Determinants and Effects of Buy Box Suppression on Amazon

Jeffrey Gleason
gleason.je@northeastern.edu
Northeastern University
Boston, Massachusetts, USA

Shuo Zhang
s.zhang@northeastern.edu
Northeastern University
Boston, Massachusetts, USA

Christo Wilson
c.wilson@northeastern.edu
Northeastern University
Boston, Massachusetts, USA

Abstract

98% of sales on Amazon.com flow through the Buy Box. However, Amazon sometimes decides not to feature any offers for a product and removes the Buy Box from the product page—a situation known as *Buy Box suppression*. Suppression may have severe consequences on individual sellers and might affect competition if it disciplines prices across online marketplaces. This paper studies suppression using a new, high-frequency dataset that tracks 17,754 products on Amazon.com at hourly intervals for eight weeks in 2024, along with corresponding offers from 59,301 unique competitors. We open-source both the dataset and collection code.

We find that the primary reason for suppression is changes to the offers for a product on Amazon. Lower competitor prices only modestly increase the probability of suppression. Suppression has substantial impacts on sellers: products immediately fall sharply in search, ad placements completely disappear within 12 hours, and sales ranks are 12% worse after 48 hours. In contrast, we find no evidence of impacts on competitor prices in the short run. Our results highlight how Buy Box suppression acts as an important and underexplored mechanism of platform governance.

CCS Concepts

• **Information systems → Online shopping**; • **Computing methodologies → Causal reasoning and diagnostics**; • **Applied computing → Economics**.

Keywords

electronic commerce; amazon; online platforms; price competition

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1 Introduction

The most important shelf space in e-commerce is Amazon's Buy Box. Amazon's share of the e-commerce market is more than six times that of its second-biggest competitor, Walmart [21]. Within Amazon, a staggering 98% of sales flow through the "Add to Cart" and "Buy Now" buttons in the Buy Box [23]. This makes occupying the Buy Box critical and lucrative for merchants. However, sometimes Amazon decides not to feature any offers for a given product and removes the Buy Box from the product page. This eliminates the "Add to Cart" and "Buy Now" buttons and forces shoppers to navigate through a less convenient "See All Buying Options" page (see Figure 1). This situation is known as *Buy Box suppression*.

Why would Amazon stifle its most profitable customer journey? According to multiple seller accounts [42–44], previous academic work [27], and the FTC's ongoing anti-trust case [23, 24], Amazon suppresses the Buy Box when it identifies lower prices on competing websites. The FTC argues that suppression discourages sellers from offering lower prices on other websites and deters price competition. For its part, Amazon's Fair Pricing Policy states that it monitors prices on and off Amazon and that it can remove the Buy Box if it identifies prices that "harm customer trust" [2]. Thus, Amazon asserts that Buy Box suppression is about enforcing low prices and high quality to protect customers [51]. These competing explanations motivate our first research question: what actually triggers Buy Box suppression?

Irrespective of Amazon's motives, the consequences of suppression for sellers are severe. First-hand accounts describe collapsing sales [44, 45], while other sources cite penalties such as demotion in search results [23–25], exclusion from ad placements [23, 25, 40], and removal from recommendation widgets [23]. Our second research question estimates these effects and charts their evolution over time. Furthermore, suppression has the potential to affect competition if it disciplines prices across platforms [23, 24]. Our final research question speaks to this by estimating how competitor short-term prices respond to suppression.

This study contributes to the growing empirical literature on online platforms, with a particular focus on Amazon. Despite its dominant role in e-commerce, Amazon remains understudied relative to other major online platforms such as Google, Facebook, and Twitter/X. Existing research on Amazon has focused primarily on the Buy Box selection algorithm [13, 33, 37] and self-preferencing [13, 14, 19, 20, 22, 26, 32, 33, 37, 50]. With the exception of Hunold et al. [27], prior research gives little attention to Buy Box suppression, which is an important tool through which Amazon can affect marketplace outcomes for third-party sellers, its own offers and other competitors. This leaves a significant gap in our understanding of how suppression operates and what consequences it has for individual sellers and competition overall.

To address this gap, we construct a new, high-frequency dataset that tracks 17,754 products on Amazon.com at hourly intervals for eight weeks in 2024, along with corresponding offers from 59,301 unique competitors. We open-source both the dataset[1] and collection code[2] to facilitate further research on Amazon and cross-platform e-commerce dynamics. We use this dataset to ask three research questions, which are motivated above:

(1) **RQ 1**: What are the determinants of Buy Box suppression?

[1]https://doi.org/10.7910/DVN/6KN9LO
[2]https://github.com/jlgleason/amazon-price-crawler

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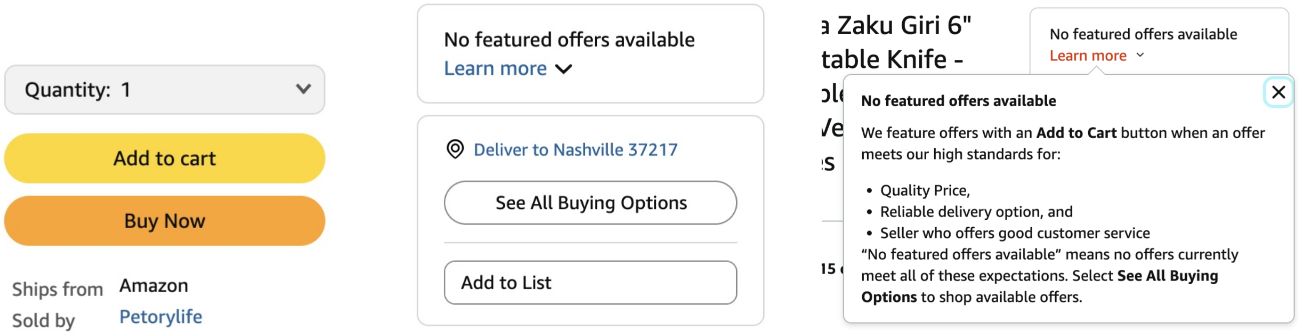

Figure 1: Examples (left-to-right) of a featured Buy Box, Buy Box suppression, and Amazon's explanation for suppression.

(2) **RQ 2**: What impact does Buy Box suppression have on sellers, measured through their search rank, sales rank, and ad placement?
(3) **RQ 3**: How do prices on competitor websites respond to suppression events?

We find that while lower competitor prices modestly increase the probability of suppression, the most important triggers are changes to the offers on Amazon itself, specifically when the last featured offer temporarily exits the market or raises its price. Suppression has sizeable impacts on sellers: products immediately fall sharply in search, ad placements completely disappear within 12 hours, and sales ranks are 12% worse after 48 hours. In contrast, we find no evidence that suppression systematically affects prices on competitor websites in the short run. These findings should not be overgeneralized: our data represent a period five years after Amazon repealed its explicit price parity policy [31] and six months after the FTC filed its lawsuit [23, 24]. Overall, our results highlight how Buy Box suppression is an important and underexplored mechanism of platform governance.

2 Background and Related Work

We begin by presenting prior work on Amazon.com, as well as recent work on causal inference with panel data.

