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PRICES AND SUPPLY DISRUPTIONS DURING NATURAL DISASTERS

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Prices and Supply Disruptions during Natural Disasters
Alberto Cavallo, Eduardo Cavallo, and Roberto Rigobon
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ABSTRACT

We study the daily behavior of supermarket prices and product availability following two recent natural disasters: the 2010 earthquake in Chile and the 2011 earthquake in Japan. In both cases there was an immediate and persistent effect on product availability. The number of goods available for sale fell 32% in Chile and 17% in Japan from the day of the disaster to its lowest point, which occurred 61 and 18 days after the earthquakes, respectively. Product availability recovered slowly, and a significant share of goods remained out of stock after six months. By contrast, prices were relatively stable and did not increase for months after the earthquakes, even for goods that were experiencing severe stockouts. These trends are present at all levels of aggregation, but appear strongly in non-perishable goods and emergency products. Our findings shed light into the determinants of sticky prices in conditions where traditional adjustment costs are less important. In particular, we look at the frequency and magnitudes of price changes in both countries and find that the results in Chile are consistent with pricing models where retailers have fear of "customer anger". In Japan, by contrast, the evidence suggests a bigger role for supply disruptions that restricted the ability of retailers to re-stock goods after the earthquake.

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1 Introduction

The economic consequences of natural disasters are always measured with significant delays. The data that are immediately available, such as the strength of the seismic waves or the number of deaths, are not really useful to determine the economic impact of the disaster. Aggregate statistics such as industrial production and GDP take months to be compiled and published, forcing governments (and Central Banks in particular) to make decisions without really knowing the magnitude of any shortages and price increases that may be affecting the economy. Furthermore, even when the data becomes available, its low frequency tends to hide the short-run effects taking place in the days immediately after the disaster. This has limited the literature's understanding of how prices and quantities react to this type of exogenous, unanticipated shocks, which is a basic and fundamental issue in economics.

In this paper we propose using online data to measure two key economic variables in the aftermath of a natural disaster: supply disruptions and pricing behaviors. We use data from the Billion Prices Project (BPP) at MIT, a large and continuing effort to collect online information from large retailers around the world on a daily basis. We construct daily price indices across various goods and categories and measure the degree of supply disruption with an index of product availability, which tracks the number of goods that are available for purchase over time.

We focus on the earthquakes in Chile (2010) and Japan (2011), two major catastrophic natural disasters that occurred in countries where the BPP was collecting data before the events. We also limit our analysis to products sold in supermarkets, such as food, beverages, and other basic necessities which are more likely to experience demand changes after a natural disaster and for which we have more comprehensive data coverage.

We show that these natural disasters had an immediate impact on product availability. A large share of goods went out of stock within days. The fall was gradual but larger in Chile, where the number of products available fell by 32% in the first two months after the earthquake, recovering slowly after that. In Japan, the fall was faster but smaller, with

product availability dropping by 17% within 18 days after the earthquake, and recovering gradually after that.

Prices, by contrast, remained surprisingly stable for several months after the earthquakes. The inflation rate started to rise only after 4 months in Japan, and 6 months in Chile.

Nearly all categories of goods experienced a drop in product availability in both countries during the first months. The recovery and price-change behaviors differed significantly across categories. Many goods that could be considered indispensable after an earthquake, such as powdered milk, diapers, and baby food, disappeared quickly from the stores and maintained stable prices for a long time. Others, such as batteries, had drops in availability but they recovered quicker with rising prices.

Natural disasters, with their unanticipated and exogenous nature, can be used to test some of the predictions of the large New Keynesian literature on price stickiness. We therefore focus on variables such as the frequency of price changes, their average size, and the shape of the hazard functions for both stockout events and price adjustments.

In Chile, the data is consistent with the predictions of a growing strand of the literature that has emphasized how fear of “consumer anger” may affect firms’ pricing decisions.¹ In particular, the frequency of price changes falls dramatically for several months after the earthquake, suggesting that firms were delaying their price adjustments.

By contrast, in Japan the evidence is more consistent with a supply shock that affected the retailer’s ability to re-stock. Product availability also fell dramatically, but the number of price changes remained stable over time. In addition, the product availability index in Japan has a surprisingly close co-movement with the official estimates of industrial production, providing more evidence of the importance of the supply disruption in this case.

This paper is part of a large empirical literature on price stickiness, with papers such as Bils and Klenow (2004), Nakamura and Steinsson (2008), Lach and Tsiddon (1996), Kashyap (1995), Levy et al. (1997), and Blinder et al. (1998). Our distinctive contribution is to analyze

¹See for example (Blinder et al. (1998), Fabiani et al. (2006), and Rotemberg (2005).

how prices and product availability behave at the time of natural disasters, which are unambiguous examples of exogenous and unanticipated aggregate shocks. Most of our findings are consistent with theories that emphasize the effects of fairness concerns on pricing decisions, such as in the work of Kahneman et al. (1986), Rotemberg (2005), and Rotemberg (2011). Our results in Japan are complementary to the analysis in Weinstein and Schell (2012), who argue that the supply disruption from the 2011 earthquake caused a much larger and persistent contraction on industrial production than previous earthquakes. Finally, in a recent paper, Gagnon and Lopez-Salido (2014) study the pricing response of U.S. supermarkets to large demand shocks such as hurricane Katrina, and consistent with our results, find almost no evidence that retailers responded to these shocks by raising prices.

2 The Earthquakes in Chile and Japan

On February 27, 2010, a strong earthquake (8.8 on the moment magnitude scale) struck off the coast of central Chile. The earthquake was felt strongly in six Chilean regions (from Valparaiso in the north to Araucania in the south) that include approximately 80% of the country's population. The earthquake also triggered a tsunami which caused widespread destruction in coastal towns of south-central Chile, prompting President Michelle Bachelet to immediately declare a "state of catastrophe" and to deploy emergency workers to the affected areas.

Chile's earthquake ranks as one of the most destructive in recent years in terms of economic damage, as Table 1 shows. The total economic damage caused by the earthquake was estimated at \$30 billion, or 19% of GDP, according to the CRED International Disaster Database (EM-DAT).

On March 11, 2011, an even stronger earthquake (9.0 on the moment magnitude scale) struck off the Pacific coast of Japan, triggering a powerful tsunami with severe human and economic consequences. Initial disruptions in Japan were larger than in Chile, particularly

Table 1: Top Natural Disasters by Total Damages (2008-2012)

Country	Date	Type	Killed	Damages (US\$ millions)	Damages (% of GDP)
Japan	11-Mar-11	Earthquake (9.0 M_w)	19,846	210,000.00	3.85
China	12-May-08	Earthquake (8.0 M_w)	87,476	91,285.30	2.43
Thailand	5-Aug-11	Flood	813	40,000.00	12.56
United States	12-Sep-08	Storm	82	32,218.34	0.21
Chile	27-Feb-10	Earthquake (8.8 M_w)	562	30,900.90	18.65

Source: Authors' calculation based on EM-DAT and WDI databases.

because the tsunami caused a nuclear accident in a power-generating plant (the Fukushima Daiichi Nuclear Power Plant complex), forcing the evacuation of thousands of residents in the vicinity of the plant. According to press reports, approximately 4.4 million households in northeastern Japan were left without electricity and 1.5 million without water for days. Nearly 20,000 people were killed as a result of the disaster.

Japan's total economic costs were estimated to be US\$ 210 billion, making this event the costliest natural disaster in recent years in nominal terms. However, this represented only 4% of GDP, about 20 percent of the estimated cost in Chile.²

In both countries, concerns about possible food scarcity and price increases even in areas that were not directly impacted by the earthquakes quickly surfaced on the news. In Chile, the national Baker's Association complained about unjustified increases to the price of flour.³ On February 28, President Bachelet announced that the government had reached an agreement with the major supermarkets which would require them to give away basic foodstuffs to people affected by the earthquake.⁴ In newspaper interviews, government officials also threatened

²The significant differences in terms of estimated economic costs and mortality, despite the similar physical intensity of the two events, warrants further discussion. As discussed in Cavallo et al. (2010), there are various determinants of the economic costs of natural disasters in addition to the physical intensity of the events. One of those determinants is the amount of capital exposed. Earthquakes are by their nature unpredictable and the exact location where they may strike is usually unknowable. Therefore, while it is possible to implement building codes and standards that better prepare infrastructure to resist possible earthquakes, it is not easy to locate wealth and populations in "safer" areas. The damages and mortality associated to earthquakes varies significantly, even for similar events.

