Journal of Law and Economics

Volume 65 | Number 4 Article 2

11-1-2022

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# 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 lower prices than its market position would seem to allow. However, recent antitrust concerns about dominant online platforms have revived questions about whether Amazon's growing market share threatens consumer welfare. Given its reputation, regulators have proposed a new focus on conduct unrelated to prices. We ask whether such a move is premature. Using the sudden and unanticipated US exit of Toys"R"Us as a natural experiment, we find that Amazon's toy prices on its US site increased by almost 5 percent in the wake of the exit relative to similar products and to toys on its Canadian site. Thus, despite Amazon's long-standing reputation, it may exploit increases in market power in traditional ways as competing retailers cease operating.

## 1. Introduction

In the quarter century since its founding, Amazon has grown to a considerable market share in US retail, for example reaching 42 percent in books and 16 percent in toys in 2017, while many of its brick-and-mortar retail competitors have disappeared (for examples, see Stone 2018; Day and Gu 2019). Its growing dominance has been accompanied by complaints of aggressive conduct toward rivals, suppliers, and workers.[1] However, consumers have not voiced similar concerns.

We would like to thank James Dana, Dominic Smith, Joel Waldfogel, Nathan Yang, and a referee for very useful suggestions. We also thank Julie Mortimer for exceptionally helpful comments. We would also like to thank seminar and conference participants at the Bureau of Labor Statistics, the Department of Justice, the 2021 International Industrial Organization Conference, Ludwig Maximilian University of Munich, the 2020 National Bureau of Economic Research productivity seminar, Northeastern University, and the University of East Anglia for numerous useful suggestions. Finally, we thank Andrew Kearns for excellent research assistance.

[1] 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.

[*Journal of Law and Economics,* vol. 65 (November 2022)]
 0022-2186/2022/6504-0033$10.00

Rather, Amazon has continued to hold a reputation for being consumer friendly and offering lower prices than its position in the market would allow. Amazon's effort is exemplified by its stated mission "to offer its customers the lowest possible prices" (Daab 2017) and by its chief executive officer 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]" (Rose 2013). Amazon is also often perceived as a friendly behemoth more widely: Yglesias (2013) describes Amazon as "a charitable organization being run by elements of the investment community for the benefit of consumers," and in 2020, 91 percent of survey respondents viewed Amazon favorably (Newton 2020).

Regulators have closely scrutinized the behavior of Amazon along with that of large technology companies such as Google, Facebook, Apple, and Microsoft, but their focus has not been on the traditional effects of 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.[2] Accordingly, 2020 presidential candidate Elizabeth Warren proposed a regulatory plan aimed at breaking up America's largest tech firms (Herndon 2019). However, while regulators continue their close scrutiny, there is little evidence to date that Amazon's exercise of market power would harm consumers directly.

In this paper, we provide such evidence. We examine how Amazon's prices changed after the exit of Toys"R"Us, a prominent brick-and-mortar retailer that specialized in selling toys and baby products. A competitor's exit may yield higher and less elastic residual demands for the remaining firms, which results in larger profit-maximizing prices.[3] Thus, the demise of Toys"R"Us, a firm accounting for 17 percent of the US retail toy market shortly before its 2018 exit (McCall and Rizzo 2019), provides a natural experiment to test for Amazon's response to market power.

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 United States but not in Canada to investigate the impact on Amazon's US toy prices relative to two unaffected groups of products: nontoys in the United States and toys in Canada, where Toys"R"Us stores continued to operate. The combined use of these groups controls for category- and country-specific shocks to prices, for example due to a toy-specific seasonality or changes in acquisition costs or region-specific changes in shipping costs. While the triple-differences analysis is our preferred specification, our main results also emerge from simple difference-in-differences analyses in which the control group is either nontoys or toys in Canada.

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

[3] This theoretical result holds very generally when the residual demand function and cost functions are well behaved. See, for example, Vives (1999), Amir and Lambson (2000), and Hoernig (2003).

We find that Toys"R"Us's exit significantly increased the prices of toys on Amazon by a sales-weighted average of about 4.7 percent. Compared with Amazon's reported 10 percent price advantage over Toys"R"Us (Townsend 2013), these price increases are substantial. The price increases set in quickly after the bankruptcy announcement, soon thereafter plateauing at a higher level. We also find that the count of reviews—a proxy for sales—increased despite the higher prices, which supports the conclusion that the observed price increases follow a rise in Amazon's residual demand. In addition to Amazon's own price levels, we find a more temporary price increase on Amazon's third-party marketplace. The shutdown also led to a decrease in the frequency of price changes for products sold directly by Amazon, which suggests that Amazon's pricing algorithm may have actively tracked and reacted to price changes at Toys"R"Us.

In addition, the price increases are strongest among products that were most likely to be directly affected by the exit of Toys"R"Us. Because brick-and-mortar retail stores were likely to dedicate their (large but not limitless) shelf space to more popular products, the price effects plausibly should be focused on these products as well, and indeed those products have the largest price increases. Likewise, the effects are strongest among the largest manufacturers and among heavier products, for which Amazon's cost advantage is 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 at the product level rather than as retail destinations.

