

Does Amazon Exercise its Market Power? Evidence from Toys R Us*

Leshui He
Bates College

Imke Reimers
Northeastern University

Benjamin Shiller
Brandeis University

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Abstract

Since its founding, Amazon has established a reputation for offering low prices — seemingly well below static profit-maximizing levels. However, recent regulatory scrutiny has revived questions about whether Amazon’s rising market power should worry consumers. Using exogenous variation in market power from the sudden exit of Toys R Us in the United States, we find that Amazon’s prices of toys increased by almost 5%. Consistent with competition being defined at the product level, the price increases are largest for popular products, which are most likely stocked by Toys R Us. Thus, Amazon’s benefits to consumers may be transitory.

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1 Introduction

In the quarter century since its founding, Amazon has grown to a considerable market share in U.S. retail, for example reaching 42% in books and 16% in toys in 2017, while many of its brick-and-mortar retail competitors have disappeared.¹ Its growing dominance has been accompanied by complaints of aggressive conduct toward rivals, suppliers, and workers.² However, Amazon seems to continue to pursue a strategy of charging lower prices to consumers than their position in the market would allow. For example, in concordance with Amazon’s stated mission “to offer its customers the lowest possible prices,” its CEO Jeff Bezos stated in a 60 minutes interview that: “we do price elasticity studies, and every time the math tells us to raise prices [but we do not].”³ From the consumers’ perspective, Amazon has been a friendly behemoth. Matthew Iglesias summarizes this common perception succinctly, calling Amazon “a charitable organization being run by elements of the investment community for the benefit of consumers.”⁴

Recently, regulators have been closely scrutinizing the behavior of Amazon and the other GAFAM companies (Google, Facebook, Apple, Microsoft).⁵ In light of this heightened scrutiny, we re-examine whether Amazon’s growing size and market power pose a threat to consumers. Specifically, we ask whether there is any direct evidence that Amazon takes advantage of the increases in market power stemming from brick-and-mortar exit by increasing its prices. While Amazon has presented itself as a champion of its consumers, its possible exercise of market power may have escaped detection in the past because many displaced retailers are too small and the exit rate too slow for their disappearance to have a noticeable

¹See <https://tinyurl.com/6rmmpwmu> and <https://tinyurl.com/3sbbmxy9>.

²Zhu and Liu (2018) document Amazon lowering suppliers’ welfare by introducing products that compete with bestsellers, and Chen and Tsai (2019) find evidence that Amazon favors its own (first-party) listings by steering consumers away from third-party sellers.

³See <https://tinyurl.com/za78b5jp> and <https://tinyurl.com/dee5t2rk>. Reimers and Waldfogel (2017) also find evidence to this effect among books at Amazon.

⁴<https://tinyurl.com/48rshk5j>

⁵As one example, in her 2020 presidential campaign, Elizabeth Warren proposed a regulatory plan aimed at breaking up America’s largest tech firms. See <https://www.nytimes.com/2019/03/08/us/politics/elizabeth-warren-amazon.html>.

effect. The sudden demise of Toys R Us, a firm accounting for 17% of the U.S. retail toy market shortly before its 2018 exit, provides an opportunity to document how Amazon’s pricing changes when it loses a major category competitor.⁶

We employ a triple-differences strategy to study how the shutdown of Toys R Us affected prices at Amazon. We take advantage of the fact that Toys R Us shut down in the U.S. but not in Canada to investigate the impact on U.S. toy prices, relative to two unimpacted groups of products: non-toys in the U.S. and toys in Canada, where Toys R Us stores continued to operate. The combined use of both control groups allows us to meaningfully control for category- and country-specific shocks to prices, for example due to a toy-specific seasonality or region-specific shipping cost changes.

We find that Toys R Us’s exit significantly increased prices of toys at Amazon, by a sales-weighted average of about 4.7%. Compared to Amazon’s reported 10% price advantage over Toys R Us, these price increases are substantial.⁷ The increases set in quickly after the (rather unexpected) bankruptcy announcement, suggesting that competition lessened quickly, and prices plateaued after the last Toys R Us stores in the U.S. closed. In addition to Amazon’s own price levels, we find a (more temporary) price increase in Amazon’s third-party marketplace. The shutdown also led to a decrease in the frequency of price changes for products sold directly by Amazon, suggesting that Amazon may have actively tracked and reacted to price changes at Toys R Us.

In addition, the price increases are strongest among those products that were most likely to be affected by Toys R Us’s exit. Assuming that the (large but not limitless) brick-and-mortar retailer offered the most popular products to best utilize its shelf space, the price effects should be focused on the most popular products; and we indeed find that the most popular products see the largest price increases. Likewise, we find that the effects are strongest among the largest manufacturers, as well as among heavier products, for which Amazon’s cost advantage was likely smallest. This heterogeneity across products suggests

⁶<https://youtu.be/W9CxiNsX0zs?t=42>

⁷<https://tinyurl.com/4bdnj5p2>

that Amazon and Toys R Us competed with each other on the product level, rather than as platforms.

While Amazon has to date pursued a strategy of gaining consumers’ trust by promising lower prices, our results indicate that Amazon does—in contrast to its ostensible concern for “trust”—use its market power to charge higher prices. This will raise questions about its effect on consumers as its competitors continue to disappear. Consequently, analyses of the effects of competitor exit could take on similar roles as retrospective merger analyses (e.g., [Miller and Weinberg, 2017](#); [Igami and Uetake, 2020](#); [Prager and Schmitt, 2021](#)) in informing regulatory policy.

The remainder of this paper proceeds as follows. In [Section 2](#), we provide an overview of the interplay between online and offline retail with a focus on the toy industry. We also provide evidence, using newspaper mentions, that the timing of Toys R Us’s bankruptcy was unexpected, and we lay out the theoretical forces that influence the effects on Amazon’s prices. [Section 3](#) explains the underlying dataset and our data collection strategy, and [Section 4](#) lays out our triple-differences estimation strategy and presents our main and ancillary results. We conclude in [Section 5](#).