³See <http://bit.ly/12zcQDg>

⁴See <http://bit.ly/18dqv8L>

to enforce a law enacted in the 1970's to penalize anyone who in the aftermath of a natural disaster sells basic staples at excessive prices.⁵ Similarly, in Japan, within days after the earthquake the press reported shortages of food and gasoline as people hoarded basic items out of fear that supplies would soon dry up.⁶ According to some reports, shoppers in the Tokyo metro area (150 miles from most affected areas) had cleaned supermarket shelves of items such as rice, bread, and yogurt. Moreover, many retailers claimed to have run out of emergency items such as blankets, sanitary pads, diapers, toilet paper, instant noodles, and flashlights.⁷

Although reports and rumors in the media were widespread, there was no reliable information on the magnitudes of the shortages and price increases in the aftermath of these events. Even though shortages and out-of-stock items can impose a significant welfare cost to consumers, they are not traditionally measured by any official statistics. Official price indices are available, but only with a significant delay, and their monthly frequency can obscure high frequency patterns that could alter expectations and economic behavior in the days after a natural disaster. In the next section, we discuss how online data can be used to construct statistics that provide information on shortages and prices in real-time.

3 Data: The Billion Prices Project

Our data were collected as part of the *Billion Prices Project* (BPP), an academic initiative at MIT that has been “scraping” daily prices from the largest online retailers around the world since 2008. In this paper we use prices from the largest supermarket in Chile and one of the leading supermarkets in Japan. Database details are shown in Table 2. We focus on a 9-month window around the day of the natural disaster: 3 months before and 6 months after the event.

The data collection method is based on the use of software that monitors the public

⁵See <http://bit.ly/17bXVTPI>

⁶See <http://bit.ly/14Qatjw>

⁷See <http://bit.ly/1basCHs>

Table 2: Data Description

	Chile	Japan
Initial Date	December 2009	December 2010
End Date	August 2010	September 2011
Products	17,141	3,982
Categories	265	26
Days with no data*	42	6

Notes: * These are days where the scraping software failed.

web pages where retailers list product and price information, scans the underlying code to identify the relevant information (such as prices and availability), then stores everything in a structured database.⁸

An example of a good in our data is “Whole Milk, Brand Name, 1 liter”. The scraping software automatically collects data on every single product on display on the retailer’s website each day. Goods are listed on the website only if they are in stock and available for sale. Out of stock items therefore immediately disappear from our database, and only reappear on the day that they are offered for sale again (if ever). We can therefore build statistics to study how the set of goods available for purchase changes over time after a natural disaster.⁹

In terms of data treatment, our prices include taxes and sale discounts, to account for the final amount paid by the consumer. We do not include shipping costs, which vary according to the location of the purchaser and are an exclusive feature of the online purchasing experience. In addition, missing prices in the data were often caused by scraping errors on days when the software fails to automatically start. For those dates, no data was collected. The number of days with failures is reported in Table 2. These gaps in the data tend to last just one or two days, until the scrape job is corrected. Finally, missing prices also occur when a good goes temporarily out of stock. For the price index calculations, if a good disappears and later

⁸See Cavallo (2012) for more technical details on the scraping methodology.

⁹Our results on product availability are only a upper bound on the degree of supply-chain disruptions because we only know if a good is completely out of stock, but not how many units are available over time if it is still offered for sale. Supply disruptions affecting the normal level of inventories are not captured in our metrics.

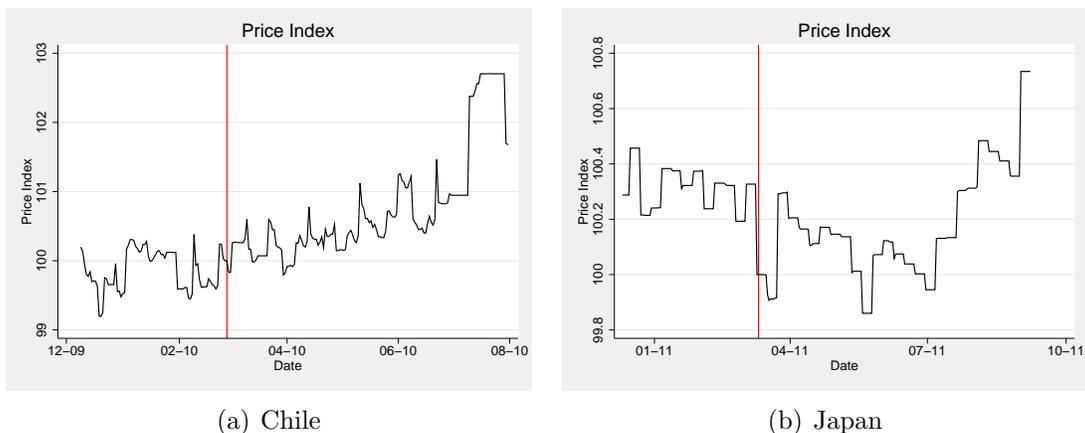
reappears in our sample, we fill missing prices with the previously available values until a new price is observed.

Although online transactions are still a small share of retail sales in most countries, we are confident that the data collected online also provides information about offline prices and product availability. In the case of Chile, Cavallo (2012) presents the results of an online-offline validation with a randomly chosen sample of 100 goods for the same Chilean retailer used in this paper. Prices were sampled at an offline store in 15-day intervals between December 2008 and January 2009, then compared to the online prices for the same goods on the same day. Only one retailer was involved in this validation exercise, but it is the same retailer whose data are included in this paper. Over 90% of goods in the offline store were also available online on the same date. Furthermore, for those available in both locations, prices were identical in 89% of the cases.¹⁰ Unfortunately we do not have direct evidence of the difference between online and offline prices in the case of Japan, but we note that Cavallo (2012) found that online retailers tend to have stable markups in percentage terms in many countries, implying similar online and offline inflation rates. We can test this prediction in the case of Japan, by comparing a supermarket price index with the official data price trends, as we do in the Section 4.

4 The Aggregate Impact: Prices and Product Availability

Natural disasters can create both supply and demand shocks that affect prices and product availability. Supply shocks originate in the destruction of production capacity and the disruption of supply chains. Demand shocks are linked to the panic that consumers may experience after natural disasters, with people rushing to the stores to purchase basic necessities and hoard goods that they fear could become unavailable in the days to come.

¹⁰Only 11 goods had different prices. They were all raw-food items that were sold online in packages with pre-defined sizes, yet sold by weight in the offline stores, creating unit-price differences across the samples.



Unweighted geometric-average price index. All the products available for sale each day are used.

Figure 1: Price Index (Online Data)

In this section, we look at aggregate prices and product availability in both Chile and Japan, and compare it to the predictions of recent pricing models.

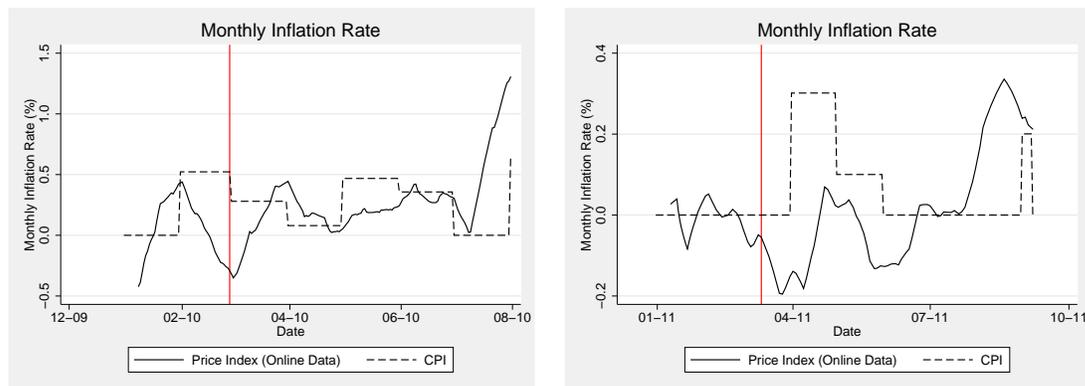
4.1 Prices

Figure 1 shows a price index constructed with the online data. The index is normalized to a value of 100 on the day of the natural disaster in order to more easily track changes after the event, as well as better compare across countries. The vertical line marks the day of the natural disaster. The index is a simple Jevons geometric-average price index that uses all the products sold by these supermarkets and implicitly assigns equal importance to all goods. Details of the methodology and motivation for this index formula are provided in the Appendix.

In both cases prices did not increase significantly during the first few months after the events. In Chile, the trend of the index remained remarkably stable after the earthquake. Prices only rose in mid-July 2010, almost 6 months after the earthquake.¹¹ In Japan, a similar pattern emerges. Before the earthquake, prices had a negative trend, which did not

¹¹Note that there is a relatively big spike in the Chilean index in late July. The scraping software failed for 10 days before this date, so this spike reflects accumulated price changes during this period. A similar thing happened at the end of August, with a large drop in the index.