While price increases coupled with higher sales point to Amazon reacting to changes in its market power, other explanations may be at play as well. An apt alternative is rising marginal costs due to diseconomies of scale. For example, rising sales could lead to higher shipping costs if regional capacity constraints force Amazon to process excess shipments through distant sorting centers. However, such scale effects would be captured by one of the controls in our triple-differences analyses unless the diseconomies of scale are both country and product (or category) specific. This is unlikely if shelf space and labor at distribution and sorting centers are fungible across product categories. Moreover, the literature finds that Amazon's fulfillment and sorting centers exhibit economies of scale rather than diseconomies of scale (Houde, Newberry, and Seim 2017).

Prices that rise with market power may be attributed to two observationally equivalent strategies: simple profit maximization and an increase in prices after a period of price predation. In either case, we find that Amazon's prices do increase as its market power rises. This may have broad effects on consumers as Amazon's competitors continue to disappear. Consequently, analyses of the effects of competitors' exit could complement the roles of retrospective merger analyses (for example, Miller and Weinberg 2017; Igami and Uetake 2020; Prager and Schmitt 2021) in informing regulatory policy. Indeed, section 2.1.2 of the US Horizontal Merger Guidelines explicitly notes the possibility of examining the effects of prior exit when evaluating mergers (United States Department of Justice and Federal Trade Commission 2010).

## 2. Background and Theoretical Framework

### *2.1. 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).[4] Compared with the general brick-and-mortar retailers, Toys"R"Us carried a much larger selection of toys and baby products. Still, because the others operated far more stores, the three brick-and-mortar-based companies had similar domestic market shares.[5] In 2016, the toy market shares (by revenue) of Toys"R"Us, Walmart, and Amazon in the United States were, respectively, 20.2 percent, 20.7 percent, and 11.4 percent.[6] However, Amazon's toy market share by revenue was growing rapidly: it grew from just 8.9 percent in 2015 and reached 12.9 percent by 2017, 17.0 percent by 2018, and 19.8 percent by 2019.

It was well known that Toys"R"Us had been struggling for quite awhile. 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 from a leveraged buyout in 2005, which saddled it with $5.3 billion in debt and resulted in interest payments of approximately $400 million annually (Vardi 2017). After a protracted period of financial difficulties, reports of attempts to restructure appeared on September 6, 2017 (Hirsch 2017), and Toys"R"Us filed for bankruptcy on September 18. It then proceeded to liquidate its US stores between March and June 2018, when all domestic stores closed.[7]

While all Toys"R"Us stores in the United States were liquidated and shuttered, Canadian stores remained open through a sale to Fairfax Financial.[8] Toys"R"Us's 2016 financial report notes that sales in the United States declined by 3.1 percent over the previous year, but sales in Canada grew by 1.1 percent (Toys"R"Us 2017). The report also presents the result of the 2016 US presidential election as an ongoing risk to its business, as tariffs threatened (but never implemented) by the Trump administration could have raised merchandise acquisition costs for its US stores. The Canadian market, in which Toys"R"Us stores were faring better and did not shut down, constitutes a useful control group for comparison with the US market.

[4] 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 percent of its revenues originated from direct-to-consumer e-commerce sales (Toys"R"Us 2017).

[5] In 2016, there were 879 Toys"R"Us stores in the United States, compared with 4,574 Walmart stores and 1,802 Target stores (Toys"R"Us 2017; Walmart 2017; Target 2017).

[6] Market shares are calculated from toy-segment domestic revenues. Domestic revenues for Walmart, Amazon, and the industry as a whole are from Fernandez (2020). Toys"R"Us's domestic revenues are from Toys"R"Us (2017).

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

[8] On April 24, 2018, 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.

### 2.2. Theoretical Framework

Firms' exit changes the remaining firms' pricing incentives. It is often assumed that exit raises profit-maximizing prices because it typically results in less elastic residual demand by both increasing captive consumers (shifting demand outward) and removing a close substitute (reducing the slope). Resulting price increases could reflect deliberate adjustments or may be passively implemented through prespecified pricing algorithms that automatically respond to changing market conditions.

However, Amazon may not wish to raise its prices despite an increase in market concentration. There are several reasons: to maintain its long-standing reputation for offering low prices (Reimers and Waldfogel 2017), to fulfill its ambition to maximize sales volume for the purposes of scale and learning ways to reduce costs, because Toys"R"Us may not be a direct competitor since it offers different shopping experiences, and to remain competitive with third-party sellers on Amazon Marketplace, who may represent Amazon's closest competitors.

Even if Amazon's prices respond to changes in the competitive environment, there may be heterogeneous impacts across products. We identify two dimensions on 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 sells several hundreds of thousands of toys.[9] It is likely that Toys"R"Us stocked more popular items (or items from larger manufacturers), whereas Amazon stocked rather unpopular ones as well. 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 1 demonstrates this point by showing the relationship between weight and standard shipping costs in the United States.[10] Toys"R"Us may have responded to these cost asymmetries by disproportionately choosing to stock and dedicate prime shelf space to larger and/or heavier products, which suggests that stores were less likely to offer close substitutes for small, lightweight items, and Toys"R"Us's exit would have little impact on Amazon's residual demand for these items.

