

The flood that caused a drought

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DOI:

[10.1111/ecin.13144](https://doi.org/10.1111/ecin.13144)

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Document Version

Publisher's PDF, also known as Version of record

Citation for published version (Harvard):

Nikolsko-Rzhevskyy, A, Talavera, O & Vu, N 2023, 'The flood that caused a drought', *Economic Inquiry*.
<https://doi.org/10.1111/ecin.13144>

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ORIGINAL ARTICLE

The flood that caused a drought

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Email: o.talavera@bham.ac.uk**Abstract**

To determine how an exogenous supply shock affects product availability, prices, and price-setting behavior, we analyzed a unique dataset representing a natural experiment concerning the 2011 flood in Thailand, which affected the production facilities of Western Digital, the world's largest producer of hard drives. The natural disaster impacted the overseas inventory of hard drives in the United States, where availability declined by more than 40% and price indexes increased by as much as 38%. However, our findings suggest that such supply shocks, when transmitted to either substitute or complementary products, are likely to be absorbed within production networks.

KEYWORDS

hard drive, inventory, natural disaster, price stickiness, supply shock

JEL CLASSIFICATION

E31, L11, L81

1 | INTRODUCTION

The Suez Canal blockage in March 2021,¹ the ketchup and lumber shortage in April 2021,² and, most recently, the global shortage of semiconductor chips³ are only a few examples of negative supply shocks of late that have affected the entire world. As economies become more globalized and supply chains, in a race to lower input costs, extend their reach, sellers often find themselves facing situations in which a break in only one of the supply chain's links will send the entire industry into a downward spiral. When that crisis occurs, two of the most pressing questions on the minds of producers and consumers alike are how the shock will propagate through the economy and how it will impact the prices of the products affected and substitute as well as complementary products.

Many theoretical works have forecasted price stickiness. Common causes proposed in earlier works to explain the substantial price rigidity reported in empirical papers include the use of time-dependent pricing models (e.g., Calvo, 1983), search costs (e.g., Burdett & Judd, 1983), menu costs (e.g., Sheshinski & Weiss, 1977), transportation and delivery costs (e.g., Betancourt & Gautschi, 1993), and bounded rationality (e.g., Akerlof & Yellen, 1985).⁴ Later investigations shifted to explaining sticky prices according to pricing models with inventory (e.g., Boileau &

Abbreviations: CPU, central processing units; HDD, hard disk drive; PCW, price comparison website; SSD, solid-state drives; WD, Western Digital Corporation.

Managing Editor: Silke Forbes

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Letendre, 2011), fear of customers' anger (e.g., Anderson & Simester, 2010; Rotemberg, 2005), and rational inattention (e.g., Reis, 2006; Sims, 2003). Although studies on dynamic pricing have often emphasized the important role of inventory in price setting, little empirical evidence supports that argument.⁵

Against that background, we tested some predictions of common price-setting models in recent works when subjected to an unanticipated exogenous supply shock. Our approach involved exploring price setters' responses to a production disruption event that consequently affected the cost and ability of restocking. To be specific, we treated the 2011 flood in Thailand as the trigger of the ensuing supply shock to sellers of hard drives around the world. The flood began on July 25, 2011 and continued for 158 days. In late October, the major hard disk drive (HDD) manufacturing facility of Western Digital Corporation (WD), the world's largest producer of hard drives, suffered damage from the flood that, in turn, caused a global supply shock for hard drives.⁶ A month later, in November 2011, the total value of hard drive imports to the United States was only 46% of that in the same period the year prior, which consequently affected the production of computers and computer components. Leading manufacturers of laptops, desktops, and central processing units (CPU) had to reduce their production as well as forecasted revenue for the quarter following the flood.⁷ The natural disaster thus provides us with a natural laboratory for estimating the impact of the supply shock on price setting not only for HDDs but also for their substitute products (e.g., solid-state drives, SSD) and complementary products (e.g., CPUs and motherboards).

For our study, we created a unique dataset of price quotes consisting of monthly seller-issued product price quotes collected from a leading price comparison website. In the dataset, each product is uniquely identified by its manufacturer part number, and each seller has a unique identifier. The sample covers 17,249 products offered by 366 online retailers within three types of products: hard drives, CPUs, and motherboards. The dataset spans from March 2010 to October 2012, encompassing the 2011 flood in Thailand. Using that comprehensive dataset, we computed product availability and price indices to track the development in each of the five broadly defined markets. Afterward, we identified the properties of price setting (e.g., frequency and size of price adjustments) and analyzed how price setting in those markets changed in response to the supply shock for hard drives in the United States. We close this paper by comparing our findings with the predictions of popular theories on pricing.

We found that the foreign supply shock substantially influenced the availability of products in local markets. Within a month after the suspension of WD's operations in Thailand, U.S. sellers' inventories were immediately affected, and the availability of hard drives was reduced by more than a full quarter, mainly due to the 44% drop in WD product availability. Although the flood had not affected the production facilities of other hard drive producers, we detected a significant fall in the product availability index of HDDs made by other manufacturers due to the considerable substitutability across hard drives. Even so, we found little evidence of the shock's immediate impact on the availability of hard drive substitutes (i.e., SSDs) and complementary products (i.e., motherboards and CPUs).

Regarding price-setting behavior, we observed that sellers of WD's hard drives responded to the shock almost immediately. In particular, sellers of WD's HDDs increased the frequency of their price increases by as much as 37%. Sellers of non-WD HDDs, by comparison, had similar responses but of lesser magnitude. Those findings suggest that sellers raised the prices immediately in anticipation of increases in time, financial, and labor costs related to obtaining new stock. Notably, the pricing of substitute products (i.e., experiencing a positive demand shock) and complementary products (i.e., experiencing a negative supply shock) showed little response to the shock. The latter result supports the literature documenting customers' anger and price rigidity and, in turn, claiming prices to be less flexible for consumer products than intermediate ones. Table 1 summarizes our results.

Our work contributes to the large body of literature examining and explaining the existence of price rigidity (e.g., Baudry et al., 2007; Dias et al., 2015). Theoretical studies focusing on price rigidity and inventory have suggested that sellers are motivated to use inventories to absorb demand and supply shocks (e.g., Blinder, 1982).⁸ Our work complements that literature by revealing the limited role of inventory in absorbing the impact of a relatively large, albeit temporary, supply shock on prices.⁹

From another angle, pricing models with rational inattention imply that prices are flexible to sectoral shocks but sticky to aggregate ones (e.g., Matějka, 2016; Maćkowiak & Wiederholt, 2015). Although evidence of the latter has often been derived from empirical studies (e.g., Gorodnichenko et al., 2018b), evidence of the former has been mixed. Many studies have shown the quick response of prices to disaggregate shocks (e.g., Beck et al., 2016),¹⁰ whereas studies on price-setting behavior following natural disasters have often revealed rigid prices in response to such events (e.g., Cavallo et al., 2014; Gagnon & López-Salido, 2020). Our work contributes to that argument by exploring the impacts of a foreign-born natural disaster on the pricing of storable and durable products (i.e., computers and computer components).

TABLE 1 Qualitative effects of the Thailand 2011 flood on select computer components.

	The affected product WD HDD	Substitutes		Complements	
		Direct competitor Non-WD HDD	Closest substitute SSD	CPU	Motherboard
Availability	--	-	=	-	-
Price	++	+	=	=	=
Price-setting behavior					
Frequency of price increases	++	+	+	=	=
Frequency of sales	--	-	+	=	=
Size of price increases	++	+	+	=	=
Size of sales	+	+	+	=	=

Note: The “+” and “-” signs show the direction of the effect, and their quantity indicates its magnitude. The “=” sign indicates there was no change or the effect was negligible. The reduction in the availability of CPUs and motherboards was delayed relative to that of the hard drives.

This paper also contributes to the literature on shock transmission. Past empirical studies have tended to furnish evidence of shock propagation and amplification via production networks (e.g., Boehm et al., 2019; Carvalho et al., 2021). Those results can be explained by a considerable contribution to the total output of affected firms (e.g., Carvalho & Gabaix, 2013; Gabaix, 2011) and/or the input–output linkages between industries (e.g., Baqaee, 2018; Caliendo et al., 2018). Beyond that, Barrot and Sauvagnat (2016) have suggested that the inventories of intermediate products in supply chains could help to delay the transmission of such shocks. We found some evidence of the latter, and this paper complements that literature by capturing the impacts of shock propagation on the availability and prices of substitute and complementary products while exploring the role of inventory in delaying shock transmission.