2 Background

2.1 Online vs. Offline Retail

For the purposes of this paper, brick-and-mortar and online retailers differ along two key dimensions. First, their services are differentiated. Brick-and-mortar retailers provide an opportunity for customers to browse and physically evaluate products, and consult with staff before purchasing an item. In fact, browsing in physical stores can be an entertainment and social experience, yielding benefits beyond anticipated consumption value. Online retailers offer a different set of amenities, including customer reviews and individualized recommendation algorithms ([Chevalier and Mayzlin, 2006](#); [Reimers and Waldfogel, 2020](#)). The

second dimension in which online and offline stores differ is their cost structures (Goldfarb and Tucker, 2019). Brick-and-mortar retailers incur costs of stocking and displaying items, providing ample room for an enjoyable experience, as well as concierge and cashier staffing expenses. Online retailers like Amazon avoid these costs, but incur last-mile shipping costs to deliver items to consumer residences. Cavallo (2017) notes that Amazon’s prices differed from offline prices about 70% of the time, and Amazon’s prices tended to be lower.⁸

Due to the inherent cost advantage maintained by many online retailers for most items, many brick-and-mortar outlets have exited their markets over the last two decades. For example, department stores’ floor space has contracted by 11.5% between 2006 and 2016 (and sales shrunk more than twice as fast), while the population grew by 8.3% over the same time period.⁹

2.2 The Toy Landscape and the Toys R Us Shutdown

In recent decades, the toy retailing landscape has been dominated by large specialized retailers (such as Toys R Us with its subsidiary Babies R Us), large general retailers (such as Target and Walmart), and online retailing (Amazon).¹⁰ Compared to the general brick-and-mortar retailers, Toys R Us carried a much larger selection of toy and baby products. Still, because the others operated far more stores, the three brick-and-mortar stores had similar domestic market share.¹¹ In 2015, the toy market shares of Toys R Us, Walmart, and Target in the United States were, respectively, 17%, 23%, and 14%.¹² At the same time, Amazon’s

⁸Resale price maintenance was legal (but presumably used infrequently) under federal law both in the U.S. and Canada over the period relevant for our empirical analyses. https://mcmillan.ca/Files/ARTICLE_Price_Maintenance_View_from_Canada_0310.pdf

⁹See <https://tinyurl.com/37pusuv4>, and <https://tinyurl.com/duhzvk6b>.

¹⁰Toys R Us did operate a website (as do Target and Walmart), but the majority of its business was conducted offline. In 2016, only 7.6% of its revenues originated from direct-to-consumer e-commerce sales. See Toys R Us (2017).

¹¹In 2016, there were 879 Toys R Us stores in the U.S., compared to 4,574 Walmart and 1,802 Target stores. See: Toys R Us (2017), <https://www.statista.com/statistics/269425/total-number-of-walmart-stores-in-the-united-states-by-type/>, and <https://www.statista.com/statistics/255965/total-number-of-target-stores-in-north-america/>.

¹²See <https://youtu.be/W9CxiNsX0zs?t=42>

toy market share was growing rapidly, reaching 12% by 2015 and 16% by 2017.¹³ In sum, the top four toy retailers accounted for about two thirds of all toy sales in 2015.

It was well-known that Toys R Us had been struggling. In financial reports, Toys R Us acknowledged net losses and declining sales, although loss amounts were shrinking: net losses were \$292 million in 2014, \$130 million in 2015, and \$36 million in 2016.¹⁴ Toys R Us also had substantial debt, \$5.2 billion in 2017, mostly attributable to a leveraged buyout in 2005.

Toys R Us filed for Chapter 11 bankruptcy on September 18, 2017 and liquidated its U.S. stores between March and June 2018, when all domestic stores closed.¹⁵ The bankruptcy announcement reportedly surprised investors, because Toys R Us had been able to reorganize its debt numerous times in previous years and no debt payments were imminently due.¹⁶

Empirical evidence from news article mentions also suggests that the bankruptcy announcement was unanticipated and therefore provides a pseudo-natural experiment for investigating the effects of changes in concentration on Amazon’s prices. We use the ProQuest database to find monthly counts of U.S. news articles including the phrase “Toys R Us” in conjunction with “bankruptcy.” Figure 1 plots the count of articles over time. Note that newspaper mentions did not increase prior to its Chapter 11 bankruptcy filing in September 2017 but rose sharply thereafter. Before bankruptcy, mentions were steady and averaged 2.5 per month. In the month that bankruptcy was announced, mentions leapt to 413 and remained above 100 until Toys R Us stores closed.

While all Toys R Us stores in the United States were liquidated and shuttered, Canadian stores remained open through a sale to Fairfax Financial.¹⁷ This was conceivably anticipated.

¹³While toy-specific statistics are difficult to ascertain, Amazon generally dominates e-commerce. For example, in 2018 it accounted for 49.1% of all e-commerce sales. The next largest e-commerce competitor only accounted for 6.6%. See <https://techcrunch.com/2018/07/13/amazons-share-of-the-us-e-commerce-market-is-now-49-or-5-of-all-retail-spend/>.

¹⁴See: [Toys R Us \(2017\)](#)

¹⁵Liquidation was announced in January 2018, and received approval from a bankruptcy court in March.

¹⁶<https://www.reuters.com/article/us-toys-r-us-bankruptcy-timeline/how-5-billion-of-debt-caught-up-with-toys-r-us-idUSKCN1BV0FQ>

¹⁷On April 24, it was announced that the Canadian division would be sold for approximately \$234 million, and would continue to operate the locations under the Toys R Us name.

The Toys R Us 2016 financial report noted that sales in the U.S. declined by 3.1% over the previous year, but sales in Canada grew by 1.1%. The report also presented the result of the 2016 U.S. presidential election as an ongoing risk to its business, as tariffs threatened (but never implemented) by the Trump administration could raise merchandise acquisition costs for its U.S. stores. The Canadian market, in which Toys R Us stores were fairing better and did not shut down, constitutes a useful control group for comparison with the U.S. market.

2.3 Theoretical Framework

A softening of competition usually implies increases in the price level. However, the impact of Toys R Us closing its stores on Amazon's prices may not be as straightforward, for three reasons. First, Amazon is known for charging prices below its profit-maximizing level in other product categories ([Reimers and Waldfogel, 2017](#)), and its prices for toys may not be statically profit-maximizing either. If Amazon's prices are not profit-maximizing, Amazon may not react to changes in competition even if the exit of Toys R Us changes the competitive environment. Second, even though online and offline retailers cannibalize each other's sales in some contexts ([Forman et al., 2009](#); [Gentzkow, 2007](#); [Pozzi, 2013](#); [Wang and Goldfarb, 2017](#)), especially for products sold in both channels ([Brynjolfsson et al., 2009](#)), it is not clear that these results extend to competition between Toys R Us and Amazon. Toys R Us offered a very different experience, one perhaps particularly relevant for toys. It provided an opportunity for customers to browse and physically evaluate products, and consult with staff before purchasing an item. Third, a small theoretical literature suggests that competition may increase prices under certain conditions ([Chen and Riordan, 2008, 2007](#); [Janssen and Moraga-González, 2004](#); [Stiglitz, 1987](#)), with some empirical support ([Chen and Savage, 2011](#)). One condition in particular, that consumers' valuations for platforms are negatively correlated, may be especially applicable for competition between online and offline retailers: Some consumers prefer to visit the store and others prefer the convenience of online shopping.