## 3. Data

We collect the data for this study in several steps. First, we identify a set of product categories that include toys and baby products, which are directly affected by Toys"R"Us's exit, and five unaffected but similar categories of discretionary purchases used in homes: home and kitchen, electronics, pet supplies, beauty,

[9] There were consumer reviews for over 634,000 toys and games in 2018 (Ni, Li, and McAuley 2019).

[10] Figure 1 shows standard shipping costs based on public notices (US Postal Service) and shipping calculators (UPS and FedEx) for shipments from Waltham, Massachusetts (02453), to Boston, Massachusetts (02108). Although standard shipping costs may differ from the true negotiated rates, it is likely that the proprietary negotiated shipping rates that Amazon faces follow similar patterns.

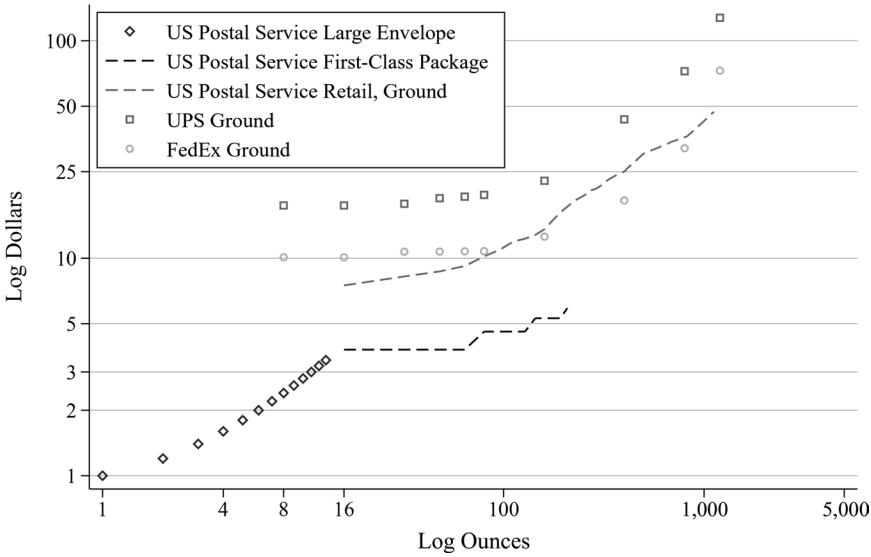


**Figure 1.** Shipping prices

and sports and hobby.[11] We use data from Ni, Li, and McAuley (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 US platform between January 2017 and August 2018. For these products, we use Keepa's application programming interface to search for and collect detailed Amazon price and availability data. Of the 200,000 products, 182,542 are tracked on Keepa, including 36,469 toys (20 percent) and 146,073 products in other categories. These make up the underlying set of products in the study.

For each product, we obtain Amazon (first-party) prices, cheapest third-party (new) prices, availability, sales ranks, and cumulative count of customer reviews from Amazon's US and Canadian websites between January 2016 and December 2018. Importantly, all information is product and platform specific.[12] That is, a product's price, ranking, and other characteristics can vary between the US and Canadian platforms. We aggregate these data, for each product and country, to the weekly level and supplement them with the product's weight and the manufacturer's identity. The final, product-week-country-level data set has a total of 24,643,498 observations, 18,312,720 on the US platform and 6,330,778 for 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 available for only

[11] Amazon's definition of the toys and baby products category includes sports equipment and other hobby goods. These products are unlikely to have been offered at Toys"R"Us, and we therefore classify them as nontoys in our analyses.

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

6,764,653 observations; it is not available for products not offered by Amazon directly or products that are out of stock. By contrast, third-party new prices are available for 17,129,848 observations.[13]

In Table 1, we summarize the main variables of interest for toys in the United States, for toys in Canada, and for other products in the United States 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 United States in the sense that they have similar mean and median prices (in US dollars), price change frequencies, weights, and counts of newly posted reviews. Third, toys are different from other products in most dimensions. On the US platform, the median Amazon price is almost 70 percent larger for nontoys than for toys, and the gap in average prices is even larger. Third-party prices have similar patterns: the median is about 27 percent larger for nontoys, and the mean is twice as large. Because these differences are substantial and significant, our main estimation does not rely solely on variation across product groups but rather utilizes variation for identical products across countries as well.

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, Table 1 suggests that toys and the other products draw similarly sized crowds. In addition, nontoys are significantly heavier than toys. An average toy on the US platform weighs only about 23 ounces (1.5 pounds), compared with 73 ounces (5.3 pounds) among other products. Again, the distributions are highly skewed.

Finally, the data include information about the product's manufacturer for about 50 percent of toys. Among those, the five most common manufacturers are well-known toy brands: Mattel, Hasbro, Konami, Disney, and Lego.