Figure 2: Price Index (Online Data) vs. the CPI



(a) Chile

(b) Japan

Notes: For

our daily measure of “monthly inflation” at time t , we are taking the average in the index from t to $t - 29$ and calculating the percentage change with respect to the same average a month before, from $t - 30$ to $t - 59$.

change during the first 4 months after the earthquake. Only in mid-August did the inflation trend change and prices start to rise.¹²

The pricing trends in the supermarket data is consistent with those later reflected in official CPI data. This can be seen in Figure 2, where we plot a daily measure of “monthly inflation” using online data and compare it to the monthly official CPI (all items, non-seasonally adjusted).

There is co-movement and even some anticipation in the online supermarket data, particularly in the case of Chile. Overall, CPI estimates were stable in both countries for several months, just as in our data. The only exception was a temporary spike in Japan’s CPI in April 2011 which was driven by a 0.2% increase in fuel and transportation, categories of goods not covered in our sample.¹³

¹²Prices for this retailer in Japan do not adjust every day, but rather on a weekly basis. This explains the stepped pattern of the index over time. In addition, many of these weekly steps are related to temporary sales, which last for about a week. The day before the earthquake there was a drop in the index associated with one of those sale events. Prices continued to fall the week of the earthquake, but recovered back to their previous level the week after.

¹³Note that the monthly online inflation rate is calculated on a daily basis using the average of the index in the previous thirty days compared to the same average a month before. A monthly rate calculated this way (instead of using a simple 30-day difference) has the advantage of being less sensitive to the daily volatility in the index. This method, however, introduces some smoothing into the results. In addition, Figure 2 does not reflect the effects of the last days of the online price index movements (shown in Figure 1) because we limited the sample to exactly 180 days after the earthquakes. Since the CPI is updated at the end of the

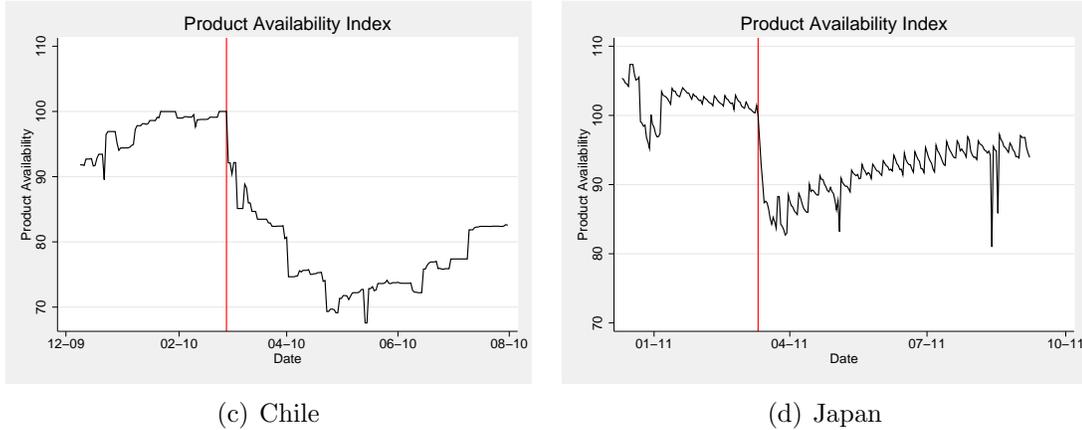


Figure 3: Product Availability

4.2 Product Availability

The rigidity of prices contrasts sharply with the behavior of goods availability in the aftermath of the earthquakes. Figure 3 shows indices of *product availability* for both countries.

We measure product availability with a simple index that captures how many items are for sale in the supermarket on a given day. We normalize the index to a value of 100 on the day of the natural disaster in order to be able to easily compute the change in product availability over time, as well as to facilitate comparisons across categories and countries. All goods sold by these retailers are included in each case, with every good having equal weight in the index. As such, these metrics are meant to show retailer-level effects. In the next section we compare results across categories.¹⁴

In the case of Chile, overall product availability fell by almost 8% the day after the earthquake and decreased an additional 25% to its lowest level, which occurred 61 days after the earthquake. Product availability did not fully recover to pre-event levels during the

month, and we are plotting the graphs only for the days with data in both the CPI and the online index, Figure 2 does not show the information for the partial results on the last month of the sample.

¹⁴We do not have product expenditure weights and are therefore not able to construct weighted indices. The potential impact of weights is not obvious for the case of product availability. For example, it is possible that the goods that disappear from the stores are those that are sold the most, making the product availability concerns even stronger than what our results imply. But it is also possible that, given the emergency, retailers shift their focus to the most widely sold products, making an effort to keep them in stock. In that case, a drop in product availability would be less worrisome (people have less variety, but the goods they buy the most are still available).

sample window. Six months after the earthquake, the number of goods sold was still 15% lower than before the earthquake.¹⁵

In Japan, product availability fell much faster and, initially, by a larger margin. It dropped approximately 17% from peak to trough (18 days after the earthquake). Japan’s product availability started to recover quickly, although it also remained below the pre-earthquake level during our sample window. After 6 months, the number of goods sold was still 5% lower than before the earthquake.

The Japanese index has two additional characteristics worth noting. First, there is a weekly pattern of ups and downs, which appears to be driven by re-stocking occurring on a weekly basis. This coincides with days in which most price changes take place, as we show later on. Second, there was a significant drop on December 22 (the day before the “Emperor’s Birthday” holiday) that lasted until January 2 (the day after the “New Year’s” holiday). We take this as evidence of how spikes in demand can affect availability.¹⁶

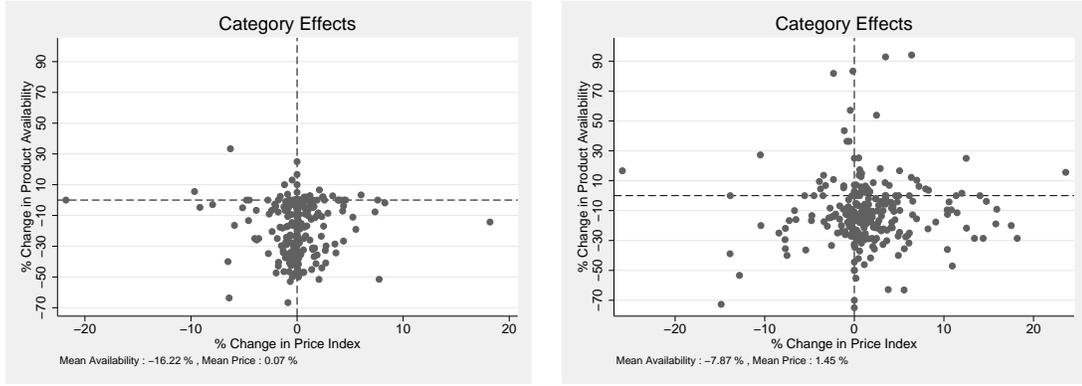
5 Category-Level Impacts

We now focus on category-level metrics. We first show that the trends identified in the previous section are present in most categories of goods. There are, however, significant category-level differences. In particular, the combination of large drops in product availability and stable prices is strongest for non-perishable goods. By contrast, perishable items had quicker price increases and less persistent shortages.

An important advantage of online data is that products are automatically categorized by the retailers, which tend to display similar products next to each other. The names that identify the product categories are typically displayed on top of each page, in an area called the “breadcrumb.” For example, the page where every “whole milk” product is shown

¹⁵The availability index immediately incorporates new goods, even if they were not sold before the earthquake. Therefore, if the pre-earthquake goods were being replaced with new varieties, these would be already included in the index

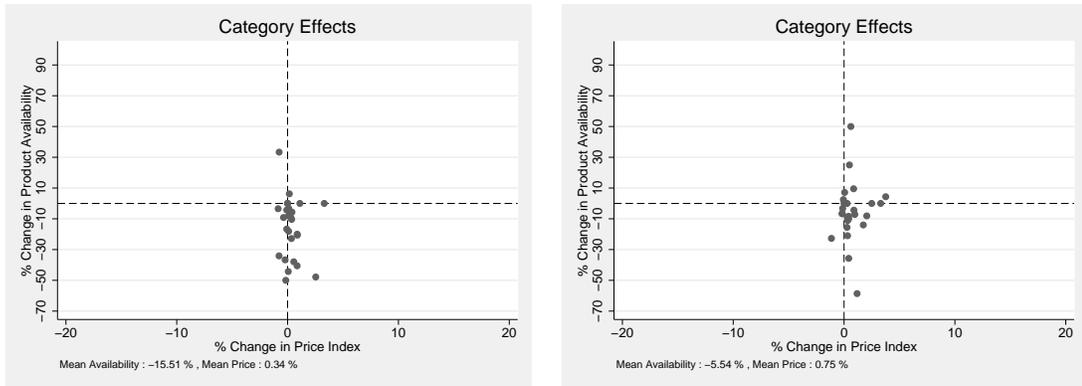
¹⁶There are also two single-day drops in September 2011 which were caused by scraping errors.



