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

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Abstract

Since its founding, Amazon has established a reputation for being consumer friendly by consistently offering low prices. However, recent antitrust concerns about dominant online platforms have revived questions about whether Amazon uses its market share to exploit consumers. Using the sudden U.S. exit of Toys R Us as a natural experiment, we find that Amazon's prices increased by almost 5% in the wake of the exit, with larger increases for popular products most likely stocked by Toys R Us. Thus, despite Amazon's long-standing reputation for low prices, it may exploit increases in market power as traditional retailers cease operating.

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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, consumers have not voiced similar concerns. Rather, Amazon has continued to hold a reputation for being consumer-friendly and offering lower prices than their position in the market would allow. Amazon's effort is exemplified by its stated mission "to offer its customers the lowest possible prices," and its CEO Jeff Bezos's statements in a 60 Minutes interview: "we do price elasticity studies, and every time the math tells us to raise prices [but we do not]."[3] Amazon is also often perceived as a friendly behemoth more widely: Matthew Yglesias famously described Amazon as "a charitable organization being run by elements of the investment community for the benefit of consumers;"[4] and in 2020, 91% of survey respondents viewed Amazon favorably.[5]

Regulators have been closely scrutinizing the behavior of Amazon and the other GAFAM companies (Google, Facebook, Apple, Microsoft), but their focus has not been on the traditional effects of their market power on pricing. In a widely cited paper (Khan, 2016), the current Chairperson of the Federal Trade Commission, argues that Amazon's long history of low prices may be predatory in nontraditional ways that harm consumers without involving eventual price increases.[6] Accordingly, 2020 presidential candidate Elizabeth Warren proposed a regulatory plan aimed at breaking up America's largest tech firms.[7] However, while regulators continue their close scrutiny, there is little evidence to date that Amazon's

[1] See `https://tinyurl.com/6rmmpwmu` and `https://tinyurl.com/3sbbmxy9`.

[2] Zhu 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.

[3] See `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`

[5] `https://tinyurl.com/4vkwxzaf`.

[6] Low prices can help build scale, deter competitors from doing the same, and gather data which can be used for advertising and personalized pricing (Kehoe et al., 2018; Shiller, 2020, 2021). The resulting dominance could harm consumers by stifling innovation and by yielding data to exploit consumer heterogeneity.

[7] See `https://www.nytimes.com/2019/03/08/us/politics/elizabeth-warren-amazon.html`.

exercise of market power would harm consumers directly.

In this paper, we provide such evidence. Specifically, we examine how Amazon's pricing changes as its competitors disappear, causing a discontinuous shift in its market power. While many of Amazon's competitors have been too small or the exit process too prolonged to have a measurable impact, 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 a clean natural experiment.[8]

We employ a triple-differences strategy to study the impacts of Toys R Us's exit. 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 Amazon's U.S. toy prices, relative to two unaffected 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 changes in acquisition costs, 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.[9] The price increases set in quickly after the (unexpected) bankruptcy announcement, soon thereafter plateauing at a higher level. 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 directly 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 these products have the largest price increases. Likewise, we find that the effects are strongest

[8] https://youtu.be/W9CxiNsX0zs?t=42
[9] https://tinyurl.com/4bdnj5p2

among the largest manufacturers, as well as among heavier products, for which Amazon's cost advantage was likely smallest. This heterogeneity across products provides evidence of the causal effect of the shutdown and suggests that Amazon and Toys R Us competed with each other on the product level, rather than as retail destinations.

Our results point to two possible pricing strategies that are observationally equivalent without strong assumptions and cost data: a reaction to market power consistent with profit-maximization, and an increase in prices after a period of price predation. In either case, we find that Amazon does use its market power to charge higher prices. This may have broad effects on consumers as Amazon's competitors continue to disappear. Consequently, analyses of the effects of competitor exit could complement the roles of retrospective merger analyses (e.g., Miller and Weinberg, 2017; Igami and Uetake, 2020; Prager and Schmitt, 2021) in informing regulatory policy.