Even if Amazon's prices respond to changes in the competitive environment, there may

be heterogeneous impacts across products. In particular, we identify two dimensions in which price effects may vary, especially if retailers compete at the product level instead of competing for visits to their platforms. First, the largest brick-and-mortar stores carry no more than several tens of thousands of products, whereas Amazon’s warehouses have seemingly unlimited space. Given more limited shelf space, it is likely that Toys R Us stocked more popular items (or items from larger manufacturers), whereas Amazon can more easily stock all toys in its warehouses, including unpopular ones. If platforms compete at the product level, exit would yield larger impacts for more popular products. Second, online retailers likely experience the largest cost advantage among lighter products, for which last-mile shipping costs are lowest. We illustrate this in Figure A.1, which depicts the relationship between weight and standard shipping costs in the U.S.¹⁸ For those products, it is possible that Toys R Us never posed a real threat to Amazon. If so, the Toys R Us exit should not affect Amazon’s strategy for the lightest products.

This simple representation leaves out two important aspects of the platform. First, like other retailers, Amazon sells products that are manufactured by others.¹⁹ With the shutdown of Toys R Us, the manufacturers lost a major retailer, and Amazon may have gained some bargaining power that could help lower wholesale prices. Since Amazon is one (global) company bargaining with toy manufacturers, its negotiated rates likely apply to Amazon’s U.S. and Canada platforms equally, making toys on Amazon Canada an apt control group in that regard.

Second, in addition to its own retailing division, Amazon includes a marketplace in which smaller sellers can offer their products. The price effects among third-party sellers may be different from those sold directly by Amazon. Third-party sellers likely compete most strongly with each other, so that the loss of an offline retailer may have limited impacts. In turn, these limited impacts could soften any effect on the prices offered directly by Amazon

¹⁸While the figure shows standard shipping costs rather than the true negotiated rates, it is likely that the proprietary negotiated shipping rates that Amazon faces follow similar patterns.

¹⁹For the purposes of this paper, we do not consider Amazon’s own product line, because these products were never offered at Toys R Us.

as well.

3 Data

We collect the data for this study in several steps. First, we identify a set of product categories for our analysis. These include toys and baby products, which are directly affected by Toys R Us’s exit, and four categories which are not, but which may be discretionary purchases used at home: home and kitchen, electronics, pet supplies, and beauty.²⁰ We use data from [Ni et al. \(2019\)](#) to draw a sample of 200,000 products from the universe of products in these categories that are available on Amazon and received at least one review on its U.S. platform between January 2017 and August 2018. For these products, we use Keepa.com’s API to search for and collect detailed price and availability data from Amazon’s U.S. and Canadian platforms. Of the 200,000 products we search for, 182,542 are tracked on Keepa, including 36,469 toys (20%) and 146,073 products in other categories. These make up the underlying set of products we study.

For each of these products, we obtain Amazon prices, cheapest third-party (new) prices, availability, sales ranks, and cumulative customer reviews, from both Amazon’s U.S. and Canadian websites between January 2016 and December 2018. Importantly, all information is product and platform specific. That is, a product’s price, ranking, and other characteristics can vary between the U.S. and Canada platforms. We aggregate these data, for each product and country, to the weekly level and we supplement them with static product characteristics such as the product’s weight and the manufacturer’s identity. The final, product-week-country level dataset includes a total of 24,643,498 observations, including 18,312,720 on the U.S. platform and 6,330,778 from Canada. Note, however, that we do not observe all variables in each product-week. For example, our main variable of interest, the Amazon price, is only available for 6,764,653 observations; it is not available for products not offered

²⁰Amazon’s definition of the toys and baby products category includes sports equipment and other hobby goods. These products should not be available at Toys R Us, and we therefore classify them as non-toys in our analyses.

by Amazon directly or products that are out of stock. By contrast, we observe third-party new prices for 23,036,007 of those observations.

In Table 1, we summarize the main variables of interest, separately for toys in the U.S., for toys in Canada, and for other products in the U.S., across all product-week combinations from 2016 through 2018. A few patterns are clear. First, the price variables are highly skewed, with the means being much larger than the medians across all product groups. As a consequence, we log transform prices in our analyses. Second, toys in Canada seem to be a good control group for toys in the U.S. in the sense that they have similar mean and median prices (in U.S. dollars), price change frequencies, weights, and counts of newly-posted reviews. Third, toys are different from other products in almost all dimensions. On the U.S. platform, the median Amazon price is almost 70% larger for non-toys than for toys (\$25.53 compared to \$15.24), and the gap in average prices is even larger (\$75.95 versus \$28.70). We see similar patterns for 3rd party prices, where the median is about 33% larger for non-toys (\$19.89 versus \$14.95) and the mean is over twice as large. Because these differences are substantial and significant, our main estimation does not solely rely on variation across product groups but rather utilizes variation for identical products across countries as well.²¹

Beyond raw prices, we report product weight, the weekly frequency of price changes, and number of new newly-posted reviews in Table 1. Unlike the raw prices, the price change frequencies and number of newly-posted reviews are quite similar across all three groups. Interpreting the number of new reviews as a proxy for demand, the table suggests that the toys and the other products draw similarly sized crowds. In the empirical estimation, we also examine whether the exit of Toys R Us affected this quantity measure. In addition, the table suggests that non-toys are significantly heavier than toys. An average toy on the U.S. platform only weighs about 23 ounces (1.5 pounds), compared to 73 ounces (5.3 pounds) among other products. Again, all distributions are highly skewed.

²¹While in our main estimation we control for level differences with an extensive set of interacted fixed effects, we also perform coarsened exact matching exercises to create better control groups in the appendix. The results from these exercises provide strong support for our main findings.

Finally, our data include information about the product’s manufacturer for about 50% of all toys. Among those, the five most common manufacturers are Mattel, Hasbro, Konami, Disney and Lego. This is reassuring: three of these—Mattel, Hasbro and Lego—are among the four toy manufacturers with the largest market shares worldwide.²²

4 Empirical Strategy and Results

4.1 Empirical Strategy

To estimate the impact of Toys R Us’ bankruptcy on toy prices at Amazon, one could use a simple difference-in-differences estimation strategy, where the control group either comprises toys in a non-impacted country (Canada) or other categories of products in the same country (United States). For example, one could compare toy prices to prices of other products by restricting the data to the U.S. and regressing:

$$\ln(P)_{it} = \beta_1 After_t \times Toy_i + \gamma_i + \mu_t + \epsilon_{it}, \quad (1)$$

where $\ln(P)_{it}$ is the natural log of the price of product i in period t , $After_t$ is an indicator that equals 1 after exit, and Toy_i is an indicator that is 1 for all toys and baby products. Further, γ_i and μ_t denote product and time fixed effects, respectively.