In what follows, Section 2 introduces our natural experiment, namely the 2011 flood in Thailand. Section 3 presents the dataset that we used and reports basic statistics, after which Section 4 describes the consequences of the 2011 flood in Thailand in terms of availability and price indices of electronic products in the United States. Next, Section 5 reports the properties of price changes (e.g., the frequency and size) for each type of product in our sample and analyses the responses of U.S. electronic sellers in particular. Last, Section 6 presents our conclusions.

2 | THE 2011 FLOOD IN THAILAND

In our analysis, we considered the 2011 flood in Thailand, which began in late July 2011 before spreading through the capital, Bangkok, and persisting in several regions until January 2012. The flood affected two-thirds of Thailand,¹¹ with total estimated economic losses in the country of approximately 12.56% of its GDP (Cavallo et al., 2014). As the natural phenomenon caused widespread disruptions in production and damaged logistics systems, the automotive and the HDD industries were among the sectors most affected.¹² In particular, the flood heavily damaged several manufacturing plants, including the primary production facilities of WD, the world’s largest manufacturer of HDDs.

WD was the only producer of HDDs that had to suspend production due to the flood, namely by halting operations in its production plant in Thailand on October 21, 2011. The plant accounted for approximately 60% of the total HDD production of the giant producer of hard drives.¹³ As a consequence, global HDD shipments fell by approximately 30% in the quarter following the disaster.¹⁴ In time, because SSDs—the faster, smaller in volume, and more expensive alternative to HDD—remained unpopular, the disrupted production of HDDs triggered a sharp supply shock across the U.S. market for hard drives, even though the production plants of other HDD and SSD manufacturers remained unaffected.

Now nearly halved, the total value of imported hard drives to the United States reached its lowest point within months after the flood. On that count, Figure 1 shows that the value of hard drives imported to the United States from Thailand fell nearly two-thirds within a single month after WD suspended the operation of its production plant in Thailand. Meanwhile, the total value of hard drives imported from other countries began to drop two months earlier but also hit bottom at the same time as the supply shock for hard drives from Thailand. Three months after hitting the

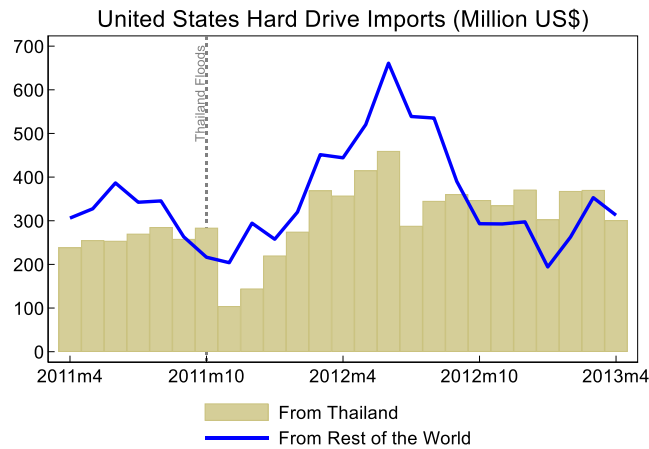


FIGURE 1 Value of United States hard drive imports. This figure shows the monthly value of hard drives (in million US\$) that were imported to the United States. The gray dashed vertical line marks the month of the shock. *Source:* UN Comtrade (2019).

lowest point, the total value of imported hard drives in the United States recuperated back to pre-shock levels, then became overshot in the following year.

Aside from being a final product, HDDs are key intermediate products in the computer industry. As a result, the shortage of hard drives heavily affected markets for other computer components as well as final products. Several large computer manufacturers announced that they were cutting back their production. Perhaps most notably, facing the reduction in computer production, Intel—the world’s largest maker of CPUs—had to curb production and revenue forecast for the quarter following the flood.¹⁵ In turn, the announcement caused Intel’s stocks to fall by more than 4% in a single day.¹⁶ Therefore, beyond hard drives, we also sought to investigate how the supply shock for hard drives impacted the availability and price-setting of their complementary and substitute products.

3 | DATA

To investigate the impacts of the supply shock for hard drives on price-setting behavior, we constructed a unique dataset of monthly product-seller price quotes of three primary products: hard drive, CPU, and motherboard. The data were collected from a leading U.S. price comparison website (PCW) for the period from March 2010 to October 2012, which encompassed the time of the shock.¹⁷ On the first day of each month, a Python script was triggered to collect websites and extract prices as well as other relevant information (e.g., product names, product descriptions, product identifications, seller identifications, and product prices for each seller). The data allowed us to identify each online seller uniquely. Added to that, each product listed online had a unique identifier, the manufacturer part number—for instance, “WD2500AAKX” refers to WD Internal 250 GB 3.5” PC Desktop Hard Disk Drive—which is necessary to categorize products by producers.

The prices in our dataset reflect net prices, which are prices before taxes and shipping fees. We excluded prices for all used, refurbished, and preorder products because they are not comparable to the prices of new products. In addition, to minimize the effects of extreme values in our data, we winsorized our variables at both the top and the bottom 1% of their distributions. Last, products with fewer than three sellers were excluded from the analysis. After the application of all of the mentioned filters, our dataset included 34,691 electronic products sold across 2005 sellers in the U.S. e-commerce market.¹⁸

Using prices collected from the PCW allowed us to limit the impact of potential problems such as outdated price quotes when, for example, sellers may not have incentives to change prices because they cannot restock. Thus, our data contained only products in stock and available for sale listed on the PCW. If a product was out of stock, it would instantly disappear from the PCW and reappear only when it became available again, if such was the case. Online merchants have incentives to keep their listings on the PCW up to date, for they pay for clicks from price aggregators to their webpages. If their listings are not updated, then they might not gain sales and thus waste their advertising money. Furthermore, it is possible that online merchants post low prices on the PCW in order to attract customers to their websites, which then offer the products at higher prices. However, Gorodnichenko and Talavera (2017) have argued

that the quoted and aggregated prices at the product level are highly consistent across such sources. Thus, the data purporting quoted prices are of reasonably high quality and can be used to capture changes in pricing behavior in response to shocks.

At the same time, a primary disadvantage of using online price data compared with offline price data is the lack of information about quantities. For instance, pricing measurements in the online book market may significantly change when products are weighted by the quantity sold (Chevalier & Goolsbee, 2003). However, recent research has shown that online scraped prices represent product prices well. Indeed, Cavallo (2017) found very little difference between the price scraped online and the offline price collected from physical stores. In that research, the online and offline prices were identical 72% of the time and had similar frequencies and sizes of adjustments. The following year, Gordnichenko et al. (2018a) found that online prices were more flexible than offline ones. Nevertheless, the results generated using unweighted measures of price stickiness were qualitatively similar to the ones using quantity-weighted measures.

Table 2 shows the average price of each percentile of the distribution over products (\bar{p}_i) as well as the mean and standard deviation of the average log price ($\overline{\log p_i}$), within the dataset. Regarding computer components, the average log prices of a CPU and a motherboard in our sample were 5.85 and 5.32 log points (or approximately \$347 and \$204), respectively. The product prices often ranged from approximately \$43 to \$2476. Our primary interest was hard drives, which was also the most common product type in our dataset, one encompassing 9707 products. In our data, the median (i.e., 50th percentile) price of a hard drive was \$140.65. A quarter of the hard drives sampled were priced at under \$89.80, whereas the top 25% of the most expensive hard drives are priced at more than \$247.07.

4 | IMPACT ON PRODUCT AVAILABILITY

Natural disasters such as earthquakes, hurricanes, and floods often disrupt production and significantly influence the inventory of sellers, thereby reducing product availability. This section describes the impact of the 2011 flood in Thailand, which hit WD's largest production plant, on the product availability of WD's HDDs, on their direct competitors (i.e., non-WD HDDs), on substitute products (i.e., SSDs), and on complementary products (i.e., CPUs and motherboards).

We constructed a simple index to capture the product availability of each type of product. In particular, we counted the total number of distinct available price quotes for each product each month. The series was then normalized to 100% in October 2011, the month of the flood's damage to WD's plant, in order to be able to easily compare availability across types of products. As mentioned in the previous section, a product was likely to be in our dataset if it was available on a seller's website. Out-of-stock products, by contrast, disappeared immediately and reappeared only if and when they were again in stock. In terms of temporal scope, we focused on a brief period surrounding the natural disaster when the entry (exit) of new (old) products and online sellers was rare. Therefore, our product availability index was able to reasonably reflect the impact of the supply shock on sellers' inventories and the availability of products in the market. Figure 2 shows the product availability indices of HDDs (e.g., WD's HDDs and HDDs made by other HDD producers), SSDs, and complementary products (i.e., motherboards and CPUs).