1 Background and Theoretical Framework

1.1 The Toy Landscape and the Toys R Us Shutdown

In recent decades, the toy retailing landscape has been dominated by large specialized retailers (most notably Toys R Us and 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 shares.[11] In 2015, the toy market shares of Toys R Us, Walmart,

[10] Toys 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).

[11] In 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/`.

and Target in the United States were, respectively, 17%, 23%, and 14%.[12] At the same time, Amazon's 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 (Toys R Us, 2017). 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.[14] The bankruptcy announcement reportedly surprised investors, because Toys R Us had been able to reorganize its debt numerous times in previous years and no major debt payments were imminently due.[15]

Empirical evidence from news article mentions also suggests that the bankruptcy announcement was unanticipated and therefore provides a quasi-experimental change in market concentration. Figure 1 plots the monthly counts of U.S. news articles including the phrase "Toys R Us" in conjunction with "bankruptcy" over time, as found on ProQuest. 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 per month until Toys R Us stores closed.

While all Toys R Us stores in the U.S. were liquidated and shuttered, Canadian stores remained open through a sale to Fairfax Financial.[16] This was conceivably anticipated. Toys

[12] See `https://youtu.be/W9CxiNsX0zs?t=42`.

[13] While 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/`.

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

[15] `https://tinyurl.com/f7veuhvm`

[16] On April 24, it was announced that the Canadian division would be sold for approximately $234 million,

R Us's 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.

1.2 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 four reasons. First, Amazon may be intrinsically motivated to be (perceived as) a force for good for consumers. It 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 goal is to maintain its reputation for low prices, it may not react to changes in competition even if the exit of Toys R Us changes the competitive environment.

Second, Amazon's low prices may reflect its ambition for high sales volume for the purposes of scale and learning ways to reduce costs. If these objectives are paramount, Amazon may not respond to competitor exit by raising its prices either.

Third, even though online and offline retailers cannibalize each other's sales in some contexts (Brynjolfsson et al., 2009; Forman et al., 2009; Gentzkow, 2007; Pozzi, 2013; Wang and Goldfarb, 2017), 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 to consult with staff before purchasing an item, whereas Amazon's advantages include low costs (Goldfarb and Tucker, 2019) and prices (Cavallo, 2017), as well

and would continue to operate the locations under the Toys R Us name.

as customer reviews and individualized recommendation algorithms (Chevalier and Mayzlin, 2006; Claussen et al., 2019; Reimers and Waldfogel, 2021).

Fourth, Amazon includes a marketplace in which smaller sellers can offer their products alongside Amazon's own listings, potentially maintaining competitive pressures. Note that 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 the loss of an offline retailer may have limited impacts on them. In turn, these limited impacts could soften any effect on the prices offered directly by Amazon as well.

Even if Amazon's prices respond to changes in the competitive environment, there may be heterogeneous impacts across products. 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 storefronts. 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. 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 retail destinations 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. Figure A.1 demonstrates this point by showing the relationship between weight and standard shipping costs in the U.S.[17] For light-weight products, it is possible that Toys R Us never posed a real threat to Amazon. If so, Toys R Us's exit should not affect Amazon's strategy for the lightest products.

This simple representation leaves out an important aspect of the retail platform. Like other retailers, Amazon sells products that are manufactured by others.[18] 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 costs and consequently lower prices. Since

[17]While 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.

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

Amazon is one (global) company bargaining with toy manufacturers, its negotiated rates likely apply to Amazon's U.S. and Canada sites equally.