Alternatively, one could compare toy prices in the U.S. to toy prices in Canada (where Toys R Us continued operations) by restricting the data to toys and regressing:

$$\ln(P)_{ict} = \beta_1 After_t \times US_c + \beta_2 Exchange_{ct} + \phi_{it} + \psi_{ic} + \epsilon_{itc}, \quad (2)$$

where the c subscript denotes the country (U.S. or Canada), US_c is an indicator equal to 1 when the country is the United States, and $Exchange_{ct}$ is the exchange rate in period t between the U.S. and country c . Note that the fixed effects can be more involved here, as ϕ_{it}

²²See <https://www.statista.com/statistics/241241/revenue-of-major-toy-companies-worldwide/>.

and ψ_{ic} denote fixed effects for pairwise combinations of product and period and of product and country, respectively.

The assumption for either of these difference-in-differences estimation strategies is that the treatment and control groups had similar shocks to demand (tastes) and supply (wholesale costs) over time. However, although each of the control groups is intuitively reasonable and similar to control groups used in other prominent papers, either or both groups may be imperfect. The first control group, non-toys in the U.S., may be an imperfect control for toys in the U.S. for three reasons. First, the seasonality of the demand for toys may differ from that of similar groups. Christmas is a prime example of this. Second, one toy retailer’s exit impacts the other retailers’ bargaining power with toy manufacturers, which may drive down Amazon’s wholesale prices for toys. Third, and counter to the second point, if quantities decline and manufacturers benefit less from economies of scale, higher manufacturing costs may be passed on via higher wholesale costs. The second control group, toys in Canada, may also be an imperfect control if demand shocks are regional or interact with cultural differences, or if there are region-specific trends in shipping costs.

For these reasons, we combine the two approaches in a triple-differences estimation strategy. That is, we follow four groups of products over time: toys and non-toys, in the U.S. and in Canada. Toys in Canada capture extraneous trends in toy prices due to supply-side factors that are unrelated to the impact of increased concentration in the downstream market to U.S. consumers. Likewise, non-toys in the U.S. form an additional control group to account for country-specific price trends. After controlling for these extraneous factors, the marginal change in the prices of toys following the shutdown reflects the impact of retailer exit in the downstream market to consumers.

Formally, we employ the following model:

$$\ln(P)_{ict} = \beta_1 US_c \times Toy_i \times After_t + \phi_{it} + \omega_{ct} + \psi_{ic} + \epsilon_{ict}, \quad (3)$$

where ϕ_{it} , ω_{ct} , and ψ_{ic} are fixed effects for each pairwise combination of product IDs, time period, and country. The fixed effects ϕ_{it} capture product-specific trends in prices over time, thus accounting for changes in Amazon’s bargaining power with toy manufacturers after Toys R Us initiated exit in the U.S. The fixed effects ω_{ct} capture regional differences in seasonality and time trends, including exchange rates and shipping costs; and the fixed effects ψ_{ic} control for ex-ante product-specific differences in the price level between the countries, for example due to taste differences.²³ Then, β_1 captures the impact of Toys R Us’s shutdown on toy prices.

4.2 Main Results

We primarily use the bankruptcy announcement as the treatment date when we apply this estimation framework to Toys R Us’s exit. Note that after a firm announces bankruptcy, their suppliers usually demand up-front payment for items instead of providing items on credit, resulting in reduced inventory at the bankrupt retailer (Ziobro, 2017). Hence, competition is reduced after the bankruptcy announcement, even before the bankrupt firm has formally exited. Note, however, that our results are robust to other choices of treatment date, as we show further below.

4.2.1 Amazon Prices

The first three columns of Table 2, Panel A, report results from the three models described in Section 4.1. Note that all three models yield comparable results. Our first specification, comparing toys and non-toys in the U.S., yields a price increase of 3.9% ($= e^{0.0384} - 1$). This approach avoids issues arising from differences across countries, but it cannot explicitly account for differences in demand or supply trends across product groups. Our second approach compares the same toys in the U.S. and in Canada, and finds a price increase of 2.7% ($= e^{0.0265} - 1$). However, this approach cannot account for country-specific trends. In

²³Note that these pairwise fixed effects are identified because four groups of products are followed over time: each combination of country and toy indicator.

our main specification, in column 3, we find that Toys R Us’s exit led to an average toy price increase of 3.2% ($= e^{0.0312} - 1$).²⁴ We later weight the price increases across toys according to their popularity, finding an even larger impact.

4.2.2 Other Outcomes

Related outcome measures bolster support for the claim that the competitive pressure from Toys R Us impacted Amazon’s pricing. We employ the full model from Equation 3 with three alternative outcome measures: prices set by third-party sellers on Amazon’s platform, the frequency in which Amazon changes the offer price, and the number of newly-posted consumer-written reviews, which we use as a proxy for the sales quantity.

We present the results in columns 4 through 6 of Table 2, Panel A. Note, in column 4, that third-party seller price increases are similar to Amazon’s — they rise by 2.8% ($= e^{0.0274} - 1$) in the U.S. following the bankruptcy announcement. Next, note in column 5 that Amazon changes the prices of its products less frequently after Toys R Us’s bankruptcy. This suggests that Amazon’s pricing algorithm incorporated copycat pricing (Assad et al., 2020; Brown and MacKay, 2020; Cavallo, 2017; Fisher et al., 2018), whereby it dynamically adjusts its price to track brick-and-mortar competitors’ (e.g., Toys R Us’s) price changes. Finally, note in column 6 that the log number of newly-posted customer reviews rises for toys on the U.S. platform, suggesting that sales of toys in the U.S. increased despite Amazon raising prices. Thus, Toys R Us appears to have cannibalized toy sales at Amazon prior to its exit.

4.2.3 Treatment Timing

The prolonged process of bankruptcy and liquidation implies that the appropriate treatment date is not obvious. We therefore delve into the timing of the price increases. Specifically, we use a model similar to the one presented in Equation 3, with one difference. We interact

²⁴One might be worried that the products from the other categories are not a good match for the treated products. We address this concern in two ways: We apply coarsened exact matching and we estimate separate regressions for each product category in the control group in the appendix, finding very similar results.

the treatment-group indicator ($U.S. \times toy$) with monthly fixed effects instead of a single indicator that equals 1 after bankruptcy filing. The coefficients on these interactions and the corresponding 95% confidence intervals are plotted in Figure 2. The figure depicts two useful observations. First, no pre-trends are apparent, which provides support for our identification strategy. Second, the price of toys gradually rose in the U.S. during the first few months after the bankruptcy announcement, before a large increase in December 2017, around Christmas. Price effects then level off, and remain above pre-bankruptcy levels through 2018. No noticeable incremental changes occur around the dates in which Toys R Us began liquidating its stores (March 2018) nor when they closed stores for good (June 2018).