## 4. Empirical Strategy and Results

### *4.1. Empirical Strategy*

To estimate the impact of Toys"R"Us's bankruptcy on toy prices on Amazon, one could use a simple difference-in-differences estimation strategy in which the control group contains either toys in a nonimpacted country (Canada) or other categories of products in the same country (United States). For example, one could compare toy prices with prices of other products by restricting the data to the United States and regressing the following equation:

$$\ln(P)_{it} = \beta_1 \text{After}_t \times \text{Toy}_i + \gamma_i + \mu_t + \varepsilon_{it}, \quad (1)$$

[13] Keepa's information about third-party prices includes Amazon's own listings but does not identify the seller. To avoid conflation, we consider only third-party prices for product-week pairs that Amazon does not directly sell, which guarantees that the reported third-party price was indeed offered by a third party.

**Table 1**
**Characteristics of the Sample**

| | *N* | Median | Mean |
|---|---|---|---|
| Toys: | | | |
| United States: | | | |
| Amazon price | 966,830 | 15.24 | 28.70 |
| Third-party price | 3,327,270 | 14.99 | 35.78 |
| Amazon price changes | 966,830 | .00 | .96 |
| New reviews | 2,806,522 | .00 | .15 |
| Weight (ounces) | 35,344 | 6.38 | 22.65 |
| Products | 25,155 | | |
| Canada: | | | |
| Amazon price | 343,967 | 17.08 | 27.59 |
| Third-party price | 1,609,564 | 29.64 | 52.85 |
| Amazon price changes | 343,967 | .00 | .84 |
| New reviews | 760,415 | .00 | .06 |
| Weight (ounces) | 22,129 | 8.01 | 22.72 |
| Products | 11,314 | | |
| Nontoys: | | | |
| United States: | | | |
| Amazon price | 4,045,406 | 25.53 | 75.95 |
| Third-party price | 9,362,424 | 18.99 | 71.42 |
| Amazon price changes | 4,045,406 | .00 | .83 |
| New reviews | 8,791,825 | .00 | .33 |
| Weight (ounces) | 140,198 | 8.78 | 73.05 |
| Products | 115,077 | | |
| Canada: | | | |
| Amazon price | 1,408,450 | 27.74 | 70.64 |
| Third-party price | 2,830,590 | 37.06 | 103.93 |
| Amazon price changes | 1,408,450 | .00 | 1.06 |
| New reviews | 1,769,422 | .00 | .17 |
| Weight (ounces) | 59,809 | 11.99 | 73.53 |
| Products | 30,996 | | |

**Note.** Prices are in US dollars. The full sample ($N = 24{,}643{,}498$) includes the 182,542 products with an Amazon review between January 2017 and August 2018. Number of (week-product-country) observations differ across variables because products may be unavailable through some channels in a particular week.

where $\ln(P)_{it}$ is the natural log of the price of product $i$ in period $t$, $\text{After}_t$ is an indicator that equals one after exit, and $\text{Toy}_i$ is an indicator that equals one for all toys and baby products. The terms $\gamma_i$ and $\mu_t$ denote product and time fixed effects, respectively.

Alternatively, one could compare toy prices in the United States with toy prices in Canada (where Toys"R"Us continued operations) by restricting the data to toys and regressing the following equation:

$$\ln(P)_{ict} = \beta_1 \text{After}_t \times \text{US}_c + \beta_2 \text{Exchange}_{ct} + \phi_{it} + \psi_{ic} + \varepsilon_{itc}, \tag{2}$$

where $c$ denotes the country (United States or Canada), $\text{US}_c$ is an indicator equal to one when the country is the United States, $\text{Exchange}_{ct}$ is the exchange rate in period $t$ between the United States and country $c$, and $\phi_{it}$ and $\psi_{ic}$ denote fixed effects for pairwise combinations of product and period and of product and country, respectively.

The assumption for either difference-in-differences estimation strategy is that the treatment and control groups had similar shocks to demand (tastes) and supply (wholesale costs) over time. However, although each control group is intuitively reasonable, either group or both groups may be imperfect. The first control group, nontoys in the United States, may be an imperfect control for toys in the United States for three reasons. First, the seasonality of the demand for toys may differ from that of similar groups, for example because of Christmas. 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 nontoys in the United States and in Canada. The control group of toys in Canada captures 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 US consumers. Similarly, the control group of nontoys in the United States accounts for country-specific price trends.[14] After controlling for these extraneous factors, the marginal change in the prices of US toys following the shutdown reflects the impact of retailers' exit in the downstream market to consumers.

Formally, we employ the following model:

$$\ln(P)_{ict} = \beta_1 \text{US}_c \times \text{Toy}_i \times \text{After}_t + \phi_{it} + \omega_{ct} + \psi_{ic} + \varepsilon_{ict}, \tag{3}$$

where $\phi_{it}$, $\omega_{ct}$, and $\psi_{ic}$ are fixed effects for each pairwise combination of product identifiers, time period, and country. The fixed effects $\phi_{it}$ 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 United States; the fixed effects $\omega_{ct}$ capture regional differences in seasonality and time trends, including exchange rates and shipping costs; and $\psi_{ic}$ controls for ex ante product-specific differences in the price level between the countries, for example

[14] 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: by simulating a control group using coarsened exact matching and by estimating separate regressions for each product category in the control group in the Appendix. The results are very similar.

because of differences in taste. The term $\beta_1$ 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. After a firm announces bankruptcy, its suppliers usually demand up-front payment for items instead of providing items on credit, which results in reduced inventory at the bankrupt retailer (Ziobro 2017). Hence, competition may be reduced after the announcement and before the bankrupt firm has formally exited. However, the choice of the treatment date does not drive our findings. The results are robust to other sensible choices, as we show below.