2 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 unaffected categories, but which are similar in that they are discretionary purchases used at home: home and kitchen, electronics, pet supplies, and beauty.[19] 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 Amazon price and availability data. 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 (first-party) prices, cheapest third-party (new) prices, availability, sales ranks, and cumulative count of 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 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

[19] Amazon'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.

available for 6,764,653 observations; it is not available for products not offered by Amazon directly or products that are out of stock. By contrast, we observe third-party new prices for 17,129,848 observations.[20]

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. and in Canada, 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 groups. 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 most 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 $28.70). We see similar patterns for 3$^{\text{rd}}$ party prices, where the median is about 27% larger for non-toys ($18.99 versus $14.99) and the mean is 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.

Beyond raw prices, we report product weight, the weekly frequency of price changes and the number of newly-posted reviews in Table 1.[21] The price change frequencies and number of newly-posted reviews are quite similar across all four groups. Interpreting the number of new reviews as a proxy for demand, the table suggests that toys and the other products draw similarly sized crowds. 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.

[20] Keepa's information on third-party prices includes Amazon's own listings, but does not identify the seller. To avoid conflation, we only consider third-party prices when Amazon does not offer the product.

[21] The data contain information listed on Amazon's product pages, but do not include other information, such as the product's country of origin.

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]

3 Empirical Strategy and Results

3.1 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:

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

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 equals 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:

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

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, $Exchange_{ct}$ is the exchange rate in period t between the U.S. and country c, and ϕ_{it} and ψ_{ic} denote fixed effects for pairwise combinations of

[22] See `https://www.statista.com/statistics/241241/revenue-of-major-toy-companies-worldwide/`.

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, 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, alleviates concerns about changes in wholesale costs because Amazon operates globally, but it may also be an imperfect control if demand shocks are country-specific or interact with cultural differences, or if there are country-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 direct 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 U.S. toys following the shutdown reflects the impact of retailer exit in the downstream market to consumers.

Formally, we employ the following model:

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

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 ψ_{ic} controls for ex-ante product-specific differences in the price level between the countries, for example due to taste differences. Then, β_1 captures the impact of Toys R Us's shutdown on toy prices.

3.2 Main Results

We primarily use the bankruptcy announcement as the treatment date when we apply this estimation framework to Toys R Us's exit. 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 may be reduced after the bankruptcy announcement, even before the bankrupt firm has formally exited. However, the choice of the specific treatment date does not drive our findings. Our results are robust to other sensible choices, as we show further below.

3.2.1 Amazon Prices

The first three columns of Table 2, Panel A, report results from the three models described in Section 3.1. 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% ($= e^{0.0384} - 1$). Our second approach compares the same toys in the U.S. and in Canada, and finds a price increase of 2.7% ($= e^{0.0265} - 1$). In our main specification, in column 3, we find that Toys R Us's exit led to an average toy price increase of 3.2% ($= e^{0.0312} - 1$).[23] We later weight the price increases across toys according to their popularity, finding an even larger impact.

[23] One 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 simulate a control group using coarsened exact matching and we estimate separate regressions for each product category in the control group in the appendix, finding very similar results.

3.2.2 Other Outcomes

Our interpretation, that Amazon's price changes are due to changes in the competitive environment, is supported by other, related, effects. 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 of changes in Amazon's own 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 sellers' price increases are significant but smaller than Amazon's, rising by 1.8% ($= e^{0.0184} - 1$) 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 Amazon's sales of toys in the U.S. increased despite rising prices. Thus, Amazon appears to have captured at least some of the consumers who would have previously bought from Toys R Us, increasing its market power.

3.2.3 Treatment Timing

The nine-month 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 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 leveled off, and remained above pre-bankruptcy levels through 2018. No noticeable incremental changes occurred 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., or alternatively that toy discounts were particularly large in Canada. Out of the concern that country-specific toy price changes during the Christmas season arise for reasons that are unrelated to Toys R Us's exit, we re-estimate the main regression from Equation 3, omitting the last four weeks of each year. We find that the treatment coefficient does not change meaningfully (0.0312, se=0.007), because the changes in toy prices around Christmas in 2017 (after bankruptcy) were similar to those around Christmas in 2016 (before bankruptcy). Hence, 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. 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, their 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. This pattern is consistent with copycat pricing, assuming that Toys R Us continued to post its prices online until its stores were closed. 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 that pressured Amazon to lower prices. Finally, in column 4, we find the increase in third-party seller prices is only statistically significant for the first two treatment periods. After Toys R Us closed, Amazon's marketplace prices seem to have returned to their old equilibrium, making Amazon's (first-party) sustained price increases particularly notable.