In Figure 2, panels A and B present the HDD availability indices. We observed that during the 7-month period prior to the flood, the number of price quotes of WD HDDs and non-WD HDDs remained stable at approximately 100% (i.e., solid line). Those values fell sharply within 1 month after the flood hit WD's plant in Thailand and did not recover to

TABLE 2 Distribution of prices, USD.

Product	Mean log price		Mean price, percentile					N
	Mean (1)	SD (2)	5% (3)	25% (4)	50% (5)	75% (6)	95% (7)	
Hard drive	5.08	0.93	48.00	89.80	140.65	247.07	1032.47	9707
CPU	5.85	1.18	52.26	135.62	349.26	846.10	2469.30	4039
Motherboard	5.32	1.04	42.99	94.89	198.99	399.99	1523.21	3503

Note: Columns (1) and (2) report the mean and standard deviation of the distribution of the average log price for a product ($\overline{\log p_i}$); columns (3)-(7) report the mean for each percentile of the average price for a product (\bar{p}_i); column (8) shows the total number of products, N .

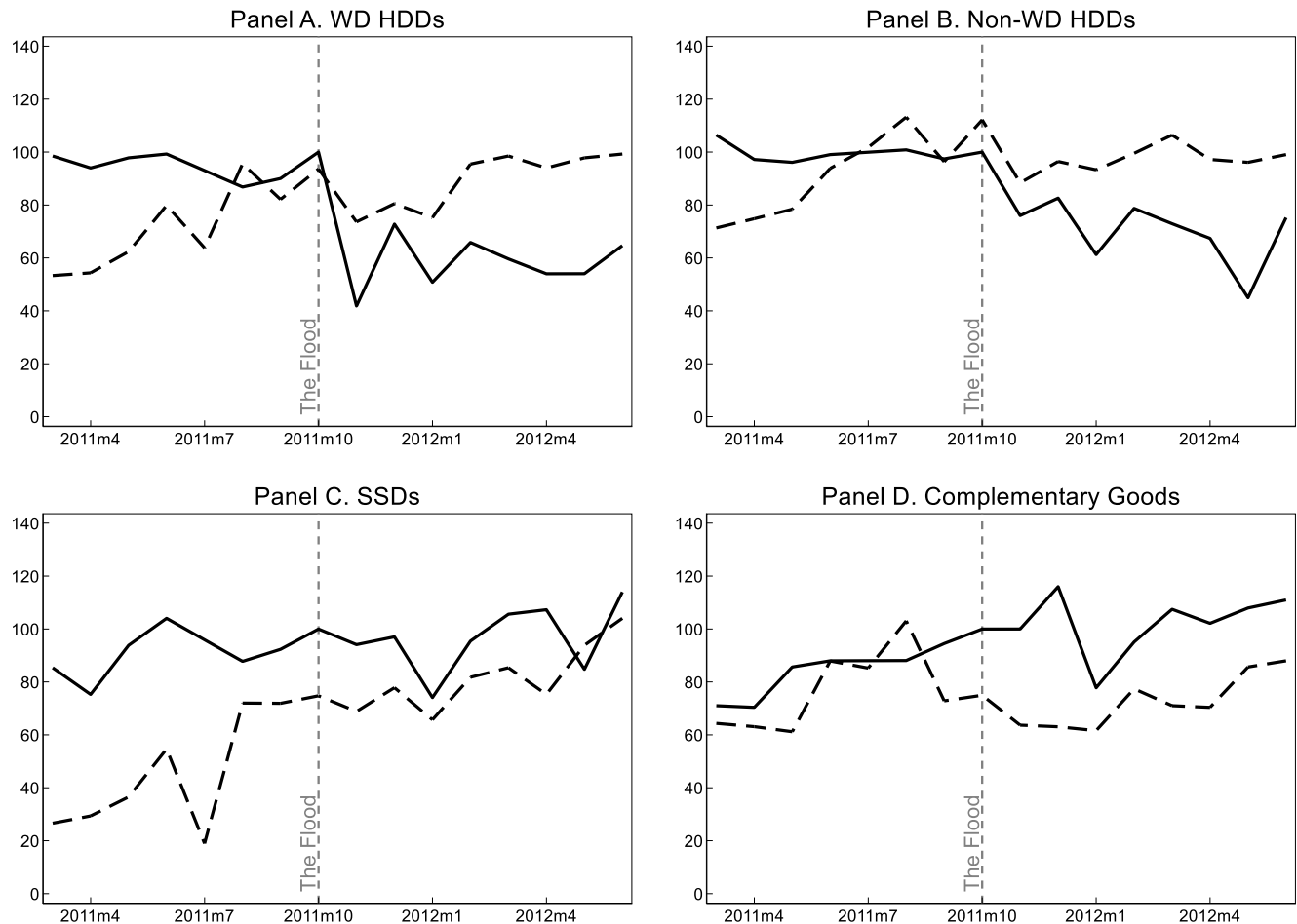


FIGURE 2 Product Availability Indices. This figure shows the monthly product availability indices. We normalize the indices to a value of 100 in October 2011, in which the WD production plant in Thailand was flooded. In all cases, the solid black line presents the availability indices from 7 months before to 9 months after the shock, between March 2011 and July 2012. The black dashed line presents the availability indices in the period of 12 months before, between March 2010 and July 2011. The vertical axis is the availability index (%). The gray dashed vertical line marks the month of the shock.

their previous levels for the next 9 months. The inventories of sellers of hard drives were affected by the supply disruption, especially in the fourth month following the damage to the WD plant, which caused the availability of WD's HDDs to decline by nearly 60%. That same month, the availability of HDDs produced by other manufacturers dropped by 24%. By contrast, we did not observe a similarly massive drop in product availability indices of HDDs in the same period of the previous year (i.e., dashed line). That difference suggests that substitutability across hard drives indeed exists and that the role of sellers' inventory in delaying a temporary supply shock's impact on the retail sector, even if only temporarily, might be less than previously thought.

Despite the large reduction in the availability of HDDs, we observed little reaction to the shock in the availability index of SSDs, the closest substitute for HDDs (see Figure 2, panel C), which remained stable for 3 months after the month that WD plant was flooded. Thereafter, it dropped by more than 20% compared with the month of the flood but returned to more than 100% in the two months after that. Similarly, panel D in Figure 2 shows that the supply shock for hard drives did not significantly influence the availability of complementary products. Three months after WD ceased their operations in Thailand, the availability index of complementary products decreased to 80% but then quickly recovered in the months that followed. That result is consistent with the findings of Barrot and Sauvagnat (2016) and other research focusing on the transmission of shocks via production networks. Moreover, it highlights the impact of the disruption of HDD production on the availability of complementary products and the role of inventories of intermediate products in delaying the shock's impact on complementary ones.

5 | PRICE SETTING

In the previous section, we have shown how the supply shock affected the availability and pricing of hard drives as well as related products. The results suggest that inventories appeared to play an important role in smoothing prices for substitute and complement products. Thus, this section extends that assessment by analyzing the response of price stickiness at a good level. Herein, we show how price setters behaved around the time of the supply shock and, consequently, the inventory shock in a market in which price friction is minimal.

5.1 | Regular and posted prices

Several studies on price setting have revealed the popular practice among sellers of briefly changing prices. The literature maintains that such temporary price changes (sales) are unlikely to affect aggregate prices (e.g., Eichenbaum et al., 2011; Kehoe & Midrigan, 2015); thus, those price quotes are often filtered out. To measure price stickiness, we followed standard methods in the literature on price-setting to compute the primary properties of price changes (i.e., frequency and size), and report the results for both posted prices (i.e., the prices in our dataset) and regular prices (i.e., the prices excluding temporary changes).

Since we do not have an identifier for temporary price changes, we follow previous studies to identify sales by a “sales filter” (e.g., Nakamura & Steinsson, 2008). In particular, we recorded an increase or decrease in price as a temporary change in price if the price returned to its previous level within a month's time. After that, we determined the regular prices by replacing the price at the time of the temporary change with the regular price (i.e., the price at the original level).

Table 3 reports the monthly frequency and size of sales for the three types of products in our dataset. Generally, the frequency and size of sales in our dataset were in a range similar to that of statistics found in other empirical studies on online prices in the United States. The average monthly frequency of sales for the three product types was similar in scale, ranging from 1.35% to 2.18%. By size, CPUs and motherboards had a similar size of sales, with medians ranging from 2.76% to 3.74%. Meanwhile, hard drives, including WD's as well as other companies' drives, often had a larger size of sales than other products, with a median size of 6.28%. Because temporary price changes were uncommon in our data, we expected the difference, if any, between the results for posted prices and regular prices to be minor.