(a) 30-days

(b) 180-days

Figure 4: Chile: Changes in Availability and Prices



(a) 30-days

(b) 180-days

Figure 5: Japan: Changes in Availability and Prices

would typically have the following breadcrumb: “Home >> Groceries >> Dairy >> Milk >> Whole Milk.” In all cases we scraped the data at the most disaggregated level available, resulting in 26 different categories in Japan, and 256 in Chile.

For a comprehensive view across all categories, we first compute a product availability and price level index at each category level. We then calculate the percentage change in the first 30 and 180 days after the earthquake, and plot results for all categories in Figures 4 and 5.¹⁷

The y-axis shows the accumulated drop in product availability. In both countries we find that most categories experienced significant availability drops in the first 30 days of the

¹⁷Time series of availability and prices for a selected number of categories are shown in the Appendix.

disaster and were closer to their pre-disaster levels after 180 days. The aggregate results on availability are therefore not driven by just a few categories. Instead, both of these earthquakes had an impact on the availability of nearly all categories of goods sold at the stores.

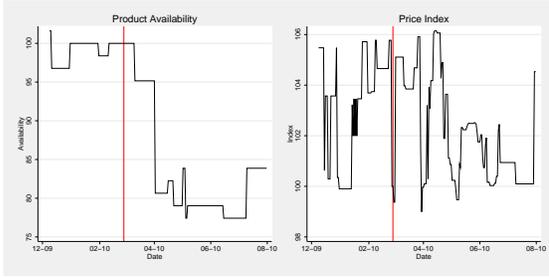
The x-axis, where the accumulated price changes in each category are plotted, shows a different pattern. There are roughly the same number of categories with price increases and decreases, both at the 30 and 180-day horizons. While the aggregate price index is stable, there is clearly significant dispersion in pricing behaviors across categories.

We can shed some light on the differences in price and availability responses by looking at individual categories over time. In Figures 6 to 9 we plot daily indices for distinct groups of goods that show different behaviors along these two dimensions. We start with Chile, where the category information is available at a more disaggregated level.

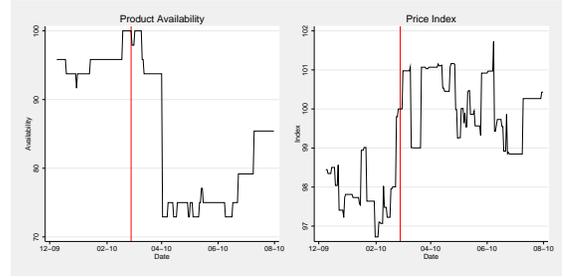
First, there is a distinct set of goods whose product availability decreased by more than 20%. In some cases product availability fell within days of the earthquake. Examples include: pasta (6(a)), powdered milk (6(b)), and basic staples like baby diapers (6(c)). In other cases, the drop was more gradual, as with baby foods (6(d)), soups (6(e)), and unflavored cookies (6(f)). Note that these are all nonperishable goods that people are likely to stock up on if they are fearful of future scarcity, which can explain why they disappeared from the stores. Interestingly, in all these cases prices remained stable for several months.

A second group of goods, as shown in Figure 7, had significant drops in product availability but started having price increases soon after the earthquake. These included perishable goods like eggs (7(a)), fresh vegetables (7(b)), and meat (7(c)).

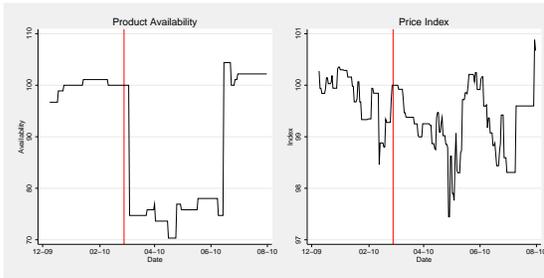
A third set of goods had no fall in product availability coupled with higher prices. These include fish (8(a)) and batteries (8(b)), which may be surprising given that coastal towns were affected by the tsunami following the earthquake and also that demand for batteries likely increased in the aftermath of the event for fear of blackouts. It is possible, however, that the large price increases helped reduce demand and prevent stockout. Finally, the case of Milk



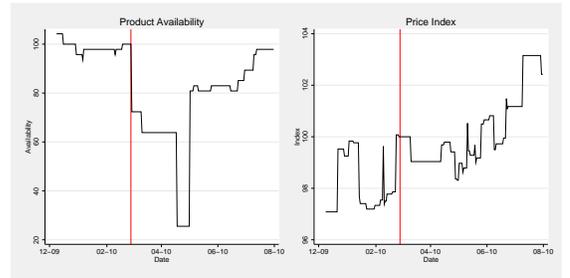
(a) Pasta



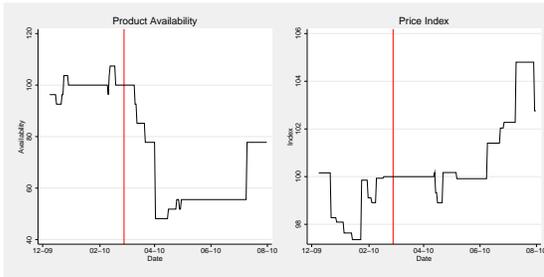
(b) Powdered Milk



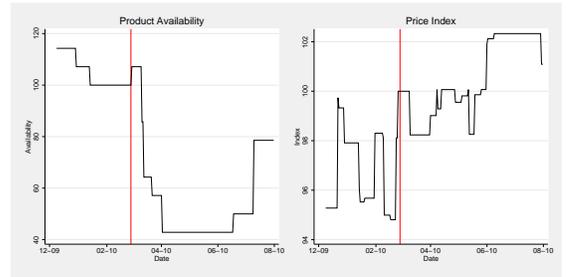
(c) Baby Diapers



(d) Baby Food



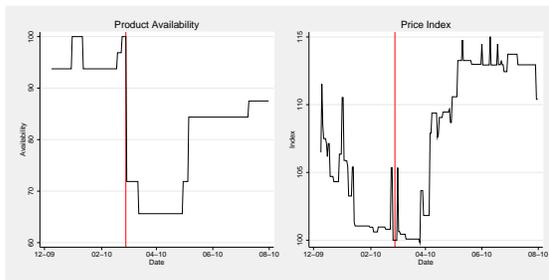
(e) Soup



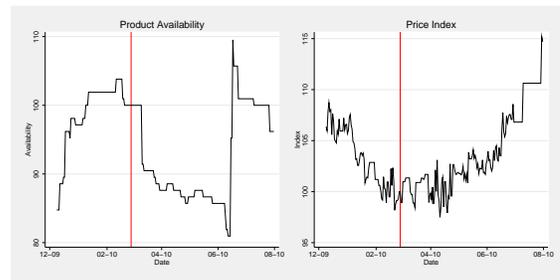
(f) Unflavored Cookies

Notes: In all cases the left graph is Availability, and the right graph is Price Index

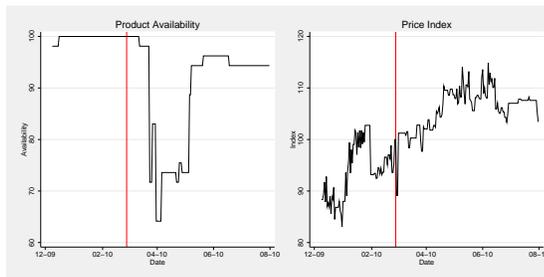
Figure 6: Chile - Drops in Product Availability and Stable Prices