3.3 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 heterogeneity depends on whether Amazon and Toys R Us competed at the retailer 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 based on their likelihood of being offered at Toys R Us, and on the likely intensity of competition. We explore the role of availability at Toys R Us by categorizing products along two dimensions: according to their popularity, which we approximate by the product's highest Amazon ranking, and according to the manufacturer's identity, finding similar results. We show the results on popularity here, and those on manufacturer identity in the appendix. In examining the impact by product popularity, we implicitly assume 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 explore the role of competition intensity by categorizing products according to 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 meaningful competitive pressures for lightweight items.

In both sets of analyses, we augment the model in Equation 3 by interacting the triple interaction ($U.S. \times Toy \times After$) with indicators for quintiles of product characteristics (popularity or weight). The results for popularity are shown in columns 1-3 of Table 3. Consistent with Brynjolfsson et al. (2009), the impacts of Toys R Us's exit are generally strongest for the most popular products, which were most likely offered at Toys R Us. 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 competitor that offered the item in question.[24] Note also that the relationship between toy price increases and popularity are similar for third-party sellers. Assuming that third-party sellers were exploiting a more concentrated market and not engaging in predatory pricing, this may suggest that Amazon's pricing was not predatory either but instead consistent with simple profit-maximization strategies.

We can use our 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.[25]

Next, in columns 4-6 of Table 3, 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, depicted in appendix Figure A.1, supports this interpretation. Because Amazon offers free and fast (two-day) shipping

[24] The 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.

[25] `https://tinyurl.com/4bdnj5p2`

on most items for their 100 million Prime subscribers in the United States (as of 2018), shipping heavy packages may be particularly costly for Amazon (Reisinger, 2019), eroding their cost advantage. In column 5, we find similar impacts of weight on prices of toys sold by third-party sellers. In column 6, we also find that price change frequencies declined the most for heavier items. Hence, we find multiple dimensions of support that Amazon primarily competed with Toys R Us at the product rather than retail destination level.

4 Conclusion

In the quarter century since its founding, Amazon has established a reputation for being exceptionally consumer-friendly, highlighting in its mission statement that it "strive[s] to offer [its] customers the lowest possible prices."[26] Similarly, the other GAFAM companies have cultivated images of being more consumer-friendly than the monopolies of old in an attempt to create trust among consumers and employees.[27] Consumers may therefore have accepted some harms in return for other benefits that accompanied these online companies' growing market power. In Amazon's case, consumers may tolerate losing opportunities to browse and physically evaluate products when brick-and-mortar retailers disappeared, if online prices remain low. However, we show that prices may indeed rise.

Despite their purported focus on consumer well-being, Amazon (much like the other GAFAM companies) has drawn considerable scrutiny from politicians and regulators, with little hard evidence of direct consumer harms. We show that 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 relatively low prices, there is non-negligible potential for consumer benefits to dissipate further as more physical retailers exit. These results support recent antitrust scrutiny, which has thus far focused on less

[26] `http://panmore.com/amazon-com-inc-vision-statement-mission-statement-analysis`

[27] See, for example, Google's initial "don't be evil" corporate code of conduct (`https://tinyurl.com/2hmnxat9`).

traditional measures of consumer harms from prominent technology companies.