2.1 Amazon Marketplace

Amazon.com launched in 1994 as an online bookstore, but quickly expanded into a general retailer. In 2000, it launched Marketplace and opened its virtual doors to third-party sellers. Their share has grown steadily, reaching 60% of U.S. sales in 2023 [17, 23]. Amazon also developed complementary services such as Prime (2005) and Fulfillment by Amazon (2006), which by 2021, handled 92% of all orders [23]. These features anchor Amazon's dominant role in e-commerce, attracting at least 120 million monthly users [23].

Buy Box Selection. Amazon states that Buy Box selection is a function of price, shipping, customer service, availability, and return options [3]. Empirical studies find that price dominates, though seller identity (i.e., sold by Amazon), shipping option (i.e., fulfilled by Amazon; FBA), seller ratings, and shipping speed also matter [13, 33, 37]. For example, Raval [37] found that a "perfect" third-party offer (i.e., 1 M ratings and 100% positive feedback) incurred a 46% price penalty relative to Amazon offers.

The closest work to ours is Hunold et al. [27], who specifically study Buy Box suppression. They tracked 3,500 products on Amazon.com at daily intervals for 12 weeks in 2020, along with corresponding offers from two competitors (Walmart and eBay). They find that suppression never occurs when Amazon is one of the sellers, is more likely when the price on Amazon is higher than the list price or higher than competitors, and significantly increases sales rank (i.e., sales rank gets worse). In contrast, we collect data at hourly intervals, track thousands of competitors instead of just Walmart and eBay, and analyze search rank, ad placement, and competitor price outcomes in addition to sales rank.

Self-Preferencing. The treatment of Amazon's own product offers in Buy Box selection connects to broader concerns about self-preferencing. As both marketplace operator and merchant, Amazon has been found to leverage its dual role, positioning its own goods and services as the default option on the product page [13, 27, 33, 37]. Evidence of preferential treatment arises across Amazon's marketplace. Amazon offers appear more prominently in search results even after controlling for observables such as price, ratings, shipping, availability, and query relevance [22, 50]. Stock-out events show that Amazon's absence reduces a product's exposure in "Frequently Bought Together" recommendations [14]. Amazon also enjoys greater visibility in sponsored recommendations compared to organic ones [19] and selectively strikes through negative reviews for FBA sellers [20]. Self-preferencing also extends to entry strategy: Zhu and Liu [52] found that Amazon was more likely to enter successful product markets, and that this entry boosted demand and lowered shipping costs, but discouraged third-party sellers from remaining active.

Complementing this empirical work, structural models have assessed the welfare implications of self-preferencing. Lee and Musolff [33] find short-term consumer benefits and negligible impacts on prices and entry in the medium and long-term. Lam [32] simulate removing Amazon as a seller and predict higher profits for third-party sellers, but also higher prices. Gutierrez [26] recommends policy interventions that preserve Prime and product variety, but increase competition in fulfillment services.

2.2 Causal Inference with Panel Data

Causal inference with panel data is an active area of research and several recent reviews provide comprehensive overviews [5, 15, 39,

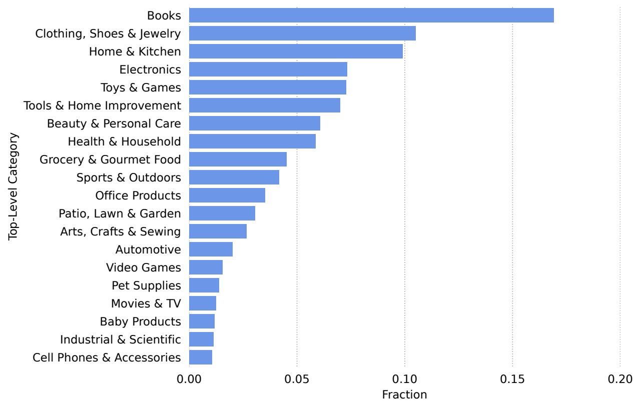

Figure 2: Top 20 product categories in our dataset.

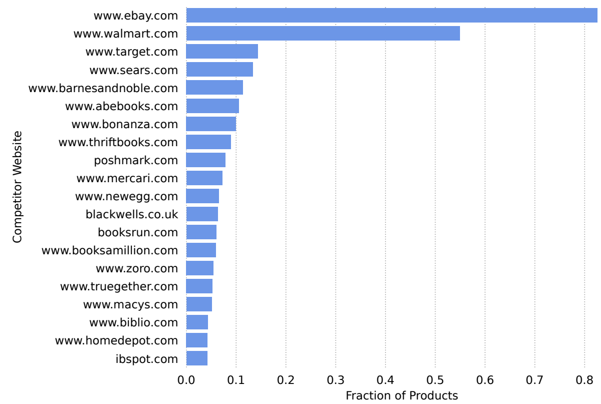

Figure 3: Top 20 competitor websites in our dataset.

49]. Rather than summarize this literature, we use this section to situate our empirical setting within the space of available estimators. Two aspects of our setting are especially important. First, Buy Box suppression represents a case of *general treatment assignment* (see § 3.3), in contrast to the more structured designs that dominate the difference-in-differences (DiD) literature, such as block assignment and staggered adoption [7]. Second, we expect that suppression in past periods has *carryover effects* on outcomes in future periods. For example, changes in sales take up to 12 hours to manifest in a product's sales rank [41].

The first feature immediately rules out a number of methods that rely on block assignment or staggered adoption. This includes heterogeneity-robust DiD estimators [11, 12, 46] and recent extensions of the synthetic control method [1, 4, 9, 10, 38]. Instead, we focus on two recent approaches that explicitly accommodate general treatment assignment: PanelMatch [28] and counterfactual estimation (FEct) [34], which generalizes matrix-completion and factor-model approaches [6, 48]. PanelMatch semiparametrically adjusts for treatment, outcome, and covariate histories, while FEct directly models untreated potential outcomes. Both approaches also permit limited carryover effects: PanelMatch matches on L lags of treatment history, while FEct can ignore a few carryover periods when fitting outcome models.

3 Data

In this section, we present the dataset that we collected, including how we filtered the data and key variables that we extracted.

3.1 Collection

We started with an open-source dataset from Amazon that contains 97,345 English-language search queries.[3] We randomly sampled 10,000 queries from this list, searched each query on Google Shopping in January 2024, and collected all products on the first results page. This yielded 346,263 products, which we filtered to 103,045 products that were sold on both Amazon.com and at least one competitor website at the time. We link competitors to Amazon.com at the product-level because Buy Box suppression occurs at the product-level. We tracked this sample of 103,045 products on Amazon.com for five days in February 2024 (2/5–2/10), at six-hour intervals. The purpose of this initial collection was to identify products with more active competition for further tracking.[4] We selected all products whose price and/or featured seller changed in more than 20% of consecutive six-hour intervals, which resulted in a final sample of 18,112 products.[5]

For each of the 18,112 products, we collected data for 8 weeks (March 13–May 7, 2024) at hourly intervals. For each product-hour, we collected the: (1) Amazon product page, (2) first page of Amazon "All Offers", (3) first page of Amazon search results, (4) Google Shopping product page, and (5) Walmart product page (if Walmart was a competitor). Appendix § A.1 shows examples of these five pages and enumerates the information we extracted from each.