5.2 | Frequency and size of price changes

Following previous studies (e.g., Bils & Klenow, 2004), we considered a price change as a change in excess of 0.1%. First, the monthly frequency of changes in price of each product was calculated as the ratio of the number of price changes to the total number of prices for that product that could have potentially changed. Second, we aggregated that measure to product type level by taking the unweighted average across products representing the type every month. Last, we calculated the average implied duration of price changes for each type of product from the average frequency. The measure translated the frequency of price changes into the implied duration during which a product kept its price

TABLE 3 Monthly frequency and size of sales.

Product	One-month two-sided sales filter			
	Mean frequency (1)	St. Dev. Frequency (2)	Median size (3)	<i>N</i> (4)
Hard drive	1.46	2.82	6.28	5420
CPU	1.35	3.44	2.76	2420
Motherboard	2.18	4.12	3.74	2500

Note: Column (1) shows the monthly average of sales frequency across products (%). Column (2) reports the standard deviation of sales frequency across products. Column (3) shows the absolute size of sales for the median product, in which the absolute size of sales is equal to the gap between the log of the sales price and the log of the regular price (multiple by 100). Column (4) shows the number of products. A sale is identified by using the 1-month, two-sided sales filter.

TABLE 4 Monthly frequency and size of price changes.

Product	Motherboard	CPU	Hard drive
Posted price			
Median frequency, %	33.33	35.56	51.30
Implied duration, months	2.47	2.28	1.39
Median absolute size, log points	5.38	12.15	14.39
Regular price			
Median frequency, %	28.57	33.33	48.62
Implied duration, months	2.97	2.47	1.50
Median absolute size, log points	5.38	12.28	14.66

Note: The first and second rows of each panel present the estimated monthly frequency and the corresponding implied duration for each product type. The last row of each panel shows the median absolute size of price adjustments for each product type. We exclude missing values and compute the regular prices based on a 1-month, two-sided sales filter.

unchanged. That value was calculated as $\bar{d}_C = (-1)/\ln(1 - \bar{f}_C)$, in which \bar{d}_C is the average implied duration of product type C and \bar{f}_C is the average frequency of that product type's price changes.

The estimated monthly frequency and corresponding implied duration of each type of product are reported in Table 4. In general, all product types in our dataset had a median implied duration of less than 2.5 months for posted prices. Filtering out temporary sales increased the implied duration by 20% for motherboards and 8% for CPUs and hard drives. Hard drives had the most flexible prices in our sample, with median implied durations of 1.39 months for posted prices and 1.5 months for regular prices. The stickiest prices in our sample were for CPUs and motherboards, which had median durations ranging from 2.28 to 2.97 months. Those results were similar to the statistics reported for the U.S. online market in past studies and lower than statistics concerning the offline market. For example, Gorodnichenko et al. (2018a) reported that the average implied duration of all products in their sample (i.e., mostly electronic products) was 1.54–2.54 months. Meanwhile, in offline markets, Nakamura and Steinsson (2008) observed slightly stickier prices, with a duration of 2.3–3.3 months for personal computers and peripheral equipment that reflects greater friction than in online markets.

As for frequency, we computed the size of price changes for each quoted price first as the absolute value of price changes. Second, we aggregated that measure to the product level by taking the raw average of price changes across sellers without seller weights. Third, at the level of product type, the average size of price changes across products within the product type was computed.

Table 4 presents the median absolute size of price adjustments for each type of product. The median change in price in our sample was close to the statistics reported in the literature for both online and offline markets.¹⁹ In particular, we observed that prices for hard drives had the largest adjustment size of all product types. The results for posted prices and regular prices were similar: 14.39% and 14.62%, respectively. More than half of the CPUs in our sample had an average size of price adjustments exceeding 12%. Meanwhile, the median sizes of price adjustments for motherboards were less, none of which exceeded 5.4%.

5.3 | Determinants of price-setting behavior

To extend our qualitative analysis of price-setting behavior, we examined price-setting using a more formal, regression-based approach. We used shock dummies that control for periods before and after the flooding disaster to estimate the regressions, with two price-setting measures (i.e., frequency and size of price changes) as dependent variables. Because the features of the market and products might relate to the heterogeneity of price stickiness across products, we controlled for those factors.

As for what the determinants of price stickiness might be, the literature often highlights the role of market power in price-setting (e.g., Ginsburgh & Michel, 1988). In our study, we used the number of sellers as a proxy for the degree of market power. After all, because a market with more sellers is more competitive, sellers in such a market are expected to have less market power and to change prices more frequently.

Second, firm entry can also affect sellers' pricing strategies (e.g., Gust et al., 2010) because a market that is easy for sellers to enter should be more competitive. Therefore, sellers in such a market can be expected to adjust their prices faster than sellers in a market that is difficult to join. We thus used the stability of sellers—that is, the ratio of the number of sellers offering a product in a given month to the number of sellers that ever sold that product in the quarter covering the given month—to reflect the degree of difficulty that sellers experienced in selling a product. Similar to the number of sellers, we anticipated that the stability of sellers would be positively associated with the degree of price rigidity.

Third, numerous studies have shown that consumers' search costs influence pricing decisions (e.g., Head et al., 2010). In that dynamic, the more intense the searches of customers, the greater the pressure on price setters to set competitive prices. Because more expensive products should have a higher return on searches, we used the log median prices to capture the returns on consumers' searches.

Last, we used the percentage of price points—that is, the quoted prices ending in 95–99 cents—to reflect the level of customers' inattention to prices when choosing a product across sellers. According to Knotek (2011), types of products with a higher share of price points usually have stickier prices. That positive association can be attributed to price friction caused by the large difference between common price points.

Given our aim of documenting the impact of the supply shock caused by the flood damage, we used data representing only the 18-month period surrounding the event (i.e., 12 months before and 6 months after the months of shock) in our regression. Because that period was relatively brief, we estimated the pricing moment and our predictors at the product–month level. For instance, we computed the monthly frequency of price changes for a specific product as the fraction of adjustments to that product's price over the course of a month, which we then used as our dependent variable. Regarding the shock's impact, we treated October 2011, when the flood hit WD's largest production plant, as the month of the shock. We ran our baseline regressions without weights while controlling for time trends for each product, following Equation (1):

$$f_{it} = \beta_1 \log S_{it} + \beta_2 \overline{\log P_{it}} + \beta_3 \overline{\log P_{it}}^2 + \beta_4 \text{SPP}_{it} + \beta_5 \text{Stab}_{it} + \beta_6 \text{AfterShock}_t + \theta_i + \text{trend}_{it} + \varepsilon_{it} \quad (1)$$

in which, f_{it} is the frequency of price changes, frequency of positive changes, frequency of negative changes, size of price changes, size of price increases, or size of price decreases for product i at month t ; S_{it} is the number of sellers offering product i in month t ; $\overline{\log P_{it}}$ is the log of the median price of product i in month t ; SPP_{it} is the share of price points of product i in month t ; Stab_{it} is the stability of the number of sellers offering product i in month t (1 quarter base); AfterShock is a dummy variable equaling 1 if the month follows the shock and 0 otherwise; and θ_i are product fixed effects; and trend_{it} are product-specific time trends, respectively.

Table 5 reports the estimated regular prices for the sample of hard drives. Most of the control variables had some predictive power. First, the median price across sellers of a product was positively (negatively) associated with the frequency of increases (decreases) in price. That finding is consistent with what Richards et al. (2014) found: that consumer searches make prices increase faster and decrease slower. Second, products with a higher proportion of price points tended to have stickier prices. That result corroborates Levy et al. (2011) findings, according to which products with prices ending with a “9” have less frequent and larger price adjustments than products with prices ending with any other numbers. Third, measures of market competitiveness demonstrated significant predictive power in relation to price setting. In particular, more sellers and less seller stability were associated with greater flexibility in pricing. That result supports the view that a more competitive market should have more flexible prices. Last, concerning our primary variable of interest, *AfterShock*, in the 6-month period after the shock, sellers in the market increased (decreased) their prices more (less) frequently by 15.1% (2.2%) than in the 6-month period before the shock. On top of that, the absolute value of both positive and negative prices changes unequivocally increased after the shock.

Aside from studying all of the drives together, we separated them into three groups—WD's HDDs, non-WD HDDs, and SSDs—and added group-specific interaction terms to the regression. Based on our previous analysis (see Figure 2), we considered that SSDs could be treated as a control group because these products were unlikely to have been affected by the shock.^{20,21}

Table 6 shows that most of the coefficients of our control variables remained qualitatively unchanged. Relative to the SSDs, the frequency of price increases (decreases) of WD HDDs rose by 17.5% (6.2%) during the 6 months aftershock. Along similar lines, sellers of non-WD HDDs exhibited a similar response after the shock but one of less magnitude.