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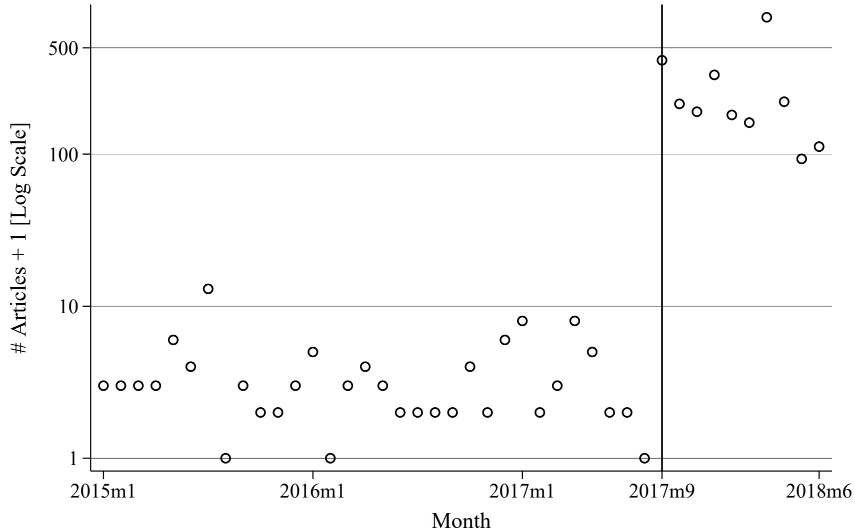
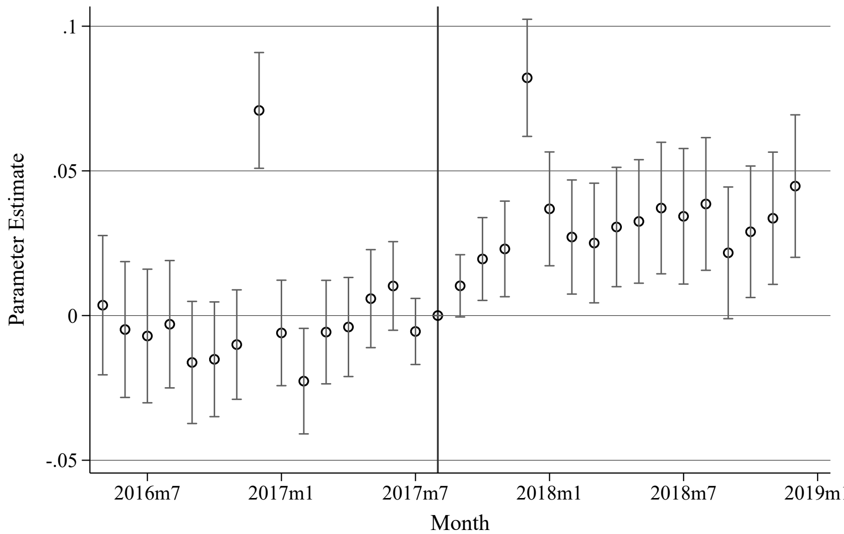
Figure 1: Monthly News Mentions of "Toys R Us" and "Bankruptcy"



Notes: This figure shows the monthly count of U.S. newspaper articles mentioning both "Toys R Us" and "bankruptcy" in the ProQuest database. The vertical line indicates the month Toys R Us formally filed for bankruptcy.

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



Notes: This figure shows coefficients from a regression of log-Amazon prices on the month-treatment pair indicators (U.S.×toy×after), using the full dataset which includes 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 the month before the Toys R Us bankruptcy announcement (August 2017).