We executed our scrapers on 20 virtual machines from AWS, evenly distributed between the Ohio and Northern Virginia regions. Each individual product was collected from a fixed AWS region for the entire collection period, which `amazon.com` infers as a fixed zip code. Data collection cost U.S. $8 per day.

3.2 Sample

In this study, we focus on available, new products. Thus, we exclude observations where the featured offer on Amazon was either in used condition or out of stock. Similarly, we disregard competitor offers that were either used or out of stock.

After filtering, we collected at least one hourly observation from 17,754 products. We tracked products for 1,344 time periods (56 days × 24 hours). This yields 22.7 M product-hour observations that are neither used nor out-of-stock. Among these products, 9,277 products (52%) have at least one Walmart price observation, 14,392 (81%) have at least one eBay price observation, and 16,869 (95%) have at least one price observation from a non-Walmart/eBay competitor. In total, we observe 118.6 M offers on Amazon (mean=5.7 per product-hour) and 204.6 M offers on competitor sites (mean=8.6

[3]https://github.com/amazon-science/esci-data

[4]It also allows us to measure suppression frequency in a representative sample. 1.5% of observations were suppressed and 2.5% of products were suppressed at least once.
[5]Although we selected products based on price dynamics on Amazon, the resulting sample exhibits substantial off-Amazon variation: half of products in our sample change prices more frequently on competitor sites than on Amazon itself.

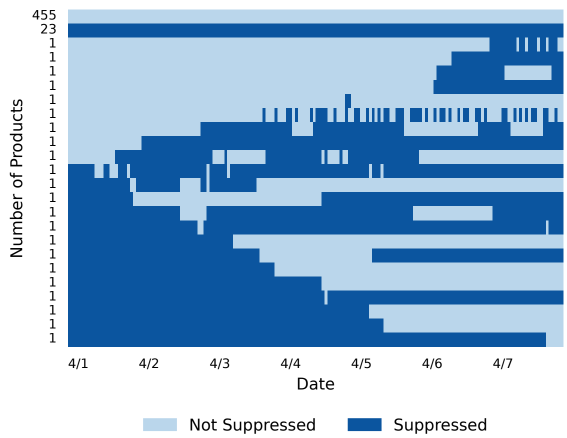

Figure 4: Sample of 500, week-long Buy Box suppression histories. Dark blue corresponds to suppression.

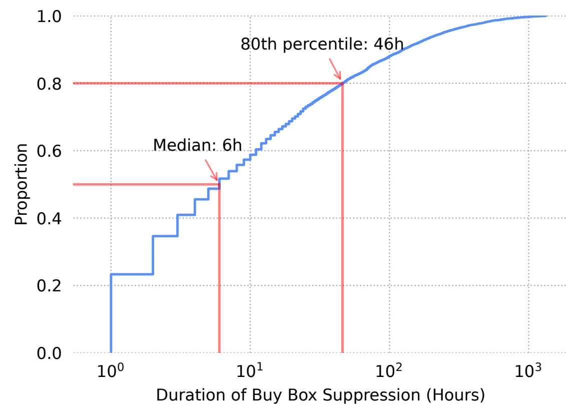

Figure 5: Empirical CDF of Buy Box suppression length.

per product-hour) across all time periods. Figure 2 shows the 20 most frequent top-level categories. The top three are Books (17%), Clothing, Shoes & Jewelry (11%), and Home & Kitchen (10%).

We identify 59,301 unique competitor websites that appeared in at least one time period for at least one product. 3,382 of them are "consistent competitors" that were present in every time period for at least one product. Figure 3 shows the top 20 competitors according to the number of products for which they appear at least once. The top three are: eBay (83%), Walmart (55%), and Target (14%), which are three of Amazon's top four competitors according to both desktop visit data [16] and consumer surveys [8]. One key competitor that our data under-represents is Temu (0.2% of products), though AliExpress is more common (2% of products). Among the top 20 competitors, 12 sell a broad range of products, five specialize in Books (ThriftBooks, Blackwell's, BooksRun, Books-A-Million, Biblio,), one specializes in Clothing, Shoes, & Jewelry (Poshmark), one specializes in Electronics (Newegg), and one specializes in Tools & Home Improvement (Home Depot).

3.3 Buy Box Suppression

Overall, the Buy Box is suppressed in 1.5 M (6.4%) product-hour observations. However, this masks considerable variation: 168 products (1%) are always suppressed and 14,450 are never suppressed (81%). Figure 4 visualizes a random sample of 500, week-long suppression histories. In this sample, 455 products are never suppressed (the topmost row), 23 are always suppressed (the second row), and 22 have other suppression patterns. Figure 4 demonstrates that Buy Box suppression is an example of general treatment assignment, where treatment status can switch on and off [5, 28].

In total, we observe 17,394 transitions (across 2,660 products) from no suppression at time $t-1$ to suppression at time t. Figure 5 shows the empirical CDF of suppression length after one of these transitions. The median suppression length is six hours and the mean suppression length is 48 hours. 23% of suppressions last for only one hour, which is the finest resolution we can observe.

3.4 Outcome Variables

We measure the impact of suppression on sellers (**RQ 2**) using three outcome variables:

- *Amazon search rank*: The highest position of an organic result (i.e., not an ad) for the product in search results when querying for the product's name. We normalize by the total number of search results, so that 0 represents the top result and 1 represents not on the page.
- *Amazon sales rank*: The "Best Sellers Rank" from the "Product Details" section on the product page. Since multiple category-rank pairs are often displayed, this variable consistently references the rank corresponding to the product's most commonly listed category.
- *Amazon ad placement*: Whether the product is displayed as an advertisement anywhere in search results when querying for the product's name.

We measure the impact of suppression on competitor prices (**RQ 2**) through three outcomes:

- *Walmart price*: The price of the featured offer on Walmart's product page. Walmart is Amazon's biggest competitor in terms of sales [21].
- *eBay price*: The minimum price across all eBay offers. eBay is Amazon's most frequent competitor in our dataset.
- *Other competitors' price*: The minimum price across all offers on non-eBay, non-Walmart competitor sites.

All three competitor price outcomes are interpolated within 24-hour windows to smooth over transient errors in data collection. In order to help readers visualize outcomes, Figure 13 shows trajectories for five products that experienced suppressed and non-suppressed periods between 4/1–4/7. The upper panel of Table 2 presents summary statistics for the six outcome variables.

3.5 Covariates

We collected rich information about available offers on Amazon to include as covariates in our analysis. This includes: (a) the total number of new offers, (b) whether there is a used offer, (c) whether there is an offer from Amazon.com, (d) whether there is an offer from a FBA seller, (e) the minimum price, (f) the maximum seller

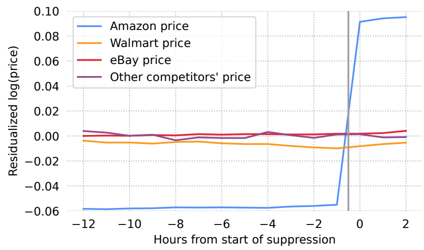

Figure 6: Amazon and competitor residualized price trajectories in the 12 hours before a suppression incident begins.

