Liquidity Constraints, Storage Costs, and Consumer Stockpiling

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Abstract

Liquidity constrained consumers may be prevented from stockpiling goods, so that they may have difficulty in consumption smoothing. This paper tests this hypothesis focusing on Japan's consumption tax hike in 2014, which provided consumers with a strong incentive to stockpile storable goods before the tax hike. The analysis provides evidence that a non-negligible fraction of consumers increased storable goods purchases before the tax hike while reducing perishable goods purchases, suggesting that these consumers could not afford to buy both goods. The regression analysis shows that a sizable fraction of consumers are constrained and that liquidity constraints affect their stockpiling behavior.

JEL codes: D12, E21, E62, H31, L81.

Keywords: Consumption, hand-to-mouth, Japan's consumption tax, storability.

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1 Introduction

Many studies have shown that a certain proportion of consumers are liquidity constrained (Campbell and Mankiw, 1989, 1990; Zeldes, 1989),[1] but most of these studies analyze durable and non-durable consumption separately. Few studies have focused on the interaction between durable and non-durable consumption. An exception is the study by Browning and Crossley (2009), who point out that when workers are faced with a transitory income drop, they tend to reduce their expenditure on small durables such as socks and coats. Because existing durables keep supplying a flow of services, consumers can substantially reduce durable