#### 4.2.1. Amazon's Prices

Columns 1–3 of Table 2 report main effects from the three models described in Section 4.1. The models yield comparable results. Comparing toys and nontoys in the United States yields a price increase of 3.9 percent ($= e^{.0384} - 1$). Comparing toys in the United States and in Canada yields a price increase of 2.7 percent ($= e^{.0265} - 1$). In the main specification in column 3, Toys"R"Us's exit led to an average toy price increase of 3.2 percent ($= e^{.0312} - 1$). These changes are economically important. They imply that Amazon's initial price advantage of 10 percent (Townsend 2013) would have decreased by almost one-third. Weighting the price increases across toys according to popularity indicates an even larger impact.

#### 4.2.2. Treatment Timing

The 9-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 by using a model similar to the one presented in equation (3) with one difference. We interact the treatment group indicator (US $\times$ Toy) with monthly fixed effects instead of a single indicator that equals one after a bankruptcy filing. The coefficients on these interactions and the corresponding 95 percent confidence intervals are plotted in Figure 2, where a vertical line for August 2017 indicates the month of the bankruptcy announcement. No pretreatment trends are apparent, which provides support for our identification strategy. The price of toys gradually rose in the United States 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 prebankruptcy levels through 2018. No noticeable incremental changes occurred around the time when Toys"R"Us began liquidating its stores (March 2018) or when it closed stores for good (June 2018).

The large positive coefficients in December of each year suggest that seasonal toy price increases may be particularly large in the United States or alternatively

**Table 2**

**Price and Demand Effects**

| | Amazon Price | | | New Reviews | Price Change Frequency | Third-Party Price |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Main effects: | | | | | | |
| Treatment | .0384** | .0265** | .0312** | .0480** | −.111** | .0184* |
| | (.00217) | (.00627) | (.00704) | (.00533) | (.0378) | (.00829) |
| Exchange Rate | | −.0409 | | | | |
| | | (.0513) | | | | |
| *N* | 4,032,512 | 489,744 | 2,603,985 | 5,397,899 | 2,603,985 | 6,526,339 |
| Adjusted $R^2$ | .974 | .967 | .980 | .474 | .369 | .960 |
| Detailed timing: | | | | | | |
| USA × Toy × Bankruptcy Announced | | | .0354** | .0329** | −.0410 | .0181* |
| | | | (.00636) | (.00510) | (.0394) | (.00756) |
| USA × Toy × Liquidation Began | | | .0277** | .0464** | −.0693 | .0346** |
| | | | (.00831) | (.00571) | (.0476) | (.00940) |
| USA × Toy × All Stores Closed | | | .0301** | .0595** | −.202** | .00590 |
| | | | (.00979) | (.00627) | (.0527) | (.0102) |
| *N* | | | 2,603,985 | 5,397,899 | 2,603,985 | 6,526,339 |
| Adjusted $R^2$ | | | .980 | .474 | .369 | .960 |

**Note.** Column 1 estimates equation (1) on the US sample and includes product and time fixed effects; column 2 estimates equation (2) on the toys sample and includes product-date and product-country fixed effects; columns 3–6 estimate equation (3) using all products and countries. Results for main effects are from regressions with a single treatment variable (USA × Toy × After Announcement); results for detailed timing are from regressions with three, mutually exclusive treatment variables representing different time periods after the bankruptcy announcement. Standard errors, clustered by product, are in parentheses.

* $p < .05$.

** $p < .01$.

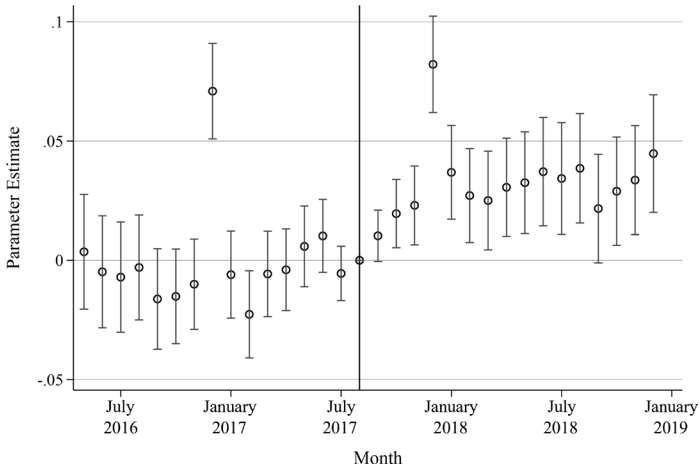


**Figure 2.** Effect of the Toys"R"Us shutdown on Amazon's prices

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 reestimate the main regression from equation (3), omitting the last 4 weeks of each year. The treatment coefficient does not change meaningfully (.0312; SE = .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.