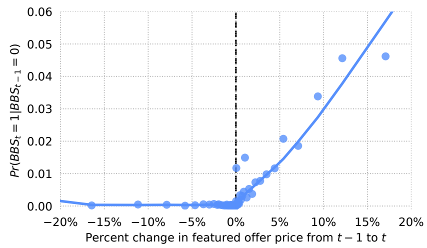

Figure 7: Probability of suppression beginning (Y) vs. change in the featured offer's price (X).

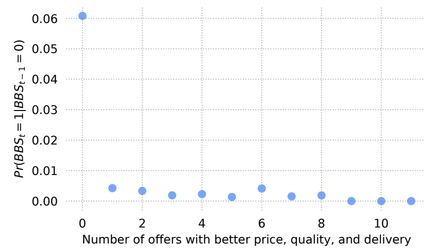

Figure 8: Probability of suppression beginning (Y) vs. number of offers with better price, quality, and delivery (X).

quality (i.e., positive feedback percentage), and (g) the maximum number of seller ratings.[6] We also include covariates that specifically describe Amazon's "featured offer," including how it changes over time and how it compares to other offers. These covariates are motivated and described in § 4. To compare offers on Amazon to offers on other platforms, we include indicators for whether (a) Walmart, (b) eBay, and (c) other competitors' have offers and indicators for whether (g) Walmart's, (h) eBay's, and (i) other competitors' minimum price is lower than the minimum price on Amazon. The lower panel of Table 2 summarizes covariate means and standard deviations for suppressed and non-suppressed observations and reveals noticeable differences for almost all covariates.

4 Determinants of Buy Box Suppression

In this section, we address **RQ 1** by investigating the triggers of Buy Box suppression. We focus on comparing Amazon's argument that it hides products with no good offers to the FTC's accusation that Amazon responds to lower prices on competitor sites.

4.1 Model-free Evidence

We start with visual evidence about what happens immediately before suppression episodes begin. Figure 6 shows residualized price trajectories (i.e., prices after removing product and time fixed effects) across Amazon, Walmart, eBay, and other competitor sites in the 12 hours before a suppression incident begins. We subset to products that were not suppressed during these 12 hours to remove any effects of suppression history. Figure 6 emphasizes that a large increase in the minimum price on Amazon precipitates suppression incidents. The minimum price on Amazon is 6% below average in the 12 hours before suppression, but increases to 9% above average in the hour when suppression begins. By contrast, minimum prices on Walmart, eBay, and other competitor platforms consistently remain within 1% of their averages. This figure provides strong evidence that suppression incidents are triggered by factors on Amazon rather than by price changes on competitor websites.

In practice, two changes could drive an increase in the minimum price: (1) the seller of the featured offer intentionally raises their price or (2) the featured offer drops out of the product market and no other offers match their price. We use the featured offer from time $t-1$ to represent a "good" reference offer because it meets all of Amazon's price, delivery, and quality expectations for this specific product, at this specific time. Figure 7 shows that the probability of suppression depends on the change in the price from the seller of the featured offer between times $t-1$ and t. When the seller remains available, a 10% price bump increases the probability of suppression to 3% (a 65-fold increase), while a price increase of 15% increases the probability of suppression to 5% (a 108-fold increase). Similarly, Figure 8 shows how the probability of suppression depends on the number of substitute "good" offers (i.e., offers with price, quality, and delivery at least as good as the last featured offer) that remain after the featured offer exits the product market. If there are zero "good" substitutes, the probability of suppression is 6%, but just one "good" substitute reduces the suppression likelihood to under 0.5%.

4.2 Model-based Evidence

To isolate the impact of different factors and quantify their relative importance, we now turn to model-based evidence. We fit linear probability models of the form

$$D_{i,t} = \mathbf{A}\mathbf{X}_{i,t} + \psi_i + \eta_t + \epsilon_{i,t}. \tag{1}$$

where $D_{i,t}$ equals 1 if product i was suppressed at time t, otherwise 0. $\mathbf{X}_{i,t}$ denotes the set of covariates that vary across products and time, ψ_i represents product fixed effects, and η_t represents time (month-day-hour) fixed effects. We restrict the sample to $\{i, t : D_{i,t-1} = 0\}$ so that models represent the conditional probability of suppression given no suppression at time $t-1$.

The first set of covariates describes the two key triggers we identified in § 4.1. To model the non-linearity in Figure 7, we include three indicators for different ranges of price increase from the last featured offer: $1-5\%$, $5-10\%$, and $10+\%$. To model the relationship in Figure 8, we include indicators for whether the last featured offer drops out of the market, whether there are zero "good" alternatives, and an interaction between these two.

The second set of covariates summarizes the available offers for the product on Amazon: the number of offers, whether Amazon itself is a seller, whether there is a FBA seller, the minimum seller price, the maximum seller quality, and the maximum number of seller ratings. The purpose of this set is to validate that our focus on the last featured offer does not miss anything important about the other Amazon offers. Finally, our third set of covariates capture the effects of competition. We include indicators for whether the

[6] Amazon (the seller) does not have a positive feedback percentage or ratings count. Following prior work [37], we assign it a positive feedback percentage of 100 and a rating count of 1 M.

	(1)	(2)	(3)
featured offer drops out	0.0068***	0.0065***	0.0065***
	(0.0005)	(0.0005)	(0.0005)
no good alternatives	0.0027***	0.0026***	0.0024***
	(0.0004)	(0.0004)	(0.0004)
drop out × no good alternatives	0.0504***	0.0478***	0.0480***
	(0.0029)	(0.0029)	(0.0029)
featured offer price ↑ 1 − 5%	0.0061***	0.0062***	0.0063***
	(0.0009)	(0.0010)	(0.0009)
featured offer price ↑ 5 − 10%	0.0188***	0.0188***	0.0190***
	(0.0030)	(0.0030)	(0.0030)
featured offer price ↑ 10 + %	0.0428***	0.0428***	0.0429***
	(0.0038)	(0.0038)	(0.0038)
number of offers on Amazon		-0.0006***	-0.0006***
		(0.0001)	(0.0001)
has FBA seller		-0.0018***	-0.0018***
		(0.0002)	(0.0002)
has Amazon.com seller		-0.0064***	-0.0064***
		(0.0008)	(0.0008)
minimum log(price) on Amazon		0.0078***	0.0067***
		(0.0007)	(0.0007)
maximum log(quality) on Amazon		-0.0006*	-0.0006*
		(0.0003)	(0.0003)
maximum log(ratings) on Amazon		-0.0004***	-0.0004***
		(0.0001)	(0.0001)
price on Walmart < price on Amazon			0.0022***
			(0.0005)
price on eBay < price on Amazon			0.0006*
			(0.0003)
price on Others' < price on Amazon			0.0005***
			(0.0001)
Observations	21.2M	21.1M	21.1M
R^2	0.101	0.104	0.104
R^2 Within	0.038	0.041	0.041

Table 1: Determinants of Buy Box Suppression. Standard errors are clustered at the product-level. *, **, and * denote significance at the 1, 5, and 10 percent levels.**

product is available on Walmart, eBay, or other competitor sites, indicators for whether the best price on Walmart, eBay, or other competitor sites is below the best price on Amazon, and indicators for whether Walmart, eBay, or other competitors lowered their price between times $t-1$ and t.