TABLE 5 Predictors of regular-price stickiness (WD, Non-WD HDD, and SSD sample between [T - 12; T + 6]).

Predictors	Frequency of price changes, % (1)	Frequency of positive changes, % (2)	Frequency of negative changes, % (3)	Absolute size of price changes, log points (4)	Absolute size of positive changes, log points (5)	Absolute size of negative changes, log points (6)
After shock	0.128*** (0.007)	0.151*** (0.007)	-0.022*** (0.007)	0.110*** (0.004)	0.097*** (0.007)	0.069*** (0.005)
Ln number of sellers	0.053*** (0.007)	0.039*** (0.007)	0.015** (0.007)	0.007* (0.004)	0.012* (0.007)	-0.016*** (0.006)
Ln median price	0.181*** (0.050)	0.543*** (0.060)	-0.362*** (0.064)	0.379*** (0.063)	0.734*** (0.091)	0.140* (0.075)
Ln median price squared	-0.017*** (0.005)	-0.029*** (0.006)	0.012* (0.007)	-0.029*** (0.006)	-0.051*** (0.009)	-0.023*** (0.007)
Share of price points	-0.133*** (0.015)	-0.035** (0.014)	-0.099*** (0.015)	0.014 (0.009)	0.022* (0.013)	0.013 (0.011)
Stability of sellers	-0.096*** (0.012)	-0.103*** (0.012)	0.007 (0.012)	-0.077*** (0.008)	-0.097*** (0.012)	0.003 (0.010)
R ²	0.563	0.458	0.456	0.597	0.640	0.564
N	38,261	38,261	38,261	24,975	17,719	21,008

Note: This table shows regression results for the sample of WD HDDs, non-WD HDDs, and SSDs using the monthly regular price adjustments between Oct 2010 and Apr 2012 on the set of dependent variables above. Particularly, *Ln Number of Sellers* and *Ln Median Price* are the natural logarithm of the number of sellers and the median price across sellers of product *i*, respectively. *Share of price points* is the proportion of price quotes that end at 95–99 cents of product *i*. *Stability of sellers* for product *i* is the ratio of the number of sellers offering product *i* in a given month to the number of sellers ever selling this product in the quarter, which covers the given month. *After shock* is a dummy variable equaling 1 if the month follows the shock and 0 otherwise. All dependent variables are unweighted price-setting measures. We run regressions at the product-month level controlling for fixed effects and product time-trends.

*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

TABLE 6 Predictors of regular-price stickiness (WD, Non-WD HDD, and SSD sample between [T - 12; T + 6]).

Predictors	Frequency of price changes, % (1)	Frequency of positive changes, % (2)	Frequency of negative changes, % (3)	Absolute size of price changes, log points (4)	Absolute size of positive changes, log points (5)	Absolute size of negative changes, log points (6)
After shock	0.001 (0.018)	0.050*** (0.015)	-0.049*** (0.019)	0.032*** (0.008)	0.016 (0.012)	0.038*** (0.010)
After shock * Non-WD HDD	0.132*** (0.019)	0.106*** (0.016)	0.026 (0.020)	0.073*** (0.009)	0.076*** (0.014)	0.019* (0.011)
After shock * WD HDD	0.238*** (0.025)	0.175*** (0.025)	0.062** (0.027)	0.195*** (0.016)	0.183*** (0.021)	0.135*** (0.022)
Ln number of sellers	0.054*** (0.007)	0.039*** (0.007)	0.015** (0.007)	0.009** (0.004)	0.014** (0.006)	-0.014** (0.006)
Ln median price	0.149*** (0.051)	0.520*** (0.060)	-0.372*** (0.064)	0.306*** (0.062)	0.641*** (0.090)	0.064 (0.074)
Ln median price squared	-0.015*** (0.005)	-0.027*** (0.006)	0.012* (0.007)	-0.023*** (0.006)	-0.043*** (0.009)	-0.016** (0.007)
Share of price points	-0.136*** (0.015)	-0.037*** (0.014)	-0.099*** (0.015)	0.013 (0.008)	0.022* (0.013)	0.013 (0.010)
Stability of sellers	-0.091*** (0.012)	-0.100*** (0.011)	0.008 (0.012)	-0.071*** (0.008)	-0.091*** (0.012)	0.005 (0.010)
R ²	0.564	0.459	0.456	0.602	0.644	0.567
N	38,261	38,261	38,261	24,975	17,719	21,008

Note: This table shows regression results for the sample of WD HDDs, non-WD HDDs, and SSDs using the monthly regular price adjustments between October 2010 and April 2012 on the set of dependent variables above. Particularly, *Ln Number of Sellers* and *Ln Median Price* are the natural logarithm of the number of sellers and the median price across sellers of product *i*, respectively. *Share of price points* is the proportion of price quotes that end at 95–99 cents of product *i*. *Stability of sellers* for product *i* is the ratio of the number of sellers offering product *i* in a given month to the number of sellers ever selling this product in the quarter, which covers the given month. *After shock* is a dummy variable equaling 1 if the month follows the shock and 0 otherwise. *WD HDD* and *Non-WD HDD* is dummy variables which equals 1 if the product is Western Digital HDD and HDD produced by other producers, respectively, and equals zero otherwise. All dependent variables are unweighted price-setting measures. We run regressions at the product-month level controlling for fixed effects and product time-trends.

*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Whereas their prices increased 10.6% more frequently, the frequency of price increases (decreases) of SSDs increased (decreased) by 5.0% (4.9%).

Next, we attempted to determine how long it took sellers of hard drives both to begin increasing prices in response to the shock and, in time, to stop increasing prices. To that end, we took a somewhat granular approach and modified Equation (1) as follows:

$$f_{it} = \beta_1 \log S_{it} + \beta_2 \overline{\log P_{it}} + \beta_3 \overline{\log P_{it}^2} + \beta_4 SPP_{it} + \beta_5 Stab_{it} + \sum_k (T+k)\alpha_k + \sum_k nonWD * (T+k) \gamma_k + \sum_k WD * (T+k) \mu_k + \theta_i + trend_{it} + \varepsilon_{it} \quad (2)$$

in which *nonWD* and *WD* are dummies equaling 1 if the product is a non-WD HDD or a WD HDD, respectively, and 0 otherwise; and $T+k$, with k from 1 to 6, is a dummy variable equaling 1 if the month is k months after the shock and 0 otherwise. We then focused on the coefficients γ_k and μ_k , which represent the monthly responses to the shock made by sellers of non-WD HDDs and WD HDDs relative to those of SSDs. The results are presented in Figure 3.²²

The first row in Figure 3 suggests that sellers of WD HDDs began increasing the frequency and size of price increases in the first month following the shock. In that same month, the frequency and size of price changes of WD HDDs increased by more than 20%. That reaction might have been caused by the plummeting supply of hard drives, as



FIGURE 3 WD and non-WD HDDs price-setting response to the flood. This figure presents the impact of the shock on the price-setting behaviors of sellers during the period 6 months after the flood by showing the coefficients and the 95% confidence interval of 6 months-dummy variables (for the full table of coefficients, please see Appendix Table A3.2) for WD (top panels) and non-WD (bottom panels) products. The left panels report results for the frequency of price changes, while the right panels show estimates for the absolute size of price changes. In all cases, the vertical axis on the left is the size of the coefficient relative to that of SSDs. The horizontal axis is the number of months after shock (from 1 to 6). The red horizontal line marks the difference being equal to zero.

well as by WD's announcement that it was going to continue suspending production.²³ However, the frequency and size of changes in price returned to pre-flood levels in the fifth month following the shock.

Those responses are consistent with what pricing models predict based on rational inattention (e.g., Maćkowiak & Wiederholt, 2009) and sticky information (e.g., Mankiw & Reis, 2002), according to which prices are flexible to sectoral shocks because sellers frequently update the conditions of the sectors. However, those models assume that sellers update information flawlessly, therefore suggesting an overly high degree of price flexibility at the micro level. Beyond that, the quoted prices in our dataset changed less often than in those models. By contrast, the model of rational inattention with discrete pricing put forward by Matějka (2016), in which sellers update information continually but not perfectly, could generate price rigidity at the micro level that more closely aligns with the characteristics of our dataset. Moreover, the instant response to the shock by sellers, despite having their products available for sale, shows the limited role of inventory in price smoothing and offers little support for models of price stickiness accounting for fear of customers' anger when it comes to intermediate products hit by a relatively large shock.