The large, positive coefficients in December of each year, apparent in Figure 2, suggest that seasonal toy price increases may be particularly large in the U.S. Out of the concern that toy price increases during the Christmas season arise for reasons that are unrelated to Toys R Us’s exit, we re-estimate the regression reported in column 3 of Table 2, Panel A, omitting the last four weeks of each year. We find that the treatment coefficient does not change meaningfully (0.0312, SE:0.0071), because the rise in toy prices around Christmas in 2017 (after bankruptcy) was similar to the rise in toy prices around Christmas in 2016 (before bankruptcy). Hence, U.S. toy prices in the pre- and post-bankruptcy periods are nearly equally impacted by Christmas seasonality.

In Panel B of Table 2, we explore whether the effect on each outcome variable is sensitive to the assumed treatment date. Specifically, we interact each of the three timing thresholds (bankruptcy announcement, liquidation, final store closings) with the treatment group determinant ($U.S. \times toy$). Each time period is defined to be non-overlapping. Hence, these coefficients reflect the change in prices relative to the period prior to Toys R Us’s bankruptcy announcement.

As expected from Figure 2, the impact of exit on Amazon’s price levels (column 3) is similar for all three time periods following the bankruptcy announcement. However, the rate

of price *changes* for toys on Amazon’s U.S. platform (column 5) did not significantly decline until after Toys R Us had fully exited the U.S. market. In column 6, newly-posted customer reviews (a proxy for sales) for toy products on Amazon’s U.S. website steadily increased over the period, and are highest after all stores closed their doors. These results offer additional evidence that Toys R Us was a reasonably close competitor for Amazon, and altered its pricing patterns following bankruptcy. Finally, in column 4, we find the increase in third-party seller prices is only statistically significant for the first two treatment periods. After store closing, marketplace prices seem to have returned to their old equilibrium, making Amazon’s (first-party) sustained price increases particularly notable.

4.3 Heterogeneous Impacts

Thus far, we have examined the average effect of Toys R Us’s exit on the prices of all toys on Amazon’s U.S. platform. However, these impacts may vary across products. The extent of heterogeneous impacts depends on whether Amazon and Toys R Us competed at the platform level, or at the product level. For example, suppose consumers visit a store based on their perception of the store’s tendency to offer low prices. Consumers may or may not know ex-ante which products, or even which category of products, they intend to purchase. Then, Amazon likely responds to Toys R Us’s presence by offering low prices on all toy products, including those not offered at Toys R Us. Alternatively, if competition is at the product level, then Toys R Us’s presence induces Amazon to lower prices only for toys also carried by Toys R Us.

We investigate heterogeneous impacts across products in two ways. First, we categorize products according to their likelihood of being offered at Toys R Us. We examine the impact by product popularity, implicitly assuming that Toys R Us was unable to allocate shelf space to the long tail of products available at Amazon ([Brynjolfsson et al., 2003](#)). Second, we categorize products by the likely intensity of competition, as proxied by their weight. Amazon may have had an insurmountable cost advantage for lightweight items, for

which last-mile shipping costs are low. It is therefore possible that Toys R Us did not provide any competitive pressures for lightweight items.

In both sets of analyses, we augment the model in Equation 3 by interacting the triple interaction ($\text{toy} \times \text{U.S.} \times \text{after}$) with indicators for quintiles of product characteristics (popularity or weight). The results for popularity are shown in columns 1-3 of Table 3. Note that consistent with Brynjolfsson et al. (2009), the impacts of Toys R Us’s exit are generally strongest for the most popular products: those which were most likely offered at Toys R Us as well. The coefficient estimates suggest that Amazon increased prices of popular toys by 5.3% ($= e^{0.052} - 1$), which can be viewed as the price impact of removing a prominent brick-and-mortar competitor that offered the item in question.²⁵

We can also use these estimates to calculate a sales-weighted average price effect across all toys on Amazon, including less popular ones. Using the number of new consumer reviews in each popularity quintile before bankruptcy as a proxy for sales, we find this weighted price effect is 4.7%. Given Amazon’s reported 10% price advantage over Toys R Us (in 2013), these effects are substantial.²⁶ An alternative approach, which measures likely Toys R Us stocking decisions based on the product’s manufacturer (in appendix Section A.3), provides equivalent results.

Next, in columns 4-6, we investigate the impacts by product weight. In column 4, we find lower, possibly even negative, price impacts for the lightest-weight items. This suggests that Amazon and Toys R Us may not have competed directly for these items. The strong relationship between weight and shipping prices supports this interpretation. Publicly available parcel rates (illustrated in appendix Figure A.1) indicate that shipping costs rise quickly with weight. The differences are further amplified with faster delivery. Because Amazon offers free and fast (two-day) shipping on most items for their 100 million Prime subscribers in the United States (as of 2018), shipping heavy packages may be particularly costly for them

²⁵The true impact may be even larger, because popularity is an imperfect measure of Toys R Us offerings. Toys R Us may not have carried all popular products, and hence the most popular group may include some products only sold on Amazon.

²⁶<https://tinyurl.com/4bdnj5p2>

(Reisinger, 2019). In column 5, we find similar impacts for toys sold by third-party sellers. In column 6, we also find that the reduction in the frequency of price changes was largest for heavier items. Hence, we find multiple dimensions of support that Amazon primarily competed with Toys R Us at the product rather than platform level.

5 Conclusion

In the quarter century since its founding, Amazon has established a reputation of being exceptionally consumer-friendly, offering prices far below the static profit-maximizing level. Its pricing strategy is also central to its mission statement, which claims it “strive[s] to offer [its] customers the lowest possible prices.”²⁷ The other GAFAM companies have similarly cultivated images of being more consumer-friendly than the monopolies of old in an attempt to create trust among consumers and employees.²⁸ Consumers may therefore have accepted some harms that accompanied these companies’ growing market power. For example, in Amazon’s case, consumers may have tolerated losing opportunities to browse and physically evaluate products when brick-and-mortar retailers disappear, so long as online prices remained low.