We present the estimation results in Table 1. Across all specifications, coefficients are largely consistent, which validates our focus on the immediate triggers of suppression.[7] The most important factor is the combination of the last featured offer exiting the product market and a lack of good alternatives. This raises the probability of suppression by 4.8 percentage points (pp), a 60-fold increase over the baseline suppression risk. The second most important factor is a large price increase from the last featured offer. A price increase of 5 − 10% increases the probability of suppression by 1.90pp (a 24-fold increase) a price increase of 10% or more increases the probability of suppression by 4.29pp (a 53-fold increase).

Turning to the second set of covariates, we see that all coefficient signs make sense: more offers on Amazon, the presence of a FBA seller, the presence of Amazon.com as a seller, higher maximum seller quality, and higher maximum seller ratings all reduce the risk of suppression, while a higher minimum price increases the risk of suppression. The presence of Amazon.com as a seller reduces the risk of suppression by 0.64pp, which aligns with evidence of self-preferencing [27, 33, 37].

Finally, turning to the effects of price competition, we find small and insignificant impacts of price decreases on competitor sites between time $t-1$ and t. However, we do observe that the interaction between competitor prices and prices on Amazon matters. For example, if the price on Walmart is below the minimum price on Amazon at time t, the risk of suppression increases by 0.22pp (a 4-fold increase). Thus, while lower prices on competitor websites do affect the probability of suppression, their impact is smaller than the immediate triggers on Amazon.

5 Effects of Buy Box Suppression

In this section, we estimate effects on seller outcomes (search rank, sales rank, and ad placement) to address **RQ 2** and effects on competitor prices to address **RQ 3**.

5.1 Estimation Approach

As noted in § 2.2, our setting is characterized by general treatment assignment and potential carryover effects. Therefore, we consider two recent estimators that accommodate these features: PanelMatch [28, 36] and FEct [34]. We adopt PanelMatch because placebo tests and pre-trends are indistinguishable from zero and simulations suggest FEct is more susceptible to carryover (see § A.2).

Estimand. Our estimand is the average treatment effect on the treated (ATT) after F hours of continuous suppression:

$$ATT_F = \mathbb{E}[Y_{i,t+F}(\mathbf{1}_F) - Y_{i,t+F}(\mathbf{0}_F) \mid \{D_{i,t+s}\}_{s=0}^{F} = \mathbf{1}_F,\ D_{i,t-1} = 0] \quad (2)$$

where $D_{i,t}$ represents whether product i was suppressed at time t and $Y_{i,t+F}(\cdots)$ represents potential outcomes after F hours. We estimate effects up to $F = 48$ hours, which is the average suppression length (see Figure 5). We restrict analysis to suppression events triggered by the last featured offer exiting the market, which is the most important trigger identified in § 4. This subset yields strong pre-suppression balance (see Figure 14) and passes placebo tests (see below). In total, 1,910 suppression events lasted for at least 48 hours after the featured offer exited.

Estimator. PanelMatch consists of three steps. First, for each product i that becomes suppressed at time t, it creates a matched set, $M_{i,t}$, of non-suppressed products with identical suppression histories over the previous L hours. We match on $L = 12$ hours of suppression history based on the reporting delay in sales ranks [41]. Second, it refines matched sets using inverse propensity weights, so that product i' in $M_{i,t}$ has weight $w_{i,t}^{i'} \propto \hat{e}_{i',t}/(1-\hat{e}_{i',t})$, where $\hat{e}_{i',t} = Pr(D_{i',t} = 1|\mathbf{Z}_{i',t})$ is estimated using logistic regression.[8] Weights are normalized to sum to one and we trim units with extreme propensity scores using the algorithm in [18]. Third, a difference-in-differences estimator is applied to the refined, matched sets:

$$\hat{ATT}_F = \frac{1}{|G|} \sum_{(i,t)\in G} \left\{ (Y_{i,t+F} - Y_{i,t-1}) - \sum_{i'\in M_{i,t}} w_{i,t}^{i'} (Y_{i',t+F} - Y_{i',t-1}) \right\} \quad (3)$$

[7] Results remain robust when we include seller fixed effects, which account for time-invariant seller characteristics such as participation in automated pricing programs.

[8] $\mathbf{Z}_{i',t}$ includes 12 lags of history for all six outcomes and the five most important covariates in Table 1, and 2 lags of history for all other variables in Table 2.

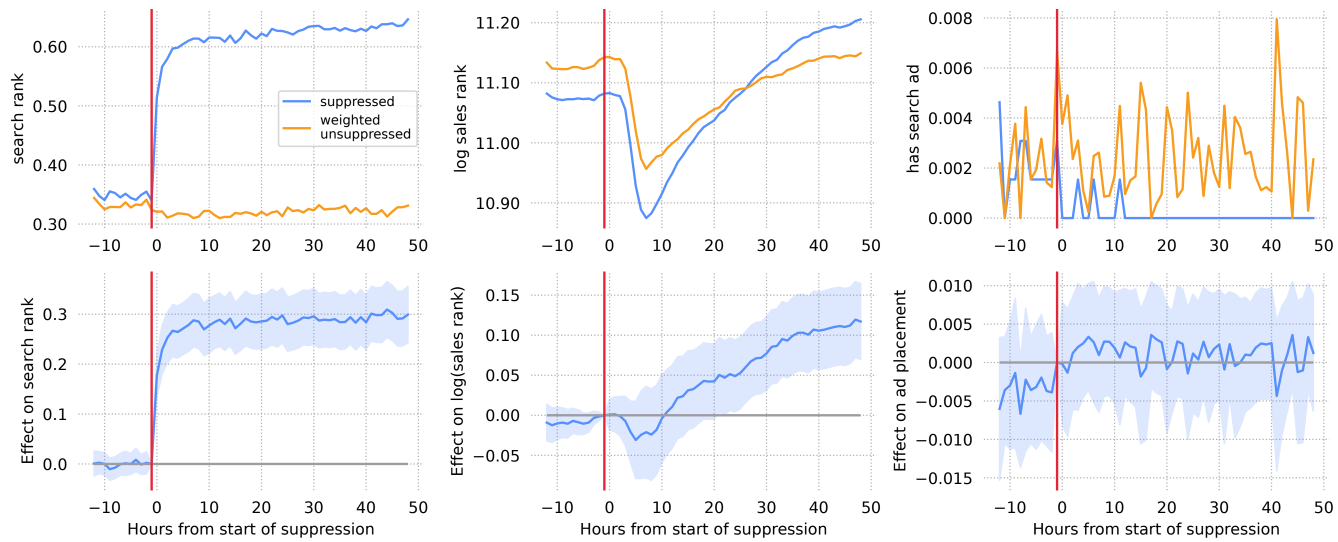

Figure 9: Estimation results for effects of Buy Box suppression on seller outcomes: search rank, sales rank, and ad placement (RQ 2). The top row shows mean trajectories for suppressed products and weighted, unsuppressed products. The bottom row shows estimated effects and 95% confidence intervals.

where G is the set of products suppressed at time t. We calculate standard errors using the first-order Taylor approximation to the asymptotic variance.