Regarding non-WD HDDs, the second row of Figure 3 suggests that the product type's price setting had a similar response, albeit of lesser magnitude, to the shock than WD HDDs. In the first month following the shock, the frequency and size of price adjustments of non-WD HDDs were approximately 10% higher than beforehand. However, in the 4 months that followed, the reaction of sellers faded. That finding suggests that the disruption of WD's production affected the pricing of HDDs made by other manufacturers, likely because the unavailability of WD's products increased the demand for substitutes and, in turn, indirectly triggered the demand shock of non-WD HDDs, albeit of a smaller magnitude.²⁴ As a result, price setting for WD HDDs reacted to the shock more strongly than non-WD HDDs.²⁵

5.4 | Controlling for trends

Both Finkelstein (2007) and Flaaen et al. (2020) have stressed the importance of controlling for potentially differential temporal trends and suggested a model that achieved that goal. Following their modified difference-in-differences approach, we re-estimated Equation (2) to allow k to assume values from -12 to 9 while normalizing the effect of the month of the shock to 0 .²⁶ In that way, the category-level time effects α , $\alpha + \gamma$, and $\alpha + \mu$ show the absolute difference in frequency and size of price changes relative to October 2011 for SSDs, non-WD HDDs, and WD HDDs, respectively. Next, to account for possible preexisting trends, we calculated the change in frequency and size of price changes after the shock in relation to the change in frequency and size of price changes beforehand. For example, for SSDs, the 4-month differential effect of the flood was calculated as:

$$\Delta_{\text{Flood}}^{4m} \bar{f}_{\text{SSD}} = (\bar{\alpha}_{-6 \text{ to } -5 \text{ months from shock}} - \bar{\alpha}_{-1 \text{ to } 0 \text{ months from shock}}) - (\bar{\alpha}_{-1 \text{ and } 0 \text{ months from shock}} - \bar{\alpha}_{+4 \text{ and } +5 \text{ months from shock}}) \quad (3)$$

TABLE 7 Difference-in-difference estimates: Price-setting effects of the flood.

	Frequency of price changes, %		Absolute size of price changes, log points	
	4-month (1)	8-month (2)	4-month (3)	8-month (4)
Δ (SSD)	0.010 (0.036)	0.047 (0.037)	0.010 (0.013)	0.005 (0.014)
Δ (Non-WD HDD)	0.115*** (0.015)	0.204*** (0.015)	0.012 (0.009)	-0.006 (0.008)
Δ (WD HDD)	0.158*** (0.035)	0.121*** (0.035)	0.006 (0.021)	-0.015 (0.021)
Observations	43,479	43,479	28,727	28,727

Note: This table presents estimates for $\Delta_{\text{Flood}}^{4\text{-month}} \bar{f}$ and $\Delta_{\text{Flood}}^{8\text{-month}} \bar{f}$ which are defined in Equation (3).

*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

in which $\bar{\alpha}$ is the average of each individual month's effect on SSDs. Along similar lines, to calculate the 8-month effect, we defined the endpoints using periods -10 to -9 months and 8 to 9 months relative to October 2011. The results for $\Delta_{\text{Flood}}^{4\text{-month}}\bar{f}$ and $\Delta_{\text{Flood}}^{8\text{-month}}\bar{f}$ appear in Table 7.

We found that the supply shock increased the frequency of price changes of WD HDDs by 15.8% across the 4-month period. However, the impact decreased to 12.1% over the 8-month period. Similarly, the frequency of changes in the price of non-WD HDDs also increased by 11.5% and 20.4% in four- and 8-month periods, respectively. Meanwhile, consistent with our previous findings, we observed limited evidence of the flood's impact on the price-setting behavior of sellers of SSDs.

6 | CONCLUSION

In a natural experiment, we investigated price-setting behavior in response to a well-known supply shock, the 2011 flood in Thailand, one that forced the closure of the primary production plant of WD, the world's largest producer of HDDs. The event triggered a large, exogenous shock to the global as well as U.S. supply of HDDs, in which the total value of imported hard drives to the United States fell drastically approximately a month after WD suspended its operations in Thailand. As a result, the inventory of sellers and the product availability in the U.S. market for hard drives were severely affected.

We used a large, comprehensive dataset of prices quoted online in the United States, one that not only allowed capturing the shock's impacts on sellers' inventory and product availability but also provided useful insights into how price setting behaves in response to such events. We found that the inventories of U.S. retailers were immediately affected by the supply shock, which precipitated the plummeting availability of hard drives. The shock also affected the availability of important computer components such as CPUs and motherboards, although those reductions were delayed and of less magnitude than that of hard drives. While the former result underscores the limited role of retailers' inventory in delaying the shock's impact, the latter result suggests that inventory in production networks can considerably absorb and delay such a shock's impact on production and, in turn, on the inventory of complementary products. That finding aligns with what Barrot and Sauvagnat (2016) documented: that inventories delay the impact of supply shock propagation via input–output linkages.

Our results concerning price setters' responses to the exogenous shock provide vital implications for macroeconomic models. We found that sellers of hard drives increased their prices almost immediately in response to the shock. Such a reaction shows little support for pricing models that consider inventory as a means in price smoothing (e.g., Boileau & Letendre, 2011). Instead, our results support price-setting models based on rational inattention (e.g., Matějka, 2016; Matějka & McKay, 2015), according to which prices are responsive to sectoral shocks. However, sellers of complementary products and more distant substitutes all showed muted as well as delayed price responses. On that count, models with bounded rationality (e.g., Dixon, 2020) and/or input–output linkages (e.g., Petrella & Santoro, 2011) can sufficiently explain the delay.

ACKNOWLEDGMENTS

Standard disclaimer applies. The authors thank Tho Pham and the participants of the ESCoE Conference on Economic Measurement for valuable comments and suggestions. Any remaining errors are our own. No external funding sources supported this research.

DATA AVAILABILITY STATEMENT

The code and data that support the findings of this study are openly available in openICPSR at <http://doi.org/10.3886/E183862V3> (Talavera et al., 2023).

ENDNOTES

¹ <https://www.wsj.com/articles/suez-canal-blockage-pressures-global-container-supply-11617027978> [Accessed 17th October, 2022].

² <https://www.wsj.com/articles/the-new-shortage-ketchup-cant-catch-up-11617645189> [Accessed 17th October, 2022].

³ <https://www.wsj.com/articles/why-the-chip-shortage-is-so-hard-to-overcome-11618844905> [Accessed 17th October, 2022].

⁴ See Chari et al. (2000) regarding time-dependent pricing, Benabou (1988) regarding search costs, Midrigan (2011) regarding menu costs, and Dixon (2020) regarding bounded rationality.