In this paper, we show that Amazon’s generosity toward consumers is not entirely unbounded. Amazon does raise its prices when presented with an increase in market power, just like other profit-maximizing firms would do. In the context of toys, the estimated price increase of around 5% cuts its original price advantage by half. Although Amazon continues to charge low prices, albeit not as low as before retailer exit, there is non-negligible potential for consumer benefits to dissipate further as more physical retailers exit. Furthermore, the COVID-19 pandemic has expedited the shift away from local retailers and towards Amazon, making concerns about Amazon’s conduct in highly-concentrated environments increasingly pertinent.

²⁷<http://panmore.com/amazon-com-inc-vision-statement-mission-statement-analysis>

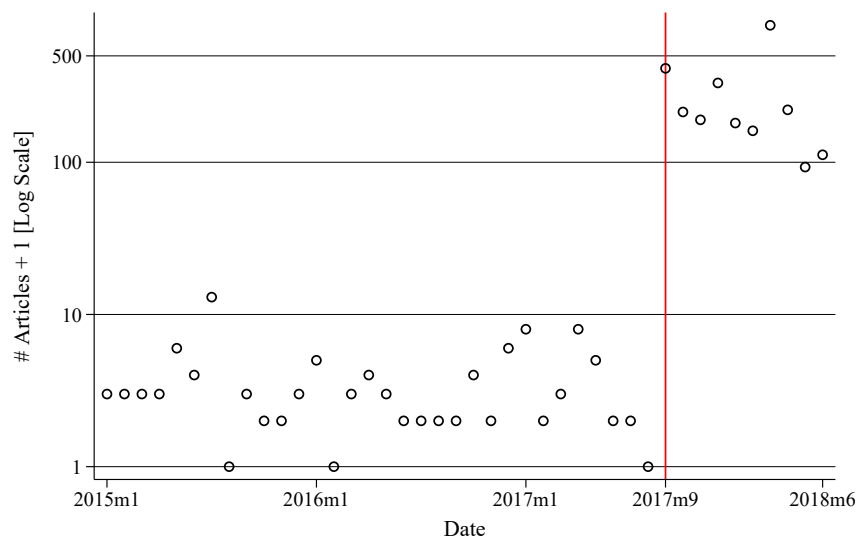
²⁸See, for example, Google’s initial “don’t be evil” corporate code of conduct (<https://gizmodo.com/google-removes-nearly-all-mentions-of-dont-be-evil-from-1826153393>).

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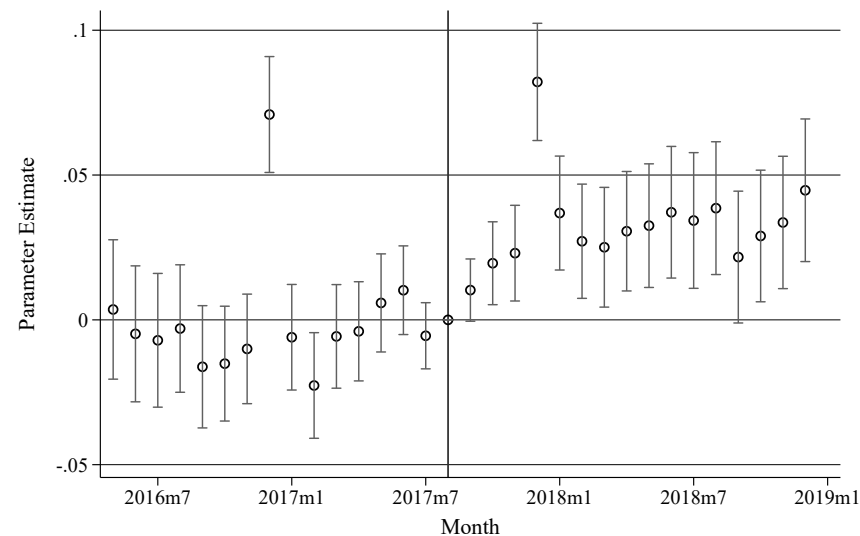
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Figure 1: Monthly News Mentions of “Toys R Us” and “Bankruptcy”



Notes: This figure shows the weekly number of US newspaper articles mentioning “Toys R Us” and “bankruptcy” in the ProQuest database. The vertical line indicates the month Toys R Us formally filed bankruptcy.

Figure 2: Monthly Effect of the Toys R Us’s Shutdown on Amazon Prices



Notes: This figure shows coefficients from a regression of log-Amazon prices on the month-treatment pair indicators, on the full dataset of all products in both countries. Product-date, product-country, and date-country fixed effects are included as controls. The bars indicate 95% confidence intervals, and the vertical line denotes August 2017 – the month before the Toys R Us bankruptcy announcement.

Table 1: Sample Characteristics

	Toys, US		Toys, CA		Non-Toys, US		Total
	Median	Mean	Median	Mean	Median	Mean	N
Amazon Price	15.24	28.70	17.08	27.59	25.53	75.95	6,764,653
3rd Party Price	14.95	33.96	26.49	48.35	19.89	71.45	23,036,007
Amazon Price Changes	0.00	0.96	0.00	0.84	0.00	0.83	6,764,653
New Reviews	0.00	0.15	0.00	0.06	0.00	0.33	14,128,184
Weight (oz)	6.38	22.65	8.01	22.72	8.78	73.05	176,272
Observations	4,368,400		1,986,361		13,944,320		24,642,498
Products	25,227		11,242		115,111		182,542

Notes: The table shows summary statistics for variables of interest, separately for toys in the U.S., toys in Canada, and non-toys in the U.S. All prices are reported in U.S. dollars. The underlying sample includes the 182,542 products. The total observations (column 7) differ across variables because products may be unavailable through some channels during a specific week. The fourth group, non-toys in Canada, is omitted from this table, but is included in the number of observations in column 7.