Assumption. Our estimates rely on conditional parallel trends: products with identical treatment, outcome, and covariate histories would have followed identical outcome trends absent suppression. This is credible given our detailed controls for Amazon and competitor offers, but could be violated by unobservables such as return rates or inventory levels.

We probe this assumption in two ways. First, pre-trend coefficients are statistically indistinguishable from zero for both product ranks (see Figure 9) and competitor prices (see Figure 10). Second, we conduct a placebo test that exploits the reporting lag in sales ranks. Because sales ranks reflect purchases with a delay of up to 12 hours [41], ranks in the hours immediately after suppression partly capture *pre*-suppression demand. Under a valid design, these hours should produce null effects, which is what we find: both suppressed products and weighted controls experience a similar 20% improvement in sales rank within seven hours of suppression. This pattern is consistent with demand-induced stockout: products sell quickly, the featured offer exits the market, and suppression begins. The impact of suppression on sales rank then emerges after the reporting delay.

5.2 Seller Outcomes

Figure 9 shows our estimation results for the effect of suppression on seller outcomes, along with estimates from the pre-suppression period. Figure 14 shows covariate balance after matching and weighting. Across $L = 12$ lags of history, all continuous covariates have standardized mean differences below 0.18 and all binary covariates have raw mean differences below 0.11. The cost of improving balance through matching and trimming is that the number of suppression events of at least 48 hours is reduced from 1,910 to 644. Imbens and Xu [29] argue that this kind of trimming is important to preserve the credibility of causal estimates.

The first column of Figure 9 shows that suppression leads to an immediate, significant increase in search rank (i.e., a worse ranking). Specifically, search position increases by 17.8pp (60%) within the first hour (95% CI 13.5–22.1pp). Within 24 hours, search position is 28.9pp (95%) higher (95% CI 23.4–34.4pp) and within 48 hours, it is 29.2pp (94%) higher (95% CI 23.6–34.7pp). These findings indicate that suppression has an immediate, substantial effect on search rank, with over 60% of the total effect realized within the first hour.

The second column of Figure 9 shows that sales rank remains stable for the first approximately 10 hours after a suppression event. After this point, suppression causes sales rank to increase (i.e., get worse). Within 24 hours, sales rank has increased by 5.1% (95% CI: 0.6–9.7%), and within 48 hours, it has increased by 12.0% (95% CI: 7.2–16.7%). Thus, Buy Box suppression has a delayed, but substantial effect on sales rank. In Figure 15, we show that results for search and sales rank are robust to alternative choices for analysis subset, lead horizon, matching window, and propensity score trimming.

The third column of Figure 9 shows that suppression completely eliminates products from search ad placements. Although the base rate of search ad placements is only 0.2% (for queries matching the product's name), the placement rate drops to zero for suppressed products after 12 hours.

5.3 Competitor Price Outcomes

Given the substantial impacts on sellers within Amazon, we now examine whether suppression's impacts extend to the broader online marketplace. To expand product coverage in the matched sample, we track the minimum listed price on Walmart and eBay, and other

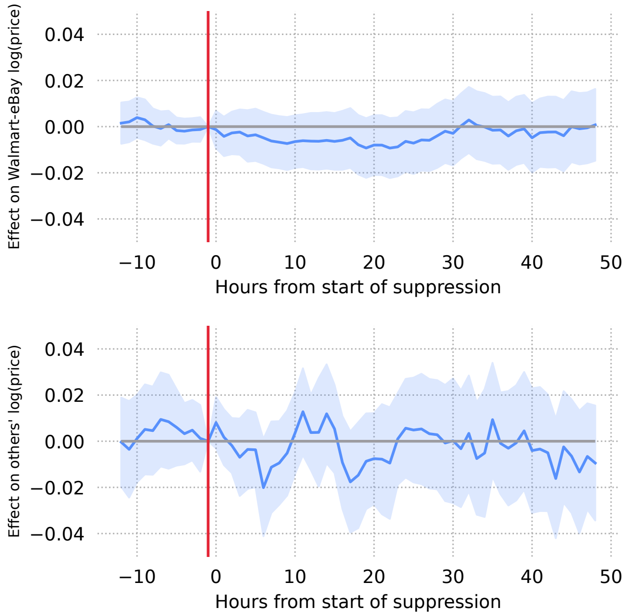

Figure 10: Estimation results for effects of suppression on competitor prices (RQ 3) with 95% confidence intervals.

external sites. Figure 10 shows no statistically significant Walmart-eBay price fluctuations following suppression, with confidence intervals never wider than ±2%. While minimum prices on non-Walmart, non-eBay sites exhibit greater variation, reflecting prices over thousands of competitors, the estimated effects remain insignificant and centered near zero, with confidence intervals never wider than ±4%. In summary, we do not find evidence that suppression affects prices on competitor websites within 48 hours.

6 Discussion

6.1 Summary

This paper examines the dynamics of Buy Box suppression on Amazon. Using a sample of 17,754 Amazon products with hourly observations from March 13 to May 7, 2024, we find that the Buy Box is suppressed in 1.5 M product-hour observations (6.4%) and the median duration of suppression is six hours.

We identify the triggers of Buy Box suppression (**RQ 1**) using a combination of descriptive evidence and regression models. While we find that lower competitor prices have a modest impact on the probability of suppression, the main triggers are changes to the available offers on Amazon. If the last featured offer exits the product market and there are no good alternatives, the probability of suppression increases by 4.8pp (60-fold). If the last featured offer raises their price by at least 10%, the probability of suppression increases by 4.29pp (53-fold). We also find evidence of self-preferencing—when Amazon's own offer is present, the chance of suppression decreases by 0.64pp.

Next, we estimate the dynamic effects of suppression on key seller outcomes (**RQ 2**): a product's search rank, sales rank, and ad placement. We find that suppression immediately causes search rank to increase (i.e., worsen) by 17.8pp within the first hour and remain elevated by 30pp over the next 48 hours. The effect of suppression on sales rank takes longer to manifest, but is also substantial: a product's sales rank is 12% higher (i.e., worse) within the first 48 hours. Buy Box suppression completely eliminates products from search ad placements within 12 hours. Finally, we do not find evidence that suppression affects prices on Walmart, eBay, or other competitor websites (**RQ 3**) within 48 hours.

6.2 Broader Implications

The purpose of **RQ 1** was to compare Amazon's argument that it hides products with no good offers to the FTC's accusation that Amazon responds to lower prices on competitor websites. Our results provide some evidence for the FTC's claims, but the predominant reasons for suppression align closely with Amazon's public explanations (see Figure 1 and [2]). However, a critical qualifier is that these results represent behavior between March and May, 2024, which is five years after Amazon repealed its explicit price parity policy and six months after the FTC filed its lawsuit. Sellers' contemporary decisions about whether or not to lower prices off-Amazon are certainly shaped by Amazon's many years of price parity policies, which other research has found to have anti-competitive effects [35, 47]. Credible fear of retaliation could still chill the competitive environment.

