, 23–40. New York: Columbia University Press.

Konczal, Mike, and Niko Lusiani. 2022. Prices, Profits, and Power: An Analysis of 2021 Firm-Level Markups. Roosevelt Institute. https://rooseveltinstitute.org/wp-content/uploads/2022/06/RI_PricesProfitsPower_202206.pdf.

Lamontanaro, Aleksandra. 2019. Bounty Hunters for Algorithmic Cartels: An Old Solution for a New Problem Notes. *Fordham Intellectual Property, Media & Entertainment Law Journal* 30 (4): 1259–1310.

Lauer, Josh, and Kenneth Lipartito. 2021. Introduction: Surveillance Under Capitalism. In *Surveillance Capitalism in America*, edited by Josh Lauer and Kenneth Lipartito, 1–26. Philadelphia, PA: University of Pennsylvania Press.

Levy, Karen, and Solon Barocas. 2017. Refractive Surveillance: Monitoring Customers to Manage Workers. *International Journal of Communication* 11: 1–24.

Luker, Kristin. 2008. *Salsa Dancing into the Social Sciences: Research in Age of Info-Glut.* Cambridge, MA: Harvard University Press.

MacKay, Alexander, and Samuel N. Weinstein. 2022. Dynamic Pricing Algorithms, Consumer Harm, and Regulatory Response. *Washington University Law Review* 100 (1): 111–174.

Marx, Karl. 1867. Chapter 21: Piece-Wages. In *Capital Vol. I.* Translated by Samual Moore and Edward Aveling. Marxists.org. https://www.marxists.org/archive/marx/works/1867-c1/ch21.htm [accessed March 3, 2024].

Marzano, Marco. 2018. The Ethics of Covert Ethnographic Research. In *The Palgrave Handbook of Ethics in Critical Research*, edited by Catriona Ida Macleod, Jacqueline Marx, Phindezwa Mnyaka, and Gareth J. Treharne, 399–413. Cheltenham, UK: Springer International Publishing.

Milkman, Ruth, Luke Elliott-Negri, Kathleen Griesbach, and Adam Reich. 2021. Gender, Class, and the Gig Economy: The Case of Platform-Based Food Delivery. *Critical Sociology* 47 (3): 357–372.

Mohammed, Rafi. 2017. How Retailers Should Think About Online Versus In-Store Pricing. *Harvard Business Review*, January 26. https://hbr.org/2017/01/how-retailers-should-think-about-online-versus-in-store-pricing [accessed March 3, 2024].

Monahan, Torin, and David Murakami Wood. 2018. Introduction: Surveillance Studies as a Transdisciplinary Endeavor. In *Surveillance Studies: A Reader*, edited by Torin Monahan and David Murakami Wood, xix–xxxiv. Oxford, UK: Oxford University Press.

Moor, Liz, and Celia Lury. 2018. Price and the Person: Markets, Discrimination, and Personhood. *Journal of Cultural Economy* 11 (6): 501–513.

Nader, Laura. 1969. Up the Anthropologist: Perspectives Gained From Studying Up. In *Reinventing Anthropology*, edited by Dell Hymes, 284–311. New York: Pantheon.

Newell, Bryce Clayton. 2023. Surveillance as Information Practice. *Journal of the Association for Information Science and Technology* 74 (4): 444–460.

Nitzan, Jonathan, and Shimshon Bichler. 2009. *Capital as Power: A Study of Order and Creorder*. New York: Routledge.

Poon, Martha. 2007. Scorecards as Devices for Consumer Credit: The Case of Fair, Isaac & Company Incorporated. *The Sociological Review 55* (2_suppl): 284–306.

Robert, Daniel. 2021. Mystery Shoppers and Self-Monitors: Managing Emotional Labor to Improve the Corporate Image. In Surveillance Capitalism in America, edited by Josh Lauer and Kenneth Lipartito, 84–96. Philadelphia, PA: University of Pennsylvania Press.