Table 1: Sample Characteristics

	Toys, US		Toys, CA		Non-Toys, US		Non-Toys, CA		Total
	Median	Mean	Median	Mean	Median	Mean	Mean	Median	N
Amazon price	15.24	28.70	17.08	27.59	25.53	75.95	27.74	70.64	6,764,653
3rd party price	14.99	35.78	29.64	52.85	18.99	71.42	37.06	103.93	17,129,848
Amazon price changes	0.00	0.96	0.00	0.84	0.00	0.83	0.00	1.06	6,764,653
New reviews	0.00	0.15	0.00	0.06	0.00	0.33	0.00	0.17	14,128,184
Weight (oz)	6.38	22.65	8.01	22.72	8.78	73.05	11.99	73.53	176,272
Observations	4,368,400		1,986,361		13,944,320		4,344,417		24,642,498
Products	25,227		11,242		115,111		31,049		182,542

Notes: The table shows summary statistics for variables of interest, separately for toys in the U.S., toys in Canada, non-toys in the U.S. and non-toys in Canada. All prices are reported in U.S. dollars. The underlying sample includes the 182,542 products with any Amazon reviews between January 2017 and August 2018. The total (week$\times$product$\times$country) observations in column 9 differ across variables because products may be unavailable through some channels during a specific week.

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***	0.0265***	0.0312***	0.0184**	-0.111***	0.0480***
	(0.00217)	(0.00627)	(0.00704)	(0.00829)	(0.0378)	(0.00533)
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	6,526,339	2,603,985	5,397,899
Adjusted R^2	0.974	0.967	0.980	0.960	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) $\ln(R+1)$
USA $\times$ Toy				
... $\times$ Bankruptcy Announced	0.0354***	0.0181**	-0.0410	0.0329***
	(0.00636)	(0.00756)	(0.0394)	(0.00510)
... $\times$ Liquidation Began	0.0277***	0.0346***	-0.0693	0.0464***
	(0.00831)	(0.00940)	(0.0476)	(0.00571)
... $\times$ All Stores Closed	0.0301***	0.00590	-0.202***	0.0595***
	(0.00979)	(0.0102)	(0.0527)	(0.00627)
Sample	All	All	All	All
Observations	2,603,985	6,526,339	2,603,985	5,397,899
Adjusted R^2	0.980	0.960	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. They include fixed effects 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		
	$\ln(p^A)$	$\ln(p^{3rd})$	$\#\Delta p^A$	$\ln(p^A)$	$\ln(p^{3rd})$	$\#\Delta p^A$
Toy × USA						
… × 1st quintile	0.0219	-0.0162	-0.188*	-0.0424**	0.0109	0.0573
	(0.0219)	(0.0112)	(0.0975)	(0.0206)	(0.0191)	(0.0917)
… × 2nd quintile	0.00899	0.0174	-0.0728	0.0373***	0.0277*	-0.0849
	(0.0152)	(0.0143)	(0.0787)	(0.0131)	(0.0142)	(0.0736)
… × 3rd quintile	0.0219	0.00980	-0.0363	0.0606***	0.00858	-0.141*
	(0.0154)	(0.0164)	(0.0812)	(0.0135)	(0.0118)	(0.0785)
… × 4th quintile	0.0402***	0.0315	-0.159**	0.0367***	0.0245**	-0.0732
	(0.0122)	(0.0199)	(0.0680)	(0.0123)	(0.0116)	(0.0717)
… × 5th quintile	0.0520***	0.0731***	-0.145**	0.0449***	0.0205	-0.262***
	(0.0108)	(0.0231)	(0.0687)	(0.0116)	(0.0128)	(0.0713)
Observations	2,358,567	5,819,391	2,358,567	2,603,226	6,470,781	2,603,226
Adjusted R^2	0.980	0.959	0.367	0.981	0.959	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 ($U.S.\times Toy\times After$) is interacted with quintiles of either popularity or weight. All specifications include fixed effects 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.

A Online Appendix

A.1 Robustness: 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 related to toys and baby products in some way. For example, like toys and baby products, electronics make popular 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 (and their impacts on price trends) 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. We create 50 categories of equal range for each of six variables: (1) the product's weight, (2) its volume, as well as pre-treatment 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 and keep exact matches along relevant subsets of these categorized variables between toys and other products. 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 columns 3–6 of Table 2, Panel A, 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 Robustness: 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 from 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.[28]

The results are reported in Table A.2, sorted from the largest control group to the smallest. The number of toys and baby products across all control groups is 10,820 for the U.S.-only specifications, and 4,900 for the full specification due to the smaller number of toys available at Amazon's

[28] We 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."