The motivation behind **RQ 2** was to understand how suppression impacts sellers. Our findings substantiate first-hand seller accounts about the considerable impact of suppression on product visibility, through search results and ads, and ultimately on sales. This demonstrates that Buy Box suppression is a strong and swift intervention that Amazon uses to discipline third-party sellers on its platform. The substantial penalties imposed on third-party sellers highlight Amazon's control over its marketplace. As a result, Buy Box suppression can shape seller behavior, potentially pressuring sellers to align with Amazon's pricing and operational preferences.

The impact of suppression might also extend to sellers on competitor websites (**RQ 3**). However, we do not find evidence of significant price responses on Walmart, eBay, or other competitor sites within 48 hours. However, these estimates are inherently limited in scope: they represent reactions to individual suppression events rather than reactions to system-wide overhauls of Amazon's suppression policies. They are also limited in time: individual seller responses might take longer than two days to play out.

6.3 Limitations

The primary limitation of our study is its timing, which takes place five years after Amazon repealed its explicit price parity policy and six months after the FTC filed its lawsuit. As a result, our findings do not describe behavior in these earlier, critical periods, nor do our results evaluate the cumulative impact of Amazon's pricing policies since their inception. Second, even though our dataset covers 59,301 unique competitor websites, it still underrepresents Temu and Shein, which is important given Amazon's significant, and increasing, fraction of sellers based in China [30]. Finally, although we collected a rich set of product covariates, as external researchers, we cannot observe all factors that may drive Buy Box suppression, such as seller return rates or inventory levels.

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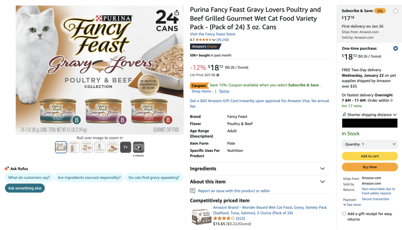
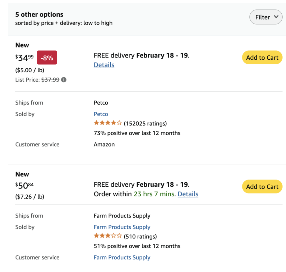
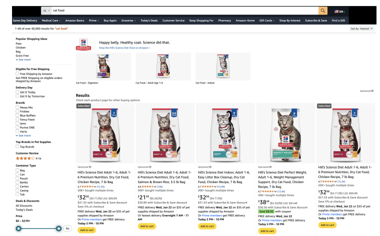


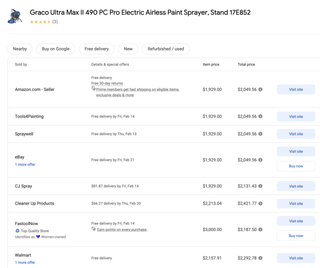
(a) Amazon product page



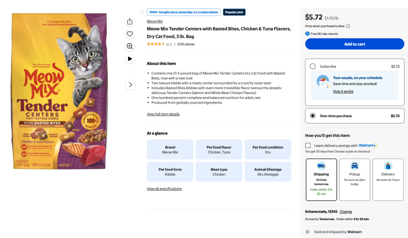
(b) Amazon All Offers page



(c) Amazon search page



(d) Google Shopping product page



(e) Walmart product page

Figure 11: Examples of the five webpages that we scraped for each product-hour.

A Appendix

A.1 Data Collection Details

On the Amazon product page, we extracted the:

- offer price
- delivery price
- list price
- featured seller
- featured seller URL
- featured shipper
- prime eligibility
- sales rank(s)
- date first available
- alternative product recommendations
- number of ratings
- rating score
- availability
- condition
- category
- number of additional offers
- whether the Buy Box was suppressed

For each offer on the first page of Amazon "All Offers" (i.e., up to 10), we extracted the:

- offer price
- delivery price
- seller
- seller URL
- shipper
- prime eligibility
- number of seller ratings
- positive feedback percentage
- condition

On the Amazon search page, we issued a query for the product's name and recorded the:

- number of results
- rank(s) of the product
- type(s) of results (i.e., ad or organic)

For each offer on the Google Shopping product page, we extracted the:

- competitor URL
- offer price
- delivery price
- condition

Note that each competitor website can list multiple offers. Finally, on the Walmart product page, we extracted the:

- offer price
- featured seller
- number of ratings
- rating score
- availability
- condition
- whether the Buy Box was suppressed

We did not collect delivery price on the Walmart product page because it would have required adding the product to the cart and navigating to the checkout page. It also depended on the total order cost.

A.2 Carryover Simulation

Our simulation builds off of the data generating process in [34]:

	Variable	Not Suppressed Mean	Not Suppressed Std	Suppressed Mean	Suppressed Std
Outcome	Amazon search rank	0.26	0.42	0.65	0.37
	Amazon sales rank	363358	911647	333141	646815
	Amazon ad placement	0.01	0.07	0.00	0.00
	Walmart price	88.18	335.86	113.03	254.12
	minimum eBay price	87.23	321.59	108.02	296.68
	minimum others' price	84.08	324.55	102.84	259.66
Amazon covariate	number of new offers	5.32	3.67	3.97	3.37
	has used offer	0.38	0.49	0.15	0.36
	has offer from Amazon.com	0.48	0.50	0.00	0.02
	has FBA offer	0.55	0.50	0.44	0.50
	minimum Amazon price	89.37	338.47	135.21	326.47
	maximum positive feedback %	98.02	6.40	90.83	15.13
	maximum number of ratings	534114	482962	65760	150551
	featured offer exits	0.01	0.09	0.63	0.48
	featured offer price change	0.00	0.03	0.04	0.17
	0 'good' alternatives	0.05	0.22	0.81	0.40
Competitor covariate	has Walmart offer	0.51	0.50	0.39	0.49
	has eBay offer	0.73	0.45	0.64	0.48
	has other competitor offer	0.89	0.31	0.88	0.33
	Walmart price < Amazon price	0.16	0.37	0.54	0.50
	eBay price < Amazon price	0.39	0.49	0.64	0.48
	others' price < Amazon price	0.54	0.50	0.83	0.38

Table 2: Means and standard deviations, conditional on suppression status, for outcomes and covariates. These statistics combine within- and between-product variation.

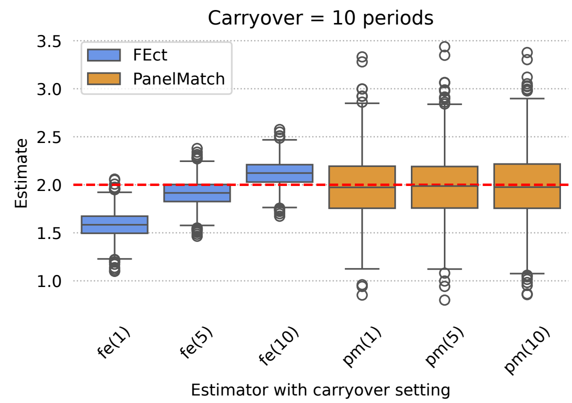


Figure 12: Simulation results comparing PanelMatch and FEct estimates under carryover.

$$Y_{i,t} = \sum_{c=0}^{C} \delta_{i,t-c} D_{i,t-c} + 5 + X_{it,1} + 3X_{it,2} + \alpha_i + \xi_t + \epsilon_{it} \quad (4)$$

where $\delta_{i,t-l} = 0.4 + e_{it}$ and $D_{it}, X_{it,1}, X_{it,2}, \alpha_i$, and ξ_t follow the same distributions as in [34]. C represents the extent of carryover from past treatments. We simulate samples with $N = 500$ units, $T = 50$ time periods, and carryover that persists for $C = 10$ periods. Figure 12 shows estimates of treatment effects $F = 5$ periods after treatment begins over 1,000 iterations of the data generating process. The true treatment effect is $5 * 0.4 = 2$. For each estimator, we compare three different settings of its respective carryover parameter: 1, 5, and 10. This represents the number of lags of treatment to match on in PanelMatch and the number of periods after treatment ends to remove in FEct. We see that FEct is more susceptible to mis-specification of its carryover parameter and that bias does not necessarily decrease as the carryover parameter approaches its true value. We observe similar results in simulations with $C = 5$ and in simulations with two unobserved factors that additionally compare against matrix completion and interactive fixed effects.