Roberts, Sarah T. 2019. *Behind the Screen: Content Moderation in the Shadows of Social Media*. New Haven, CT: Yale University Press.

Rosenblat, Alex, Karen E.C. Levy, Solon Barocas, and Tim Hwang. 2017. Discriminating Tastes: Uber's Customer Ratings as Vehicles for Workplace Discrimination. *Policy & Internet* 9 (3): 256–279.

Ruckenstein, Minna, and Julia Granroth. 2020. Algorithms, Advertising and the Intimacy of Surveillance. *Journal of Cultural Economy* 13 (1): 12–24.

Scheper-Hughes, Nancy. 2007. The Last Commodity: Post-Human Ethics and the Global Traffic in "Fresh" Organs. In *Global Assemblages*, 145–167. Hoboken, NK: John Wiley & Sons.

Schreer, George E., Saundra Smith, and Kirsten Thomas. 2009. "Shopping While Black": Examining Racial Discrimination in a Retail Setting. *Journal of Applied Social Psychology* 39 (6): 1432–1444.

Sewell, Graham, and Barry Wilkinson. 1992. "Someone to Watch Over Me": Surveillance, Discipline and the Just-in-Time Labour Process." *Sociology* 26 (2): 271–289.

Shaikh, Riyaj, Airi Lampinen, and Barry Brown. 2023. The Work to Make Piecework Work: An Ethnographic Study of Food Delivery Work in India During the COVID-19 Pandemic. *Proceedings of the ACM on Human-Computer Interaction 7 (CSCW2)* 243:1–23.

Shapiro, Aaron. 2020. *Design, Control, Predict: Logistical Governance in the Smart City*. Minneapolis, MN: University of Minnesota Press.

Spicker, Paul. 2011. Ethical Covert Research. *Sociology* 45 (1): 118–133.

Stark, David, and Ivana Pais. 2020. Algorithmic Management in the Platform Economy. *Sociologica* 14 (3): 47–72.

Statista.com. 2023. U.S. e-Commerce Share of Annual Retail Sales 2022. Statista. https://www.statista.com/statistics/185351/share-of-e-commerce-in-total-value-of-us-retail-wholesale-trade-sales/ [accessed March 3, 2024].

Stucke, Maurice E., and Ariel Ezrachi. 2016. How Pricing Bots Could Form Cartels and Make Things More Expensive. *Harvard Business Review*, October 27. https://hbr.org/2016/10/how-pricing-bots-could-form-cartels-and-make-things-more-expensive [accessed March 3, 2024].

Tkacik, Maureen. 2023. The [REDACTED] Case Against Amazon. *The American Prospect*, September 27. https://prospect.org/power/2023-09-27-redacted-case-against-amazon/ [accessed March 3, 2024].

Turow, Joseph. 2005. Audience Construction and Culture Production: Marketing Surveillance in the Digital Age. *The Annals of the American Academy of Political and Social Science* 597 (1): 103–121.

US Department of Justice [DOJ]. 2023. Justice Department Sues Agri Stats for Operating Extensive Information Exchanges Among Meat Processors. September 28. https://www.justice.gov/opa/pr/justice-department-sues-agri-stats-operating-extensive-information-exchanges-among-meat [accessed March 3, 2024].

Vallas, Steven, and Juliet B. Schor. 2020. What Do Platforms Do? Understanding the Gig Economy. *Annual Review of Sociology* 46 (1): 273–294.

Vaska, Michael K. 1985. Conscious Parallelism and Price Fixing: Defining the Boundary. *The University of Chicago Law Review* 52 (2): 508–535.

WebDataGuru. 2022. About Competitive Price Monitoring Tracking. *Medium* (blog). August 5. https://medium.com/@Web_Scraping/about-competitive-price-monitoring-tracking-5ddb92224d76 [accessed March 3, 2024].

Weber, Isabella M., and Evan Wasner. 2023. Sellers' Inflation, Profits and Conflict: Why Can Large Firms Hike Prices in an Emergency? *Review of Keynesian Economics* 11 (2): 183–213.