- ⁵ See Bilotkach et al. (2010) and Bilotkach et al. (2012) regarding dynamic pricing, and Lloyd et al. (2001) for evidence of unresponsive prices following the supply shock in the UK beef market.
- ⁶ See “Thai floods hit global hard drive production” (*Financial Times*, October 20, 2011) (Available at: <https://tinyurl.com/yczhv35a>) [Accessed 17th October, 2022].
- ⁷ See “Intel cuts revenue forecast as Thai floods hit PC sales” (*The Guardian*, December 12, 2011) (Available at: <https://tinyurl.com/ybz4hcnb>) [Accessed 17th October, 2022].
- ⁸ See Amihud and Mendelson (1983) and Aguirregabiria (1999).
- ⁹ Evidence shows that at least some major hardware sellers rely on the just-in-time model, which could provide another explanation of the phenomenon (<https://www.wsj.com/articles/SB1003699648280549640>) [Accessed 17th October, 2022].
- ¹⁰ See Maćkowiak et al. (2009) as well as Kaufmann and Lein (2013).
- ¹¹ See “Thailand floods disrupt production and supply chains” (*BBC*, October 13, 2011) (Available at: <https://www.bbc.co.uk/news/business-15285149>) [Accessed 17th October, 2022].
- ¹² See “Thai prime minister to take command of flood control efforts” (*The New York Times*, October 21, 2011) (Available at: <https://tinyurl.com/yaul42o5>) [Accessed 17th October, 2022].
- ¹³ See “Capital equipment costs to repair flooded HDD factories in Thailand will be considerable” (*Forbes*, November 7, 2011) (Available at: <https://tinyurl.com/ybuu9caq>) [Accessed 17th October, 2022].
- ¹⁴ See “Hard disk drive (HDD) unit shipments worldwide from 2010 to 2021, by quarter” (Thomas Alsop, 2022) (Available at: <https://tinyurl.com/y982az7a>) [Accessed 17th October, 2022].
- ¹⁵ See “Intel cuts revenue forecast as Thai floods hit PC sales” (*The Guardian*, December 12, 2011) (Available at: <https://tinyurl.com/ybz4hcnb>) [Accessed 17th October, 2022].
- ¹⁶ See “Intel cuts revenue forecasts because of shortages” (*BBC*, December 12, 2011) (Available at: <https://www.bbc.co.uk/news/business-16146355>), [Accessed 17th October, 2022].
- ¹⁷ See Gorodnichenko and Talavera (2017) for a detailed discussion of a similar dataset.
- ¹⁸ A limitation of our dataset is that it includes online retail prices that could behave differently from wholesale prices.
- ¹⁹ For the U.S. online market, Gorodnichenko et al. (2018a) have reported that the median size of changes in price has varied from 10.9% to 11.0% for all products and been slightly higher for hardware products, from 13.7% to 13.8%. Similarly, for the U.S. offline market, Nakamura and Steinsson (2008) have reported that the median change in price was from 8.5% to 10.7% for all products and from 9.3% to 11.3% for personal computers and peripheral equipment.
- ²⁰ The by-group estimation results appear in the Appendix Tables A1.1–3.
- ²¹ For the formal placebo test, in which the regressions were run over a similar 18-month span of data but one full year before the flood, refer to Tables A2.1–3 in the Appendix.
- ²² For full regression results, see the Appendix Table A3.1.
- ²³ See “WD: Thailand floods worse than feared” (*The Register*, October 17, 2011) (Available at: <https://tinyurl.com/yb5qfu63>) [Accessed 17th October, 2022].
- ²⁴ For the effects of out-of-stock products on substitute products, see Ge et al. (2009).
- ²⁵ Results for the complementary products (i.e., motherboards and CPUs) appear in Table A4 in the Appendix. In general, we found little evidence of the shock’s impact on the price setting of those products. The slight response of sellers of other computer components might be due to sticky cost behavior (e.g., Özkaya, 2021).
- ²⁶ Flaaen et al. (2020) have suggested using hedonic characteristics instead of product-specific fixed effects, because prices may move as new features are introduced or the existing technology becomes cheaper. We manually collected data regarding the features of WD’s hard drives and compared the results with fixed effects to those without fixed effects but with hedonic factors (see the Appendix Table A5). Just as Flaaen et al. (2020) found, they remained qualitatively and quantitatively similar.

REFERENCES

- Aguirregabiria, V. (1999) The dynamics of markups and inventories in retailing firms. *Review of Economic Studies*, 66(2), 275–308. Available from: <https://doi.org/10.1111/1467-937x.00088>
- Akerlof, G.A. & Yellen, J.L. (1985) A near-rational model of the business cycle, with wage and price inertia. *The Quarterly Journal of Economics*, 100(Supplement), 823–838. Available from: <https://doi.org/10.2307/1882925>
- Amihud, Y. & Mendelson, H. (1983) Price smoothing and inventory. *The Review of Economic Studies*, 50(1), 87–98. Available from: <https://doi.org/10.2307/2296956>
- Anderson, E.T. & Simester, D.I. (2010) Price stickiness and customer antagonism. *Quarterly Journal of Economics*, 125(2), 729–765. Available from: <https://doi.org/10.1162/qjec.2010.125.2.729>

- Baqae, D.R. (2018) Cascading failures in production networks. *Econometrica*, 86(5), 1819–1838. Available from: <https://doi.org/10.3982/ecta15280>
- Barrot, J.-N. & Sauvagnat, J. (2016) Input specificity and the propagation of idiosyncratic shocks in production networks. *The Quarterly Journal of Economics*, 131(3), 1543–1592. Available from: <https://doi.org/10.1093/qje/qjw018>
- Baudry, L., Le Bihan, H., Sevestre, P. & Tarrieu, S. (2007) What do thirteen million price records have to say about consumer price rigidity? *Oxford Bulletin of Economics & Statistics*, 69(2), 139–183. Available from: <https://doi.org/10.1111/j.1468-0084.2007.00473.x>
- Beck, G.W., Hubrich, K. & Marcellino, M. (2016) On the importance of sectoral and regional shocks for price-setting. *Journal of Applied Econometrics*, 31(7), 1234–1253. Available from: <https://doi.org/10.1002/jae.2490>
- Benabou, R. (1988) Search, price setting and inflation. *The Review of Economic Studies*, 55(3), 353–376. Available from: <https://doi.org/10.2307/2297389>
- Betancourt, R.R. & Gautschi, D. (1993) Two essential characteristics of retail markets and their economic consequences. *Journal of Economic Behavior & Organization*, 21(3), 277–294. Available from: [https://doi.org/10.1016/0167-2681\(93\)90053-r](https://doi.org/10.1016/0167-2681(93)90053-r)
- Bilotkach, V., Gorodnichenko, Y. & Talavera, O. (2010) Are airlines' price-setting strategies different? *Journal of Air Transport Management*, 16(1), 1–6. Available from: <https://doi.org/10.1016/j.jairtraman.2009.04.004>
- Bilotkach, V., Gorodnichenko, Y. & Talavera, O. (2012) Sensitivity of prices to demand shocks: a natural experiment in the San Francisco Bay Area. *Transportation Research Part A: Policy and Practice*, 46(7), 1137–1151. Available from: <https://doi.org/10.1016/j.tra.2012.02.018>
- Bils, M. & Klenow, P.J. (2004) Some evidence on the importance of sticky prices. *Journal of Political Economy*, 112(5), 947–985. Available from: <https://doi.org/10.1086/422559>
- Blinder, A.S. (1982) Inventories and sticky prices: more on the microfoundations of macroeconomics. *The American Economic Review*, 72(3), 334–348.
- Boehm, C.E., Flaaen, A. & Pandalai-Nayar, N. (2019) Input linkages and the transmission of shocks: firm-level evidence from the 2011 Tōhoku earthquake. *Review of Economics and Statistics*, 101(1), 60–75. Available from: https://doi.org/10.1162/rest_a_00750
- Boileau, M. & Letendre, M.-A. (2011) Inventories, sticky prices, and the persistence of output and inflation. *Applied Economics*, 43(10), 1161–1174. Available from: <https://doi.org/10.1080/00036840802600343>
- Burdett, K. & Judd, K.L. (1983) Equilibrium price dispersion. *Econometrica*, 51(4), 955–969. Available from: <https://doi.org/10.2307/1912045>
- Caliendo, L., Parro, F., Rossi-Hansberg, E. & Sarte, P.-D. (2018) The impact of regional and sectoral productivity changes on the U.S. Economy. *The Review of Economic Studies*, 85(4), 2042–2096. Available from: <https://doi.org/10.1093/restud/rdx082>
- Calvo, G.A. (1983) Staggered prices in a utility-maximizing framework. *Journal of Monetary Economics*, 12(3), 383–398. Available from: [https://doi.org/10.1016/0304-3932\(83\)90060-0](https://doi.org/10.1016/0304-3932(83)90060-0)
- Carvalho, V. & Gabaix, X. (2013) The great diversification and its undoing. *American Economic Review*, 103(5), 1697–1727. Available from: <https://doi.org/10.1257/aer.103.5.1697>
- Cavallo, A. (2017) Are online and offline prices similar? Evidence from large multi-channel retailers. *American Economic Review*, 107(1), 283–303. Available from: <https://doi.org/10.1257/aer.20160542>
- Cavallo, A., Cavallo, E. & Rigobon, R. (2014) Prices and supply disruptions during natural disasters. *Review of Income and Wealth*, 60(Specialissue2), S449–S471. Available from: <https://doi.org/10.1111/roiw.12141>
- Carvalho, V.M., Nirei, M., Saito, Y.U. & Tahbaz-Salehi, A. (2021) Supply chain disruptions: evidence from the Great East Japan Earthquake. *The Quarterly Journal of Economics*, 136(2), 1255–1321. Available from: <https://doi.org/10.1093/qje/qjaa044>
- Chari, V.V., Kehoe, P.J. & McGrattan, E.R. (2000) Sticky price models of the business cycle: can the contract multiplier solve the persistence problem? *Econometrica*, 68(5), 1151–1179. Available from: <https://doi.org/10.1111/1468-0262.00154>
- Chevalier, J. & Goolsbee, A. (2003) Measuring prices and price competition online: Amazon.com and BarnesandNoble.com. *Quantitative Marketing and Economics*, 1(2), 203–222. Available from: <https://doi.org/10.1023/a:1024634613982>
- Dias, D.A., Marques, C.R., Martins, F. & Santos Silva, J.M.C. (2015) Understanding price stickiness: firm-level evidence on price adjustment lags and their asymmetries. *Oxford Bulletin of Economics & Statistics*, 77(5), 701–718. Available from: <https://doi.org/10.1111/obes.12083>
- Dixon, H. (2020) Almost-maximization as a behavioral theory of the firm: static, dynamic and evolutionary perspectives. *Review of Industrial Organization*, 56(2), 237–258. Available from: <https://doi.org/10.1007/s11151-019-09727-0>
- Eichenbaum, M., Jaimovich, N. & Rebelo, S. (2011) Reference prices, costs, and nominal rigidities. *American Economic Review*, 101(1), 234–262. Available from: <https://doi.org/10.1257/aer.101.1.234>
- Finkelstein, A. (2007) The aggregate effects of health insurance: evidence from the introduction of Medicare. *The Quarterly Journal of Economics*, 122(1), 1–37. Available from: <https://doi.org/10.1162/qjec.122.1.1>
- Flaaen, A., Hortaçsu, A. & Tintelnot, F. (2020) The production relocation and price effects of US trade policy: the case of washing machines. *American Economic Review*, 110(7), 2103–2127. Available from: <https://doi.org/10.1257/aer.20190611>
- Gabaix, X. (2011) The granular origins of aggregate fluctuations. *Econometrica*, 79(3), 733–772.
- Gagnon, E. & López-Salido, D. (2020) Small price responses to large demand shocks. *Journal of the European Economic Association*, 18(2), 792–828. Available from: <https://doi.org/10.1093/jeea/jvz002>
- Ge, X., Messinger, P.R. & Li, J. (2009) Influence of soldout products on consumer choice. *Journal of Retailing*, 85(3), 274–287. Available from: <https://doi.org/10.1016/j.jretai.2009.05.009>
- Ginsburgh, V. & Michel, P. (1988) Adjustment costs, concentration and price behaviour. *The Journal of Industrial Economics*, 36(4), 477–481. Available from: <https://doi.org/10.2307/2098451>
- Gorodnichenko, Y., Sheremirov, V. & Talavera, O. (2018a) Price setting in online markets: does it click? *Journal of the European Economic Association*, 16(6), 1764–1811. Available from: <https://doi.org/10.1093/jeea/jvx050>