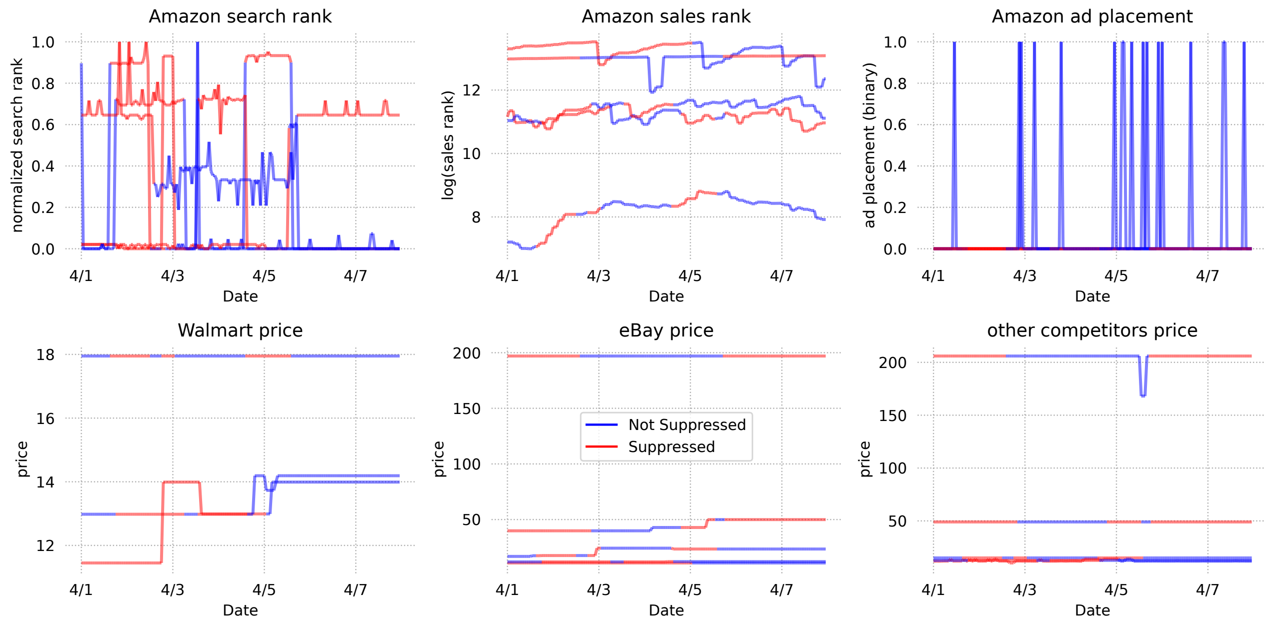


Figure 13: Example trajectories for seller outcome variables (search rank, sales rank, ad placement) and competitor price variables (Walmart, eBay, other competitors). Trajectories are from five example products over the course of one week. Hourly observations where the product was suppressed are highlighted in red.

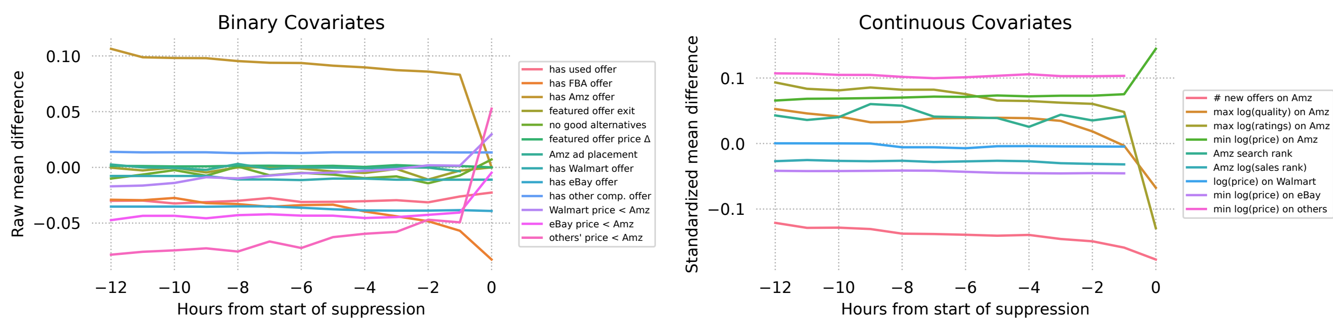


Figure 14: Balance for binary and continuous covariates during the pre-suppression period after matching and weighting. Lagged outcomes are shown through time $t-1$ and covariates are shown through time t.

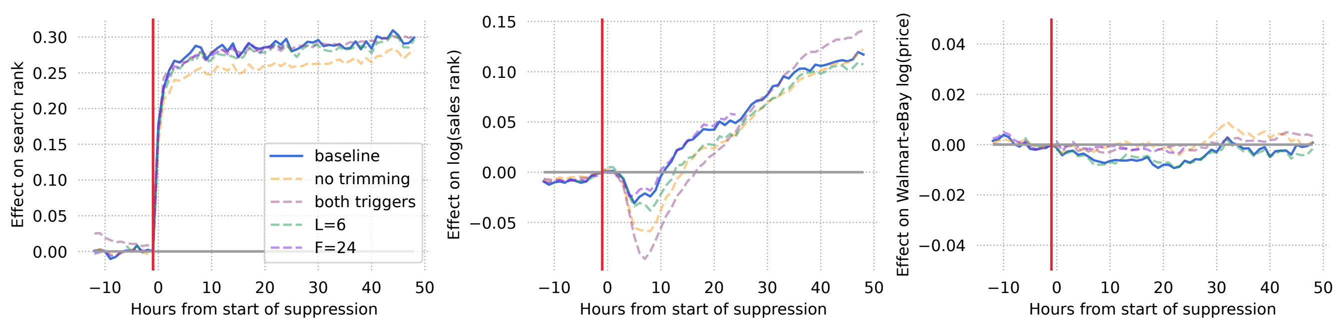


Figure 15: Comparison of estimates for search rank, sales rank, and Walmart-eBay price outcomes under four alternative specifications: (1) analysis subset includes both suppression triggers, (2) lead horizon of $F = 24$ hours, (3) matching window of $L = 6$ hours, and (4) no propensity score trimming.