### 4.2.3. Evidence of Market Power Effects

Our interpretation—that changes in the competitive environment resulted in higher prices on Amazon—is supported by other, related effects. We employ the full model from equation (3) with three alternative outcome measures: the number of newly posted consumer-written reviews as a proxy for the sales quantity, the frequency of changes in Amazon's offer price, and prices set by third-party sellers on Amazon's platform. The results are presented in Table 2.[15] Detailed timing regressions in Table 2 also disentangle the timing of the effects through interactions of three successive thresholds (bankruptcy announcement, start of liquidation, and final store closings) with the treatment group determinant (US × Toy). Each period is defined to be nonoverlapping; hence, the coefficients reflect the change in prices relative to the period prior to Toys"R"Us's bankruptcy announcement.

Table 2 shows that the number of new reviews increased after the Toys"R"Us bankruptcy, despite the main finding that its prices increased. This is suggestive

[15] Unreported simple difference-in-differences specifications—analogous to equations (1) and (2)—with these additional dependent variables yield similar results.

evidence that Amazon's residual demand indeed increased. Second, if Amazon's price increases were driven by changes in costs, there would be no obvious reason for the frequency of price changes to decrease. However, Table 2 shows that Amazon changed the prices of its products less frequently after Toys"R"Us's bankruptcy, with the largest and most significant impacts occurring after Toys"R"Us completed bankruptcy proceedings and closed its stores. This may suggest that Amazon's pricing algorithm incorporated copycat pricing (Assad et al. 2020; Brown and MacKay 2021; Cavallo 2017; Fisher, Gallino, and Li 2018) whereby it dynamically adjusts its prices to track brick-and-mortar competitors' price changes. Finally, we examine the prices of Amazon's marketplace sellers—an environment that is likely characterized by competition regardless of the presence of Toys"R"Us. There is a (smaller) price increase among marketplace sellers, but while Amazon's price increases are lasting, the increase in third-party sellers' prices is statistically significant for only the first two treatment periods. This suggests that transitory impacts—such as sticky capacity constraints for remaining sellers—dissipate in the longer term. Therefore, transitory cost shocks are unlikely to explain the lasting price increases for Amazon's first-party sellers.

### *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 US 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 on the basis of 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. Amazon (or its automated pricing algorithm) 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 on the basis of their likelihood of being offered and/or featured at Toys"R"Us. We explore the role of availability at Toys"R"Us by categorizing products along two dimensions: popularity and weight. We approximate popularity by the product's highest Amazon ranking and by the manufacturer's identity, finding similar results. Results for popularity are in Table 3, and results for manufacturers' identity are in the Appendix. In examining the impact by a product's popularity, we implicitly assume that Toys"R"Us was unable to allocate shelf space to the long tail of products available on Amazon (Brynjolfsson, Hu, and Smith 2003). Similarly, because of Amazon's large cost advantage for lightweight products for which last-mile shipping costs are low, Toys"R"Us may have opted against stocking and/or featuring such items. It is therefore possible that Toys"R"Us did not carry close substitutes for Amazon's lightweight items.

**Table 3**

**Price and Demand Effects by Popularity and Weight**

| | Popularity | | | Weight | | |
|---|---|---|---|---|---|---|
| | Amazon's Price (1) | Third-Party Price (2) | Price Change Frequency (3) | Amazon's Price (4) | Third-Party Price (5) | Price Change Frequency (6) |
| 1st Quintile | .0219 | −.0162 | −.188+ | −.0424* | .0109 | .0573 |
| | (.0219) | (.0112) | (.0975) | (.0206) | (.0191) | (.0917) |
| 2nd Quintile | .00899 | .0174 | −.0728 | .0373** | .0277+ | −.0849 |
| | (.0152) | (.0143) | (.0787) | (.0131) | (.0142) | (.0736) |
| 3rd Quintile | .0219 | .00980 | −.0363 | .0606** | .00858 | −.141+ |
| | (.0154) | (.0164) | (.0812) | (.0135) | (.0118) | (.0785) |
| 4th Quintile | .0402** | .0315 | −.159* | .0367** | .0245* | −.0732 |
| | (.0122) | (.0199) | (.0680) | (.0123) | (.0116) | (.0717) |
| 5th Quintile | .0520** | .0731** | −.145* | .0449** | .0205 | −.262** |
| | (.0108) | (.0231) | (.0687) | (.0116) | (.0128) | (.0713) |
| $N$ | 2,358,567 | 5,819,391 | 2,358,567 | 2,603,226 | 6,470,781 | 2,603,226 |
| Adjusted $R^2$ | .980 | .959 | .367 | .981 | .959 | .369 |

**Note.** Results are from estimates of a variant of equation (3) using toys in Canada and nontoys in the United States as control groups. The reported coefficients are the four-way interactions between the quintile and the treatment indicator US × Toy × After. All specifications include fixed effects for each pairwise combination of product, time, and country. Standard errors, clustered by product, are in parentheses.