Table 2: Price and Demand Effects

Panel A: Main Effects						
	Amazon Price			3rd-Party Price	Price Change Frequency	New Reviews
	(1) $\ln(p^A)$	(2) $\ln(p^A)$	(3) $\ln(p^A)$	(4) $\ln(p^{3rd})$	(5) $\# \Delta p^A$	(6) $\ln(R + 1)$
Treatment	0.0384*** (0.0022)	0.0265*** (0.0063)	0.0312*** (0.0070)	0.0274*** (0.0061)	-0.111*** (0.0378)	0.0480*** (0.0053)
Exchange Rate		-0.0409 (0.0513)				
Sample	U.S. only	Toys only	All	All	All	All
Observations	4,032,512	489,744	2,603,985	10,789,660	2,603,985	5,397,899
Adjusted R^2	0.974	0.967	0.980	0.956	0.369	0.474

Panel B: Detailed Timing						
	Amazon Price			3rd-Party Price	Price Change Frequency	New Reviews
	(3) $\ln(p^A)$	(4) $\ln(p^{3rd})$	(5) $\# \Delta p^A$	(6) $\ln(R + 1)$		
<u>Toy \times USA</u>						
... \times Bankruptcy Announced	0.0354*** (0.0064)	0.0274*** (0.0057)	-0.0410 (0.0394)	0.0329*** (0.0051)		
... \times Liquidation Began	0.0277*** (0.0083)	0.0474*** (0.0070)	-0.0693 (0.0476)	0.0464*** (0.0057)		
... \times All Stores Closed	0.0301*** (0.0098)	0.0118 (0.0074)	-0.202*** (0.0527)	0.0595*** (0.0063)		
Sample	All	All	All	All		
Observations	2,603,985	10,789,660	2,603,985	5,397,899		
Adjusted R^2	0.980	0.956	0.369	0.474		

Notes: In Panel A, the first column estimates Equation 1 on the U.S. sample and includes product and time fixed effects; column 2 estimates Equation 2 on the toys sample and includes interacted fixed effects for product and date, and for product and country; columns 3–6 estimate the model in Equation 3—using all products and countries—for various outcome variables. In columns 3–6, fixed effects are included for each pairwise combination of product, time, and country. Panel B repeats columns 3–6, now interacting the treatment indicator with indicators for three non-overlapping time periods (bankruptcy announcement, liquidation, store closings). Standard errors, clustered by product, are reported in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Price and Demand Effects by Popularity and Weight

	Popularity			Weight		
	$\ln(p^A)$	$\ln(p^{3rd})$	$\#\Delta p^A$	$\ln(p^A)$	$\ln(p^{3rd})$	$\#\Delta p^A$
<u>Toy \times USA</u>						
$\dots \times 1^{st}$ Quintile	0.0219 (0.0219)	-0.00955 (0.00993)	-0.188* (0.0975)	-0.0424** (0.0206)	0.0236 (0.0161)	0.0573 (0.0917)
$\dots \times 2^{nd}$ Quintile	0.00899 (0.0152)	0.0198* (0.0111)	-0.0728 (0.0787)	0.0373*** (0.0131)	0.0333*** (0.0111)	-0.0849 (0.0736)
$\dots \times 3^{rd}$ Quintile	0.0219 (0.0154)	0.0124 (0.0119)	-0.0363 (0.0812)	0.0606*** (0.0135)	0.0178** (0.00910)	-0.141* (0.0785)
$\dots \times 4^{th}$ Quintile	0.0402*** (0.0122)	0.0451*** (0.0121)	-0.159** (0.0680)	0.0367*** (0.0123)	0.0318*** (0.00867)	-0.0732 (0.0717)
$\dots \times 5^{th}$ Quintile	0.0520*** (0.0108)	0.0658*** (0.0122)	-0.145** (0.0687)	0.0449*** (0.0116)	0.0305*** (0.00902)	-0.262*** (0.0713)
Observations	2,358,567	9,687,472	2,358,567	2,603,226	10,732,808	2,603,226
Adjusted R^2	0.980	0.956	0.367	0.981	0.956	0.369

Notes: A variant of the model in Equation 3—using both toys in Canada and non-toys in the U.S. as control groups—is estimated for various outcome variables. The treatment indicator (toy \times country=usa \times after) is interacted with product characteristics (quintiles of either popularity or weight). All specifications include fixed effects for each pairwise combination of date, product id, and country. Standard errors, clustered by product, are reported in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

A Robustness Analyses

A.1 Coarsened Exact Matching

The main analysis uses a large set of control products, including beauty, electronics, home and kitchen, and pet supplies. We chose these groups because they are somewhat related to toys and baby products. For example, like toys and baby products, electronics are popular as Christmas presents, and all products are designed predominantly for home use. However, as we show in Table 1, there are significant differences across the product groups, which raises issues if these differences are not captured by our large set of interacted fixed effects. We therefore try to provide a closer control group here, by using coarsened exact matching.

We first match the toys in our dataset with products from the other categories on several pre-treatment dimensions. In particular, we create 50 categories of equal range for each of six variables: (1) the product’s weight, (2) its volume, as well as averages of (3) Amazon price, (4) third-party price, (5) weekly price change frequency, and (6) weekly new reviews, between January and August 2017. We find exact matches along the relevant categorized variables between toys and other products. Specifically, we choose subsets of these dimensions to keep the numbers of observations for each regression large. For the Amazon price and Amazon price change regressions, we match products along dimensions (1), (2), (3), (5) and (6); and for the third-party price and reviews regressions, we use dimensions (1), (2), (4) and (6). We use these observations to run (weighted) regressions of the general form given in Equation (3).

The results, which mirror those in Table 2, are reported in Table A.1. The estimated effects on both Amazon and third-party prices are almost identical to those in the main analyses, suggesting increases of 3.0% and 3.2%, respectively. That is, the price effects we estimate in the main analysis are very robust to our choice of the control group. By contrast, the effects on the frequency of price changes and the number of new reviews are much smaller here than in the main analysis and no longer statistically significant.

A.2 Individual Control Groups

The control group in the main paper consists of five product categories: home and kitchen; electronics; pet supplies; hobby (which we spun off the toy category); and beauty. To see if the results are driven by one or two specific product groups, we estimate the regressions from equations (1) and (3) for each individual control group, dropping all products from the other control product groups.²⁹

The results are reported in Table A.2, sorted from the largest control group to the smallest, while the number of toys and baby products across all control groups is 10,820 for the U.S.-only

²⁹We also created an “Unassigned” control group category, which includes subcategories that appear to be an odd fit for the parent category. The largest subcategory here is “Automotive Parts and Accessories.”