- Gorodnichenko, Y., Sheremirov, V. & Talavera, O. (2018b) The responses of internet retail prices to aggregate shocks: a high-frequency approach. *Economics Letters*, 164, 124–127. Available from: <https://doi.org/10.1016/j.econlet.2018.01.014>
- Gorodnichenko, Y. & Talavera, O. (2017) Price setting in online markets: basic facts, international comparisons, and cross-border integration. *American Economic Review*, 107(1), 249–282. Available from: <https://doi.org/10.1257/aer.20141127>
- Gust, C., Leduc, S. & Vigfusson, R. (2010) Trade integration, competition, and the decline in exchange-rate pass-through. *Journal of Monetary Economics*, 57(3), 309–324. Available from: <https://doi.org/10.1016/j.jmoneco.2010.02.001>
- Head, A., Kumar, A. & Lapham, B. (2010) Market power, price adjustment, and inflation. *International Economic Review*, 51(1), 73–98. Available from: <https://doi.org/10.1111/j.1468-2354.2009.00571.x>
- Kaufmann, D. & Lein, S.M. (2013) Sticky prices or rational inattention – what can we learn from sectoral price data? *European Economic Review*, 64, 384–394. Available from: <https://doi.org/10.1016/j.euroecorev.2013.10.001>
- Kehoe, P. & Midrigan, V. (2015) Prices are sticky after all. *Journal of Monetary Economics*, 75, 35–53. Available from: <https://doi.org/10.1016/j.jmoneco.2014.12.004>
- Knotek, E.S. (2011) Convenient prices and price rigidity: cross-sectional evidence. *Review of Economics and Statistics*, 93(3), 1076–1086. Available from: https://doi.org/10.1162/rest_a_00124
- Levy, D., Lee, D., Chen, H.A., Kauffman, R.J. & Bergen, M. (2011) Price points and price rigidity. *Review of Economics and Statistics*, 93(4), 1417–1431. Available from: https://doi.org/10.1162/rest_a_00178
- Lloyd, T., McCorriston, S., Morgan, C.W. & Rayner, A.J. (2001) The impact of food scares on price adjustment in the UK beef market. *Agricultural Economics*, 25(2–3), 347–357. Available from: <https://doi.org/10.1111/j.1574-0862.2001.tb00214.x>
- Maćkowiak, B., Moench, E. & Wiederholt, M. (2009) Sectoral price data and models of price setting. *Journal of Monetary Economics*, 56, S78–S99. Available from: <https://doi.org/10.1016/j.jmoneco.2009.06.012>
- Maćkowiak, B. & Wiederholt, M. (2009) Optimal sticky prices under rational inattention. *American Economic Review*, 99(3), 769–803. Available from: <https://doi.org/10.1257/aer.99.3.769>
- Maćkowiak, B. & Wiederholt, M. (2015) Business cycle dynamics under rational inattention. *The Review of Economic Studies*, 82(4), 1502–1532. Available from: <https://doi.org/10.1093/restud/rdv027>
- Mankiw, N.G. & Reis, R. (2002) Sticky information versus sticky prices: a proposal to replace the new Keynesian Phillips curve. *The Quarterly Journal of Economics*, 117(4), 1295–1328. Available from: <https://doi.org/10.1162/003355302320935034>
- Matějka, F. (2016) Rationally inattentive seller: sales and discrete pricing. *The Review of Economic Studies*, 83(3), 1125–1155. Available from: <https://doi.org/10.1093/restud/rdv049>
- Matějka, F. & McKay, A. (2015) Rational inattention to discrete choices: a new foundation for the multinomial logit model. *American Economic Review*, 105(1), 272–298. Available from: <https://doi.org/10.1257/aer.20130047>
- Midrigan, V. (2011) Menu costs, multiproduct firms, and aggregate fluctuations. *Econometrica*, 79(4), 1139–1180.
- Nakamura, E. & Steinsson, J. (2008) Five facts about prices: a reevaluation of menu cost models. *Quarterly Journal of Economics*, 123(4), 1415–1464. Available from: <https://doi.org/10.1162/qjec.2008.123.4.1415>
- Özkaya, H. (2021) Sticky cost behavior: evidence from small and medium sized enterprises in Turkey. *Eurasian Business Review*, 11(2), 349–369. Available from: <https://doi.org/10.1007/s40821-020-00156-8>
- Petrella, I. & Santoro, E. (2011) Input-output interactions and optimal monetary policy. *Journal of Economic Dynamics and Control*, 35(11), 1817–1830. Available from: <https://doi.org/10.1016/j.jedc.2011.04.015>
- Reis, R. (2006) Inattentive producers. *The Review of Economic Studies*, 73(3), 793–821. Available from: <https://doi.org/10.1111/j.1467-937x.2006.00396.x>
- Richards, T.J., Gómez, M.I. & Lee, J. (2014) Pass-through and consumer search: an empirical analysis. *American Journal of Agricultural Economics*, 96(4), 1049–1069. Available from: <https://doi.org/10.1093/ajae/aau009>
- Rotemberg, J.J. (2005) Customer anger at price increases, changes in the frequency of price adjustment and monetary policy. *Journal of Monetary Economics*, 52(4 SPEC. ISS), 829–852. Available from: <https://doi.org/10.1016/j.jmoneco.2005.03.004>
- Sheshinski, E. & Weiss, Y. (1977) Inflation and costs of price adjustment. *The Review of Economic Studies*, 44(2), 303. Available from: <https://doi.org/10.2307/2297067>
- Sims, C.A. (2003) Implications of rational inattention. *Journal of Monetary Economics*, 50(3), 665–690. Available from: [https://doi.org/10.1016/s0304-3932\(03\)00029-1](https://doi.org/10.1016/s0304-3932(03)00029-1)
- Talavera, O., Nikolsko-Rzhevskyy, A. & Vu, N. (2023) *ECIN replication package for “The flood that caused a drought”*. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor]. Available from: <https://doi.org/10.3886/E183862V3>
- Thomas, A. (2022) *Hard disk drive (HDD) unit shipments worldwide from 2010 to 2021, by quarter*. Statista. Available at: <https://www.statista.com/statistics/275336/global-shipment-figures-for-hard-disk-drives-from-4th-quarter-2010/>

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Nikolsko-Rzhevskyy, A., Talavera, O. & Vu, N. (2023) The flood that caused a drought. *Economic Inquiry*, 1–17. Available from: <https://doi.org/10.1111/ecin.13144>