+ $p < .1$.

* $p < .05$.

** $p < .01$.

In both sets of analyses, we augment the model in equation (3) by interacting the treatment variable (US × Toy × After) with indicators for quintiles of products' characteristics (popularity or weight). Consistent with Brynjolfsson, Hu, and Rahman (2009), Table 3 indicates that 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 in column 1 suggest that Amazon's prices of the most popular toy products increased by 5.3 percent ($= e^{.052} - 1$), which can be viewed as the price impact of removing a prominent competitor that offers the item in question.[16] Note also that the relationship between toy price increases and popularity are similar for third-party sellers (column 2). If we assume that third-party sellers exploit a more concentrated market and are not engaging in predatory pricing, this may suggest that Amazon's pricing was not predatory either but instead was 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 that this weighted price effect is 4.7 percent. Given Amazon's reported 10 percent price advantage over Toys"R"Us (Townsend 2013), these effects are substantial.

Table 3 also investigates the impacts by product weight. Column 4 shows lower, possibly even negative, Amazon's price impacts for the lightest items, which suggests that Amazon and Toys"R"Us may not have competed directly on these items. The strong relationship between weight and shipping prices, shown in Figure 1, supports this interpretation. Because Amazon offers free and fast (2-day) shipping on most items for its 100 million Prime subscribers in the United States (as of 2018), shipping heavy packages may be particularly costly for Amazon (Reisinger 2019), which erodes its cost advantage. Table 3 indicates similar impacts of weight on the prices of toys sold by third-party sellers (column 5). Column 6 shows that price change frequencies declined the most for heavier items. Hence, we find multiple dimensions of support for the idea that Amazon competed with Toys"R"Us primarily at the product level rather than at the retail destination level.

## 5. 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" (Gregory 2019). Similarly, other big five tech companies (Google, Facebook, Apple, and Microsoft) have cultivated images of being more consumer friendly than the monopolies of old in an attempt to create trust among consumers and employees.[17]

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

[17] Consider, for example, Google's initial "don't be evil" corporate code of conduct.

Consumers may therefore accept some harms in return for other benefits that accompany online companies' growing market power. In Amazon's case, consumers may tolerate losing the opportunity to browse and physically evaluate products when brick-and-mortar retailers disappear if online prices remain low. However, we show that prices may indeed rise.

Despite its purported focus on consumers' well-being, Amazon (much like the other big five tech companies) has drawn considerable scrutiny from politicians and regulators despite little hard evidence of direct harms to consumers. Using retrospective exit analyses, we provide evidence suggesting that Amazon's prices do rise after competitors exit, just as one typically expects from other profit-maximizing firms. In the context of toys, the estimated price increase of around 5 percent cuts its original price advantage by half. Although Amazon continues to charge relatively low prices, there is nonnegligible potential for benefits to consumers to dissipate further as more physical retailers exit.

While frequent changes in price for tens of millions of products suggest that Amazon's prices are set algorithmically, it is also possible that Amazon responded to Toys"R"Us's exit by changing the rules in the algorithm. Hence, it is challenging to infer whether the price increase reflects a deliberate reaction to the news of its competitor's demise or passive reactions according to prespecified rules in its pricing algorithm. We leave this distinction for future research. Consumers, however, may be less concerned with the root mechanism behind price changes than they are with the resulting increase in prices. Our results show that consumers are indeed harmed, which complements and supports antitrust scrutiny that focuses on less traditional measures of harms to consumers from prominent technology companies.

## Appendix

## Robustness Checks and Supplemental Analyses

### *A1. 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 is shown 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 by using coarsened exact matching.

We first match the toys in our data set with products from the other categories on several pretreatment dimensions. We create 50 categories of equal range for each of six variables: (1) the product's weight, (2) its volume, and the pretreatment averages of (3) Amazon's price, (4) third-parties' price, (5) weekly price change frequency, and (6) weekly new reviews between January and August 2017.

**Table A1**
**Price and Demand Effects: Coarsened Exact Matching**

| | Amazon Price | Third-Party Price | Price Change Frequency | New Reviews |
|---|---|---|---|---|
| Treatment | .0294** | .0230** | −.0126 | .00559 |
| | (.00790) | (.00839) | (.0425) | (.00418) |
| $N$ | 1,815,777 | 4,797,393 | 1,815,777 | 3,386,474 |
| Adjusted $R^2$ | .963 | .958 | .364 | .359 |

**Note.** Results are estimates from equation (3) 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 in parentheses.

** $p < .01$.

We find and retain 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 all dimensions except third-party prices, 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, are reported in Table A1. The estimated effects on both Amazon's and third-parties' prices are almost identical to those in the main analyses, suggesting increases of 3.0 percent and 2.3 percent, respectively. That is, the price effects in the main analysis are very robust to the choice of control group. By contrast, the effects on the frequency of price changes and the number of new reviews are much smaller than those in the main analysis and are no longer statistically significant.