(a) Eggs



(b) Vegetables



(c) Meat

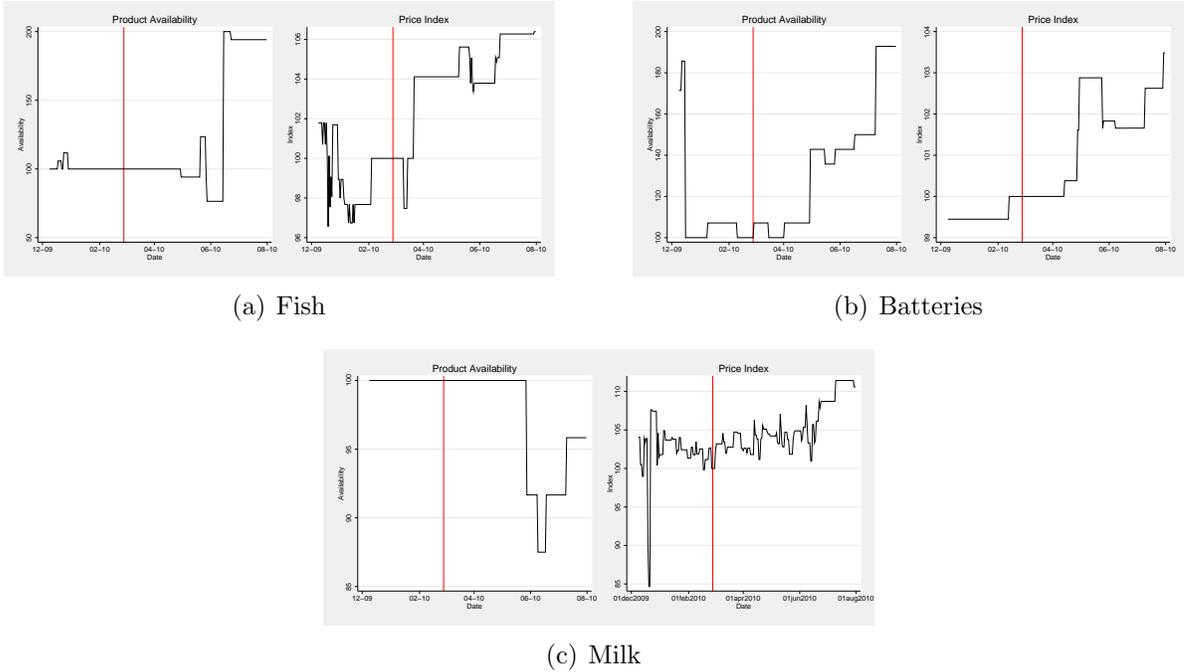
Note: In all cases the graph on the left is Product Availability, and the graph on the right is the Price Index

Figure 7: Chile - Drops in Product Availability and Higher Prices

(8(c)) is interesting because the Chilean government explicitly announced policies intended to secure its availability at stable prices to victims of the earthquake.¹⁸ These policies appear to have worked successfully, at least during the first four months after the earthquake.

In Japan the product categories are much more broadly defined, due to the way the retailer chooses to group products on its website. Still, some interesting patterns emerge as shown in Figure 9. First, we find fresh fish (9(a)) among the categories where stocks fell sharply after the earthquake. This is not surprising because many fishing ports in Japan were washed out by the tsunami, and health concerns arose due to the nuclear accident in Fukushima. Similarly, the stock of meat (9(b)) fell after the earthquake. Notwithstanding the fall in product availability, in both cases prices did not change much after the earthquake. Another category where product availability fell was baby food (9(c)). However, in this case, the price increased sharply (for Japanese standards) about a month after the earthquake, as product availability began to recover. Other categories, such as tea (9(d)), suffered only

¹⁸See <http://bit.ly/13HyNY4>



Note: In all cases the graph on the left is Product Availability, and the graph on the right is the Price Index

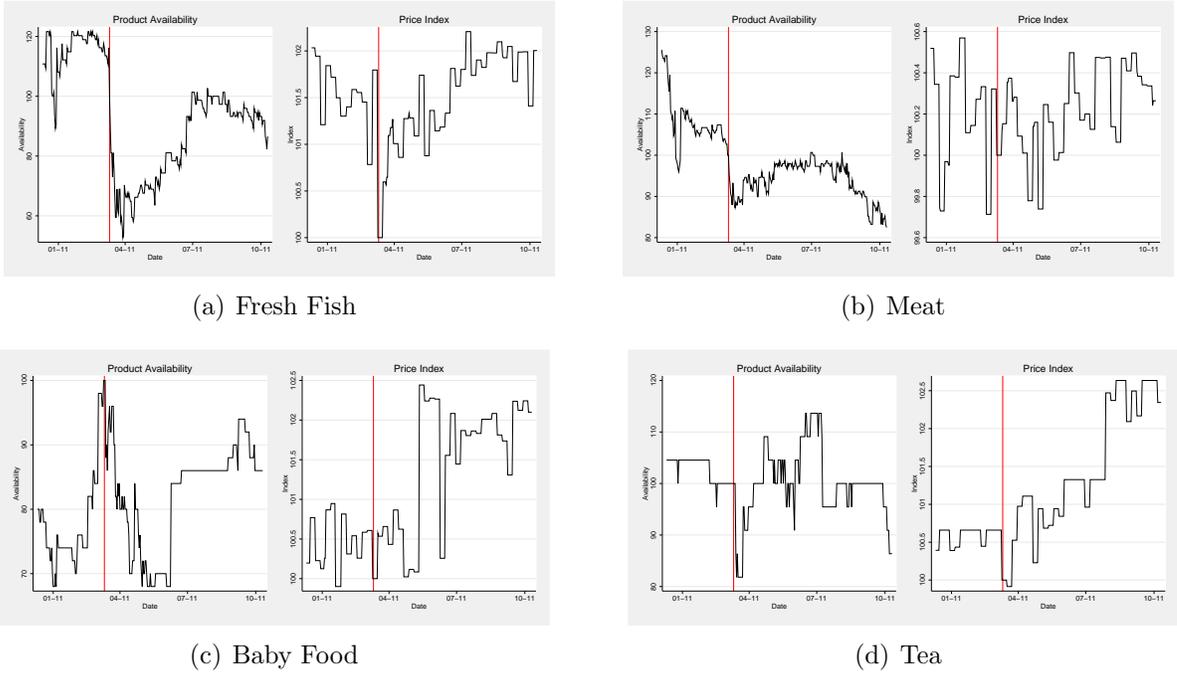
Figure 8: Chile - Stable Product Availability

mild decreases in availability, while prices increased steadily after the shock.

Understanding the specific trends in each category of goods is beyond the scope of this paper, as many of the trends observed in these graphs may not be related at all with the earthquake but rather to individual shocks and seasonal patterns in each group. There are, however, two main trends that stand out from the previous analysis. First, the fall in product availability observed in the aggregate data affected the vast majority of categories, while prices remained stable on average. Second, there is significant heterogeneity across categories, particularly in terms of pricing behaviors and their interaction with product availability after the earthquake. In the next section, we explore potential explanations for these trends.

6 Supply Shocks and Consumer Anger

It is not surprising to see items that go out of stock in the days after an earthquake: people get scared, demand for some basic goods rises suddenly, and retailers have no time to



Notes: In all cases the left graph is Availability, and the right graph is Price Index

Figure 9: Japan: Categories

react either with prices or stocks. What is harder to understand is how the combination of large stockout and stable prices can persist for many months.

One possibility is that retailers are unable to re-stock (and re-price) due to a persistent supply disruption. In particular, suppose that a retailer sets a simple markup over marginal cost, and that this marginal cost becomes known only at the time when goods are purchased from the wholesaler. If the supply chain is broken because of the earthquake, either because goods are not being produced or they cannot be transported, then the retailer will simply not be updating those prices at all. That is, this would be a setup where prices only change when new inventory is added. The combination of a cost-based pricing strategy and a persistent supply shock could therefore explain why so many goods remain out of stock and prices do not change for so long.¹⁹

Another possibility is that retailers are able to re-stock at a higher cost, but they are unable to increase their own price due to fear of “customer anger”. If they can not charge

¹⁹A necessary condition is also that the prices of available goods should not be significantly affected by the lack of availability in related goods that disappear.

higher prices, they have less incentive to replace goods that have disappeared from the stores.²⁰

In macroeconomics, the importance of customer relationships and the effect on price changes goes back to the work of Okun (1981). Okun emphasized how firms with repeated customer interactions may refrain from raising prices when facing increases in demand. The fear of antagonizing customers is also frequently mentioned by retailers in surveys as a reason for not changing prices often (Blinder et al. (1998), Fabiani et al. (2006)). More recent papers such as Renner and Tyran (2004) and Nakamura and Steinsson (2011) have focused on the existence of “customer markets” and their implications for price-setting decisions.