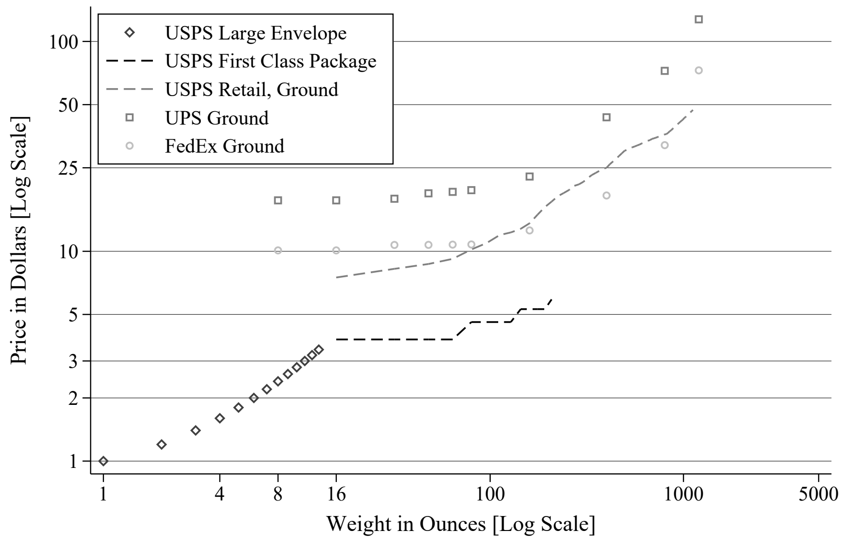
Canadian platform together with the elaborate set of interacted fixed effects. The odd-numbered columns show the coefficients from the simple difference-in-differences analysis using only U.S. data, and the even-numbered columns report results from the full triple-differences model. All estimated coefficients 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 goods produced 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."[29] 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 point estimates of the effects on third-party prices and Amazon price changes are largest 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.

[29] See `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.

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

	ln(Price)		Price changes	Quantity
	(1)	(2)	(3)	(4)
	Amazon	3rd party	Amazon	ln(Δ reviews)
Treatment	0.0294***	0.0230***	-0.0126	0.00559
	(0.00790)	(0.00839)	(0.0425)	(0.00418)
Observations	1,815,777	4,797,393	1,815,777	3,386,474
Adjusted R^2	0.963	0.958	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***	0.0383***	0.0292***	0.0213**	0.0418***	0.0206*	0.0238***	0.0232	0.0531***	0.0327	0.0406***	0.0377***
	(0.002)	(0.008)	(0.003)	(0.009)	(0.003)	(0.011)	(0.005)	(0.017)	(0.010)	(0.040)	(0.002)	(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, restricting the control group to various subsets of products. In odd-numbered columns ("US"), fixed effects are included for each product and week. In even-numbered columns (" Both"), 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.3: Price and Demand Effects across Manufacturers

	ln(Price)		Price changes	Quantity
	(1) Amazon	(2) 3rd party	(3) Amazon	(4) ln(Δ reviews)
Toy × USA				
… × No manufacturer listed	0.0279***	0.0147	-0.0645	0.0517***
	(0.00906)	(0.0100)	(0.0506)	(0.00621)
… × other manufacturer	0.0322***	0.0213*	-0.148***	0.0504***
	(0.0101)	(0.0120)	(0.0533)	(0.00669)
… × major manufacturer	0.0477*	0.0250	-0.222*	0.0230**
	(0.0251)	(0.0145)	(0.0187)	(0.0114)
Observations	2,603,985	6,526,339	2,603,985	5,397,899
Adjusted R^2	0.980	0.960	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 ($U.S. \times Toy \times After$) is interacted with manufacturer type. All specifications include fixed effects 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.