### *A2. Robustness: Individual Control Groups*

The control group in the main analysis consists of five product categories: home and kitchen, electronics, pet supplies, hobby (spun off from the toy category), and beauty. To see if the results are driven by a particular product group, we estimate the regressions from equations (1) and (3) for each control group, excluding the products from the other control groups.[18]

The results are reported in Table A2. The number of toys and baby products across all control groups is 10,820 for the US-only specifications and 4,900 for the full specification because of the smaller number of toys available at Amazon's Canadian platform and the elaborate set of interacted fixed effects. The coefficients from the simple difference-in-differences analysis using only US data are reported with the results from the full triple-differences model. All estimated coefficients are positive and similar in magnitude, ranging from .021 to .053. The simple difference-in-differences coefficients are highly statistically significant for all data sets. The coefficients from the full model are statistically significant for all

[18] The unassigned control group category includes subcategories that appear to be an odd fit for the parent category. The largest subcategory in that group is automotive parts and accessories.

**Table A2**
**Price Effects: Separate Control Groups**

| | Treatment | *N* | Adjusted $R^2$ | Control Amazon Identifiers |
|---|---|---|---|---|
| Home: | | | | |
| United States | .0410** | 2,819,485 | .972 | 27,285 |
| | (.002) | | | |
| United States and Canada | .0383** | 1,778,368 | .978 | 12,754 |
| | (.008) | | | |
| Electronics: | | | | |
| United States | .0292** | 1,354,002 | .978 | 9,006 |
| | (.003) | | | |
| United States and Canada | .0213* | 922,340 | .984 | 4,120 |
| | (.009) | | | |
| Pets: | | | | |
| United States | .0418** | 1,264,830 | .954 | 6,205 |
| | (.003) | | | |
| United States and Canada | .0206+ | 781,744 | .969 | 2,629 |
| | (.011) | | | |
| Hobby: | | | | |
| United States | .0238** | 845,593 | .962 | 987 |
| | (.005) | | | |
| United States and Canada | .0232 | 551,802 | .973 | 542 |
| | (.017) | | | |
| Beauty: | | | | |
| United States | .0531** | 796,384 | .956 | 452 |
| | (.010) | | | |
| United States and Canada | .0327 | 505,755 | .967 | 169 |
| | (.040) | | | |
| Unassigned: | | | | |
| United States | .0406** | 2,849,311 | .972 | 27,647 |
| | (.002) | | | |
| United States and Canada | .0377** | 1,801,311 | .978 | 12,963 |
| | (.008) | | | |

**Note.** Results are estimates from equations (1) and (3). Fixed effects for product and week are included in the US estimates; fixed effects for each pairwise combination of product, time, and country are included in the estimates that include Canada. Standard errors, clustered by product, are in parentheses.

$^{+}$ $p < .1$.
$^{*}$ $p < .05$.
$^{**}$ $p < .01$.

samples except when the control groups are limited to the hobby ($p = .16$; 542 control products) and beauty ($p = .42$; 169 control products) categories.

### *A3. Heterogeneity by Manufacturer*

In the main analysis, 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 for

**Table A3**
**Price and Demand Effects across Manufacturers**

| | Amazon Price | Third-Party Price | Price Change Frequency | New Reviews |
|---|---|---|---|---|
| No Manufacturer | .0279** | .0147 | −.0645 | .0517** |
| | (.00906) | (.0100) | (.0506) | (.00621) |
| Other Manufacturer | .0322** | .0213+ | −.148** | .0504** |
| | (.0101) | (.0120) | (.0533) | (.00669) |
| Major Manufacturer | .0477+ | .0250 | −.222+ | .0230* |
| | (.0251) | (.0145) | (.0187) | (.0114) |
| $N$ | 2,603,985 | 6,526,339 | 2,603,985 | 5,397,899 |
| Adjusted $R^2$ | .980 | .960 | .369 | .474 |

**Note.** Results are from estimates of a variant of equation (3) using toys in Canada and nontoys in the United States as control groups. The reported coefficients are the four-way interactions between the manufacturers' dummies and the treatment indicator US × Toy × After. All specifications include fixed effects for each pairwise combination of product, time, and country. Standard errors, clustered by product, are in parentheses.

+ $p < .1$.
* $p < .05$.
** $p < .01$.

which we observe the manufacturer's identity, we assign the dummy Major Manufacturer to those listed among the "Top 30 Toy Brands in the World."[19] We thus divide the toys into three groups: those without information about the manufacturer (18,125 products), those by small manufacturers not in the top 30 (16,251 products), and those by major manufacturers included on the list (2,010 products). We repeat our analyses from above, interacting these size indicators with the treatment indicator, in Table A3. Consistent with the results across popularity quintiles, the positive Amazon price effects are largest among large manufacturers, although the coefficient is somewhat imprecisely estimated, likely because of the relatively small group. The remaining columns also support these patterns, as the point estimates of the effects on third-parties' prices and Amazon's price changes are largest for the largest manufacturers. The only exception, the proxy for demand, increased the least for large manufacturers, perhaps because the larger price increases disproportionately drew consumers to other toys that were now relatively cheaper.

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[19] See Farmtoysforkidsandfun.com, Top 30 Toy Brands in the World (https://farmtoysforkidsandfun.com/toy-brands-list/).

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