In the context of an earthquake, perhaps the most relevant theoretical literature is the one that touches on aspects of “fairness” in pricing. The seminal paper by Kahneman et al. (1986) spurred a large literature that explores how considerations of fairness can affect perceptions of price changes. More recent theoretical papers such as Rotemberg (2005) and Rotemberg (2011) provide models where consumers experience disappointment with price changes that they consider “unfair”, ultimately affecting the price-setting decisions of firms. In Rotemberg (2005) fairness considerations enter directly into the utility function. Consumers expect producers to have a certain degree of altruism and form expectations about the size of price change that is acceptable. The level of altruism can change exogenously. For example, during a natural disaster consumers could simply expect retailers to reduce their margins and be more altruistic. This threshold of fairness can also change with the amount and quality of information available to consumers. For example, if consumers think that the retailer’s costs have increased, then they may tolerate higher price changes. This could, for example, explain why the prices of perishable goods increased in Chile. After all, consumers can easily understand that an earthquake will affect the supply of goods such as eggs and meat, but they may not understand why the cost of easy-to-stock items such

²⁰It is possible, however, that there are indirect incentives to re-stock even when price changes are not possible. For example, retailers may derive reputational advantages to being seen as a reliable supplier. This would be consistent with “sensitive” good categories that experienced both stable availability and prices after the earthquake, such as Milk in Chile.

as pasta, powdered milk, or baby food may be affected. In Rotemberg (2011), fairness is linked to regrets that customers have from not buying the good before a price increase. In the context of an earthquake, for example, consumers may regret not having bought the products needed for an emergency kit. Similarly, perishable goods would be less affected by regret considerations.²¹

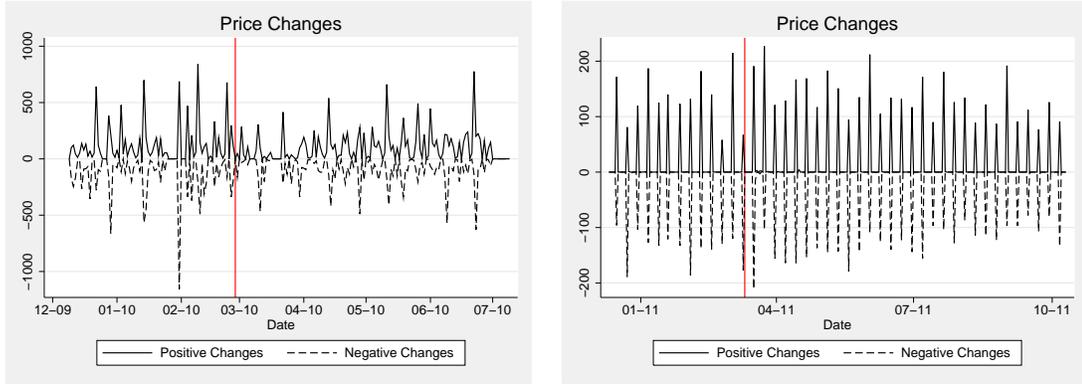
Regardless of the specific mechanism taking place, natural disasters will tend to both cause significant supply disruptions and increase concerns about fairness. So the two explanations for the aggregate results described above are plausible and not mutually exclusive.²² However, we can learn more about their relative importance in each country by looking closely at some price-stickiness statistics.

The effects of the earthquakes are noticeably different when we consider the number, frequency, and size of price changes in each country. Starting with Figure 10, we can see that in Chile the number of daily changes fell immediately after the earthquake, consistent with the fear of “consumer anger”. In Japan, by contrast, there is little change in the number of price changes over time. About 100 prices changed each week, both before and after the earthquake. The earthquake did not change the number of prices that changed per week, even though it had a large impact on the number of products available for sale.

An interesting feature in both countries is that price changes appear to occur periodically, both for price increases and price decreases. This pattern is particularly strong in the case of Japan, where prices are changed only once a week. This is consistent with time-dependent pricing decisions, and they are likely connected to the times when stocks are replenished in the stores. Indeed, the index of product availability for Japan in Figure 3 has a similar pattern of weekly spikes, suggesting that the timing of re-stockings and price changes is closely related. A large number of papers have found evidence of synchronization and time-dependent pricing,

²¹Even if retailers are not worried about customer reactions, they may be afraid of government sanctions. For example, in the case of Chile, a few days after the earthquake the government publicly threatened to apply a law from the 1970’s that penalizes people who sell goods at “excessive” prices. The wording of the law is ambiguous; it states that it is unlawful to sell during times of emergency at higher than “official prices”.

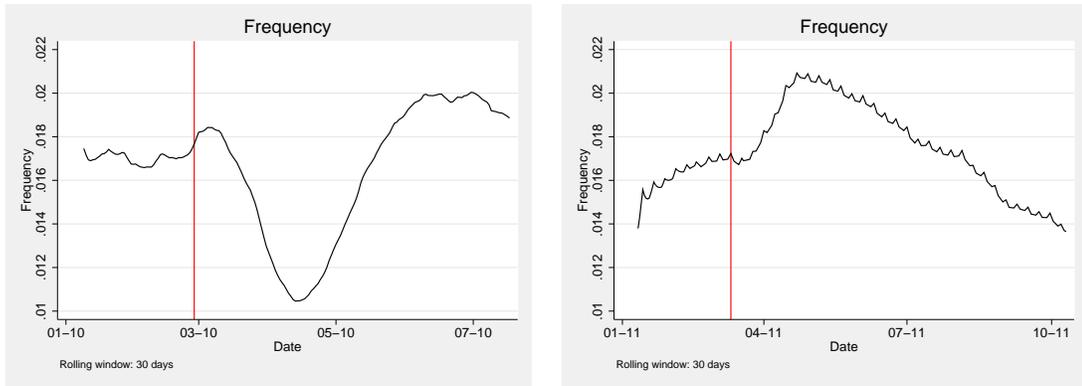
²²Okun (1981) emphasized how worries about customer relationships could explain why so many firms use a cost-plus pricing strategy in the first place.



(a) Chile

(b) Japan

Figure 10: Price Changes



(a) Chile

(b) Japan

Figure 11: Price Stickiness: Frequency of Price Changes

particularly in developed economies. Examples include Lach and Tsiddon (1992), Lach and Tsiddon (1996), Dutta et al. (2002), Owen and Trzepacz (2002), and Midrigan (2011).

In Figure 11, we plot the “frequency of price changes” over time, defined as the number of changes by the total number of prices that can change each day. This is essentially an unconditional probability of daily price change, computed over a rolling window of 30-day averages to smooth out the daily volatility. In Chile the frequency of changes fell from 0.018 to 0.01 after the disaster, with an implied duration of the average price spell (measured as $1/\text{frequency}$) that goes from 55 to 100 days. The effect was both strong and persistent, lasting over 3 months.

In Japan, by contrast, the frequency of price changes *increased* after the earthquake. This

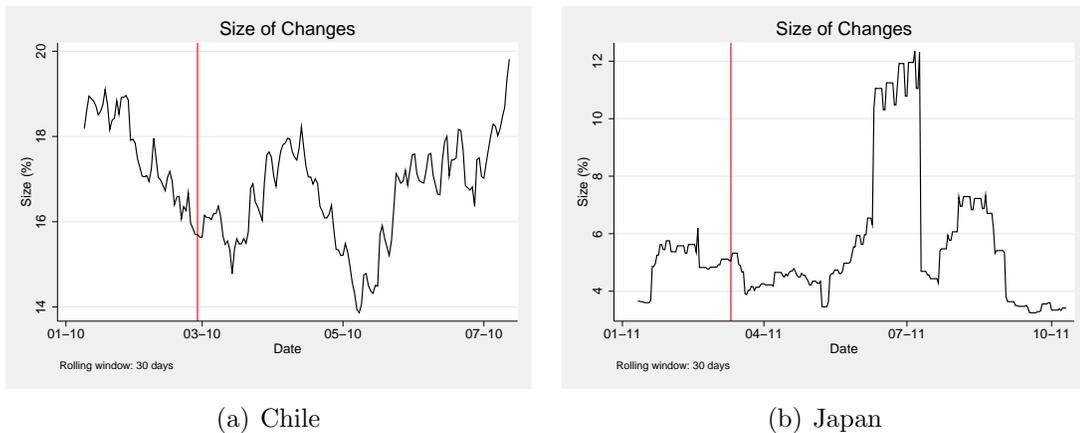
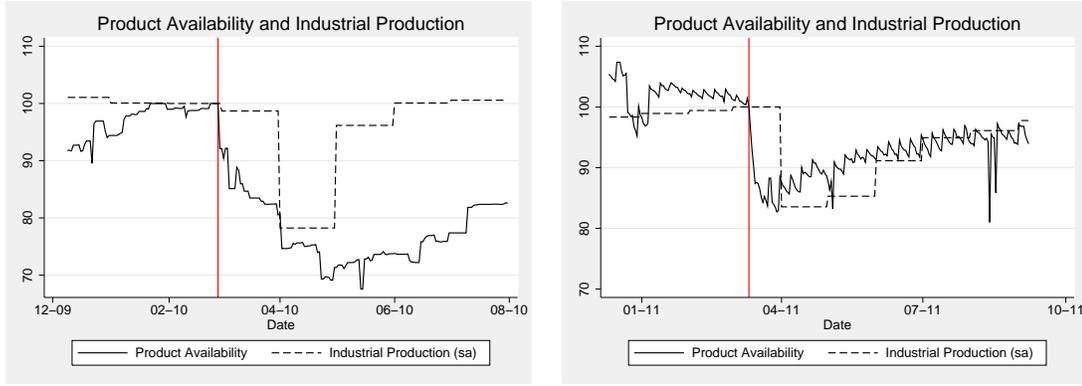