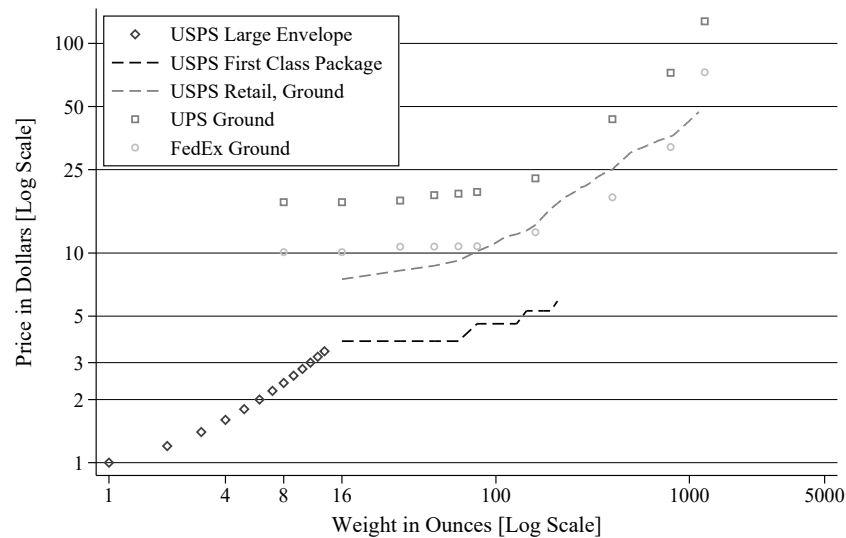
specifications, and 4,900 for the full specifications due to the smaller number of toys available at Amazon’s Canadian platform together with the elaborate set of interacted fixed effects. The odd-numbered columns show the coefficients from the simple difference-in-differences analysis using only U.S. data, and the even-numbered columns report results from the full triple-differences model. All estimated coefficients are positive and similar in magnitude, ranging from 0.021 to 0.042. The simple difference-in-differences coefficients are highly statistically significant for all datasets. The coefficients from the full model are statistically significant for all samples except when the controls groups are limited to the “hobby” (p-value = 0.16, with 542 unique control products) and “beauty” (p-value = 0.42, with 169 unique control products) categories.

A.3 Heterogeneity by Manufacturer

In the main text, we use a product’s popularity on Amazon to proxy for its availability at Toys R Us. An alternative approach distinguishes between products by different manufacturers. For the 18,261 toys and baby products in our data for which we observe the manufacturer’s identity, we assign a “major manufacturer” dummy to those that are listed among the “Top 30 Toy Brands in the World.”³⁰ We thus divide the toys in our dataset into three groups: those without manufacturer information (18,125 products), those by “small” manufacturers that are not in the Top 30 (16,251 products), and “major” manufacturers that are included in the list (2,010 products). We then repeat our analyses from above, interacting these manufacturer “size” indicators with the treatment indicator, in Table A.3. Consistent with the results across popularity quintiles, we find evidence that the positive Amazon price effects are largest among larger manufacturers (column 1), although the coefficient is somewhat imprecisely estimated, likely due to the relatively small group size. The remaining columns also support these patterns, as the effects on third-party prices and Amazon price changes are strongest for the largest manufacturers. The only exception, our proxy for demand, increased the least for large manufacturers, perhaps because the larger price increases disproportionately drew consumers to other toys, which were now relatively cheaper.

³⁰See <https://farmtoysforkidsandfun.com/toy-brands-list/>. While this list is not necessarily exhaustive, it does identify the undisputed top brands.

Figure A.1: Shipping Prices



Notes: Shipping costs were obtained from public notices and shipping calculators [shipping from Waltham MA (02453) to Boston MA (02108)]. United States Postal Service commercial parcel prices (local, zones 1 and 2) were obtained from public notices: https://pe.usps.com/text/dmm300/Notice123.htm#_c096. For FedEx and United Parcel Service (UPS), weight-varying prices were obtained from online price calculators by varying weight for a 100 cubic inch parcel shipped from Waltham Massachusetts (ZIP code 02453) to Boston Massachusetts (ZIP code 02108).

Table A.1: Price and Demand Effects — Coarsened Exact Matching

	Amazon Price	3rd-Party Price	Price Change Frequency	New Reviews
	(3) $\ln(p^A)$	(4) $\ln(p^{3rd})$	(5) $\# \Delta p^A$	(6) $\ln(R + 1)$
Treatment	0.0294*** (0.00790)	0.0313*** (0.00622)	-0.0126 (0.0425)	0.00559 (0.00418)
Observations	1,815,777	8,674,014	1,815,777	3,386,474
Adjusted R^2	0.963	0.952	0.364	0.359

Notes: The model in Equation 3 is estimated for various outcome variables, using weights from coarsened exact matching. Fixed effects are included for each pairwise combination of product, time, and country. Standard errors, clustered by product, are reported in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.2: Price Effects — Separate Control Groups

	Home			Electronics		Pets		Hobby		Beauty		Unassigned	
	(1) US	(2) Both	(3) US	(4) Both	(5) US	(6) Both	(7) US	(8) Both	(9) US	(10) Both	(11) US	(12) Both	
Treatment	0.0410*** (0.002)	0.0383*** (0.008)	0.0292*** (0.003)	0.0213*** (0.009)	0.0418*** (0.003)	0.0206* (0.011)	0.0238*** (0.005)	0.0232 (0.017)	0.0531*** (0.010)	0.0327 (0.040)	0.0406*** (0.002)	0.0377*** (0.008)	
Observations	2,819,485	1,778,368	1,354,002	922,340	1,264,830	781,744	845,593	551,802	796,384	505,755	2,849,311	1,801,311	
Adjusted R^2	0.972	0.978	0.978	0.984	0.954	0.969	0.962	0.973	0.956	0.967	0.972	0.978	
Control ASINs	27,285	12,754	9,006	4,120	6,205	2,629	987	542	452	169	27,647	12,963	

Notes: The models in Equations 1 and 3 are estimated for the log-Amazon price variable, including toys and subsets of the control groups. In odd-numbered columns (“US”), fixed effects are included for each product i and week t . In even-numbered columns (“Both”), fixed effects include each pairwise combination of product, time, and country. Standard errors, clustered by product, are reported in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.3: Price and Demand Effects across Manufacturers

	Amazon Price	3rd-Party Price	Price Change Frequency	New Reviews
	(3) $\ln(p^A)$	(4) $\ln(p^{3rd})$	(5) $\# \Delta p^A$	(6) $\ln(R + 1)$
<hr/> Toy \times USA <hr/>				
... \times No Manufacturer Listed	0.0279*** (0.00906)	0.0264*** (0.00757)	-0.0645 (0.0506)	0.0517*** (0.00621)
... \times Other Manufacturer	0.0322*** (0.0101)	0.0233*** (0.00877)	-0.148*** (0.0533)	0.0504*** (0.00669)
... \times Major Manufacturer	0.0477* (0.0251)	0.0483*** (0.0145)	-0.222* (0.134)	0.0230** (0.0114)
Observations	2,603,985	10,789,660	2,603,985	5,397,899
Adjusted R^2	0.980	0.956	0.369	0.474

Notes: A variant of the model in Equation 3 — using both toys in Canada and non-toys in the U.S. as control groups — is estimated for various outcome variables. The treatment indicator (toy \times country=usa \times after) is interacted with manufacturer type. All specifications include fixed effects for each pairwise combination of date, product id, and country=US. Standard errors, clustered by product, are reported in parentheses, *** p<0.01, ** p<0.05, * p<0.1.