Figure 12: Mean Size of Price Changes

is just reflecting that the number of price changes remained stable while the availability of product was falling. This behavior is in sharp contrast to the predictions of a simple model of customer anger. Overall, the data in Japan appears to be more consistent with a supply shock affecting the capacity of the retailers to replenish their stocks. The retailer continued implementing the same number of price changes per week as before. The average size of price changes remained stable for a couple of months, as shown in Figure 12, but it rose suddenly in June 2011, probably reflecting increases in wholesale prices that were being passed-on to consumers after months of delays.²³

The idea that Japan suffered a persistent supply shock is intuitive given the Fukushima nuclear disaster that followed the earthquake. Indeed, in a recent paper Weinstein and Schell (2012) argue that the 2011 earthquake in Japan caused a much larger and persistent contraction of industrial production than previous earthquakes, and show that this was directly linked to the reduction in energy production. Could this have affected product availability? The evidence in Figure 13, where we plot our index of product availability and the official index of industrial production in both countries, suggests it did. In Japan, there is a surprising co-movement between both indices. Industrial production fell by 15% in the month

²³This is consistent with standard menu cost models, such as Mankiw (1985), where small price changes are not optimal. In the presence of an adjustment cost, prices remain fixed until the accumulated difference with the optimal price becomes large enough to cover it.



(a) Chile

(b) Japan

Figure 13: Availability and Industrial Production

after the earthquake, and recovered at a very similar rate as our product availability index over time. By contrast, industrial production in Chile, although negatively affected by the earthquake, recovered quickly to its previous level within a couple of months.

7 Survival Analysis

In Section 4 we showed that the immediate effects of the natural disaster were mostly in product availability, not in prices. Section 5 shows that this applies to most categories of goods. We now extend the analysis to study good-level effects of price changes and stockout. Our objective is to estimate the “Hazard Rate” of price changes (or stockout). This is the probability of a price change (or stockout) conditional on the number of days since the natural disaster. We want to understand if, at the good level, there is evidence that the hazard rate of stockout decreases with time after the disaster, while the hazard rate of price changes increases. We also want to see if goods that are considered necessities after an earthquake (e.g. those in a typical emergency kit) tend to behave differently in terms of their good-level hazards.

To measure hazard rates, we use standard methods in Survival Analysis, a technique that focuses on the time elapsed from the “onset of risk” until the occurrence of a “failure” event. In our context, the “risk” starts on the day of the natural disaster, and the “failure” is a

stockout (or a price change). Formally, if T is a random variable measuring the duration of the price spell, with density function $f(t)$ and cumulative density $F(t)$, the hazard $h(t)$ is the limiting probability that a failure occurs at time t , conditional on the days passed since the natural disaster:

$$h(t) = \lim_{\Delta t \rightarrow 0} \frac{\Pr(t < T < t + \Delta t | t < T)}{\Delta t} \quad (1)$$

The hazard measures the instantaneous risk of a stockout over time, conditional on survival until that day. To estimate it, we use a non-parametric approach from Nelson (1972) and Aalen (1978), which does not require any distributional assumptions.²⁴ It starts with a simple estimate of the cumulative hazard function $H(t)$, given by:

$$\hat{H}(t) = \sum_{j|t_j \leq t} \frac{c_j}{n_j} \quad (2)$$

where c_j is the number of failures at time t_j and n_j is the number of goods that can still fail at time t_j . The incremental steps c_j/n_j are an estimate for the probability of failure at t_j , taking into account only those goods that have survived until that point in time. Unlike the product availability index in previous sections, the hazard rate for stockout will therefore not consider goods that are new after the earthquake (goods that were not available for sale before the earthquake, but that appear some time later on). This allows us to isolate the effects of the earthquake on goods that existed at the time of the disaster.

To obtain the smoothed hazard function $\hat{h}(t)$, we take the discrete changes in $\hat{H}(t)$ and weight them using a kernel function:

$$\hat{h}(t) = \frac{1}{b} \sum_{j \in D} K\left(\frac{t - t_j}{b}\right) \Delta \hat{H}(t_j) \quad (3)$$

where K is a symmetric kernel density, b is the smoothing bandwidth, and D is the set

²⁴Results are robust to the use of a semi-parametric Cox model that can incorporate covariates and account for unobserved heterogeneity at the category level.

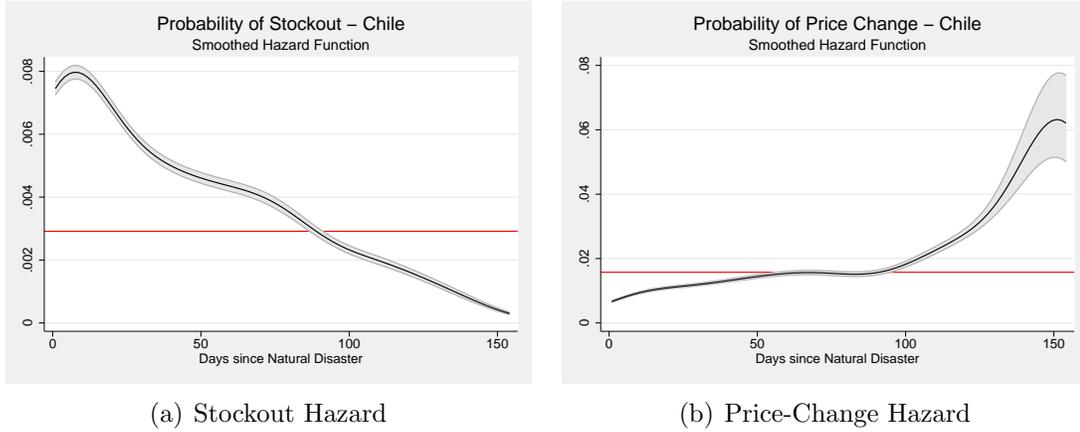


Figure 14: Hazards in Chile

of times with failures.

We conduct the analysis separately for price changes and stockout. Only the first occurrence of each of the failure events is considered for each good. That is, a good that disappears from the store at time t will not be used to compute the stockout hazard rate from then on, even if it re-appears later on. This is a fair assumption because any subsequent stockout will not likely be linked to the natural disaster itself. Similarly, if a good has a price change after the natural disaster at time t , it will drop from our price-change hazard estimates from then on. We are implicitly assuming that the retailers fully adjust to the earthquake at the time when the first price change is implemented. An alternative assumption would be that retailers adjust gradually, implementing a series of small price changes over time. We do not, however, find any evidence of this behavior in this data.

Figures 14 and 15 plot the estimated hazard functions with 95% confidence intervals for both countries. In all cases, we include a horizontal line at the unconditional probability over the sample period.

These hazards show that the daily probability of going out of stock immediately after the earthquake was close to 0.8% in both countries (approximately 20% in a month). This is significantly higher than the unconditional daily probability 0.3% per day in Chile (9% per month) and 0.4% in Japan (12% per month). This initial similarity between countries

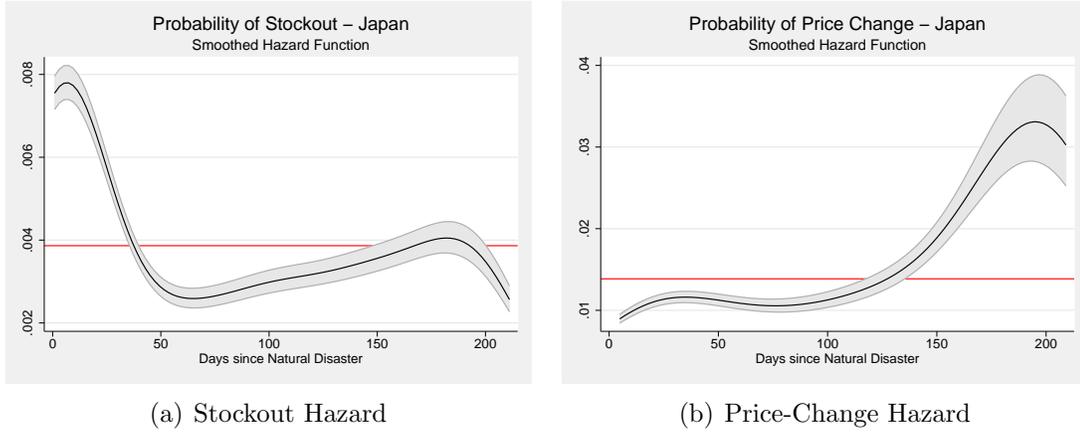


Figure 15: Hazards in Japan

disappears after the first week. In Chile the stockout hazard falls gradually. The longer the amount of time since the disaster, the lower the probability a good has of disappearing from the store. The effect is persistent, with the stockout hazard remaining above the unconditional probability until around 90 days.

In Japan the stockout hazard falls much quicker and starts to increase again 50 days after the disaster, as seen in Figure 15. Most of the stockout risk happens within a narrow window of time. If a good does not disappear quickly from the store, then it is not very likely to disappear at all. Once again, this result is consistent with disruptions in the supply chain. Those goods that managed to remain in stock are likely the goods that did not have any supply-chain problems to begin with, and therefore the retailer can keep them in stock over time.

The price change hazards in both countries start at similarly low levels immediately after the earthquake, around 0.01% (an implied duration of 100 days). This level represents a significant drop in Chile compared to the unconditional daily probability of 0.018% (an implied duration of 55 days), but only a small drop for Japan, where prices are usually stickier and the unconditional probability is 0.014% (an implied duration of 75 days). From then on, these hazard rates remains low for several months in both countries, reflecting the reluctance of these retailers to make any price changes at all.

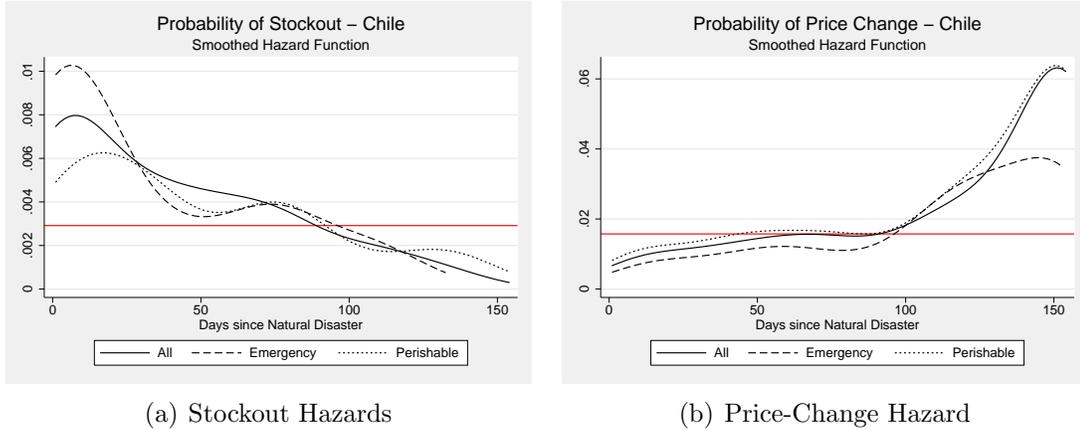


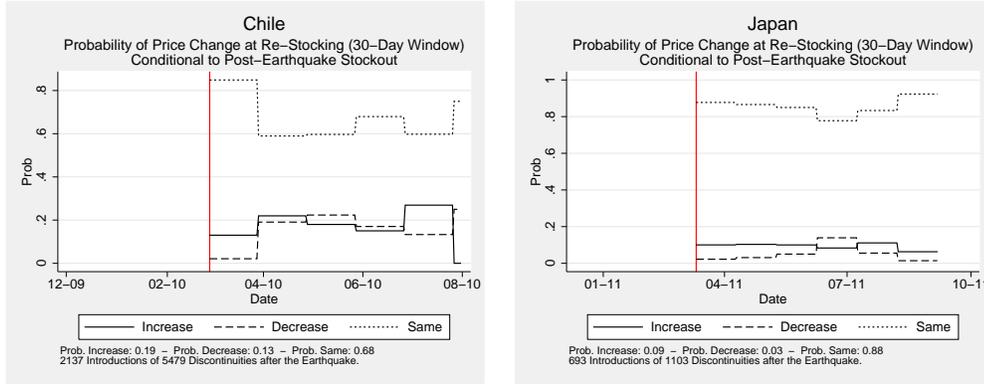
Figure 16: Perishable and Emergency Goods In Chile

We can also compute hazards for different types of goods and see if there are any differences for “Emergency” products and “Perishable” goods, as suggested by the results in Section 5. We do this only for Chile, where we have more detailed category information to classify goods into these two groups. Emergency products are those listed by the Chilean government as part of a suggested emergency kit in case of natural disasters.²⁵

Customer anger theories tend to have different predictions about the post-earthquake behavior of these two types of goods. The probability of a price change should be lower for emergency goods immediately after an earthquake (because people consider increases to be unfair), while the probability of a stockout should be higher (they are in high demand and their prices are not rising). Perishable items, by contrast, are the type of goods that are not likely to experience such a big demand shock and consumers would be more likely to consider price increases as fair (either because it is easier to understand that the cost to supply things like fresh vegetables goes up after an earthquake, or because people may actually experience less regret for not buying them before the earthquake). This is exactly what we find in Figure 16 for the earthquake in Chile.

Finally, while these hazard rates provide evidence on the likelihood of both stockout and hazards as time from the earthquake increases, they do not directly link goods that

²⁵See <http://www.onemi.cl/kit-de-emergencia.html>



(a) Chile

(b) Japan

Figure 17: Prices at time of Re-Stocking

had stockout with those that had price changes.²⁶ To examine this, we compute (on a monthly basis) the share of price increases, price decreases, or identical prices on the day of re-introduction. Results are shown in Figure 17.²⁷

In both countries the vast majority of goods that went out stock after the earthquake, and later reappeared, did so at exactly the same price they had before (collapsing the time series, we find that 67% of re-introductions had identical prices in Chile and 87% in Japan). This suggest that either wholesale prices did not increase, or the retailers were not able or willing to pass-through any higher costs to consumers immediately upon re-stocking.²⁸

8 Conclusions

We study the aggregate behavior of prices and product availability in the aftermath of two recent catastrophic natural disasters: the 2010 earthquake in Chile and the 2011 earthquake in Japan. We show that in both cases, the margin of adjustment during the disaster was in

²⁶For example, the price change hazard in Figures 14(b) and 15(b) include observations from good that had both stockouts and those that did not. An interesting question is what happens to prices of goods that go out of stock once they are re-introduced at the stores.

²⁷We use only to goods that were available on the day of the earthquake, go out of stock later on, and re-appear at some point during our sample period, To avoid the effects of potential scraping error, we required goods to disappear from the database for at least 3 days before we consider them as having a stockout.

²⁸The size of price changes in Japan did increase considerably in June 2011, as shown in Figure 12. However, these were price changes from goods that were already in stock at the time.

product availability, not prices. We find that this is consistent with the expected response in the context of “customer anger” models, such as Rotemberg (2005), particularly in Chile, where the frequency of price changes fell significantly after the earthquake. In Japan, we find evidence more closely linked to supply disruption and the retailer’s inability to re-stock items than pricing behavior linked to consumer anger.

Our metrics capture the effects of both demand and supply conditions. The demand shock is associated with the needs and fears that people experience in the immediate aftermath of the disaster. Goods that disappear quickly from the stores are mostly nonperishable items that people are likely to hoard in fear of future supply disruptions. The supply shock affects the ability of retailers to replenish their stocks over time, even after the initial spike in demand dissipates. In some cases, as we showed for Japan, product availability disruptions could serve as early indicators of the magnitude of industrial production changes.

Online data have many advantages in the context of natural disasters. Data can be collected remotely, in real time, and without requiring any resources from the retailers involved. But there are also important limitations. Relatively few retailers and categories of goods are currently available online, particularly in poor countries. Even when retailers are online, their servers could stop operating during natural disasters, so there is no way to scrape data. In other cases, retailers may simply stop updating prices and stock information online, voluntarily suspending their online service during the time of the disaster. The reliability of online data sources under extreme circumstances needs to be determined, and will likely depend on the country and context under which the natural disaster occurs.

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A Appendix

A.1 Index Methodologies

In order to study the short-run impacts of natural disasters on product availability and prices, we apply an event study approach. We use daily price and product availability information, focusing on a window of 9 months around the date of the natural disaster.

We base our analysis on 2 simple statistics:

- **Product Availability Index:** At different levels of aggregation, we count the number of distinct products available for sale each day. We repeat this calculation for each day on a 9-month window around the earthquake to see the impact of the earthquake on the number of products available over time. We normalize the series to a value of 100 on the day of the natural disaster in order to be able to compare results across categories and countries.
- **Price Index:** We use a Jevons geometric-index formulation used by most national statistical agencies for basic-level indices (the narrowest level of aggregation). First, we compute the daily price relative to all individual goods at each day of the sample. Each “price relative” is equal to the price at t over the price at $t - 1$. Second, we calculate an unweighted geometric average of all good-level price relatives on day t and category z . Third, at time $t = 0$ we compute the index as the previous day’s index value times the geometric average of price relatives for that day (calculated before). We start with an index value of 100 on the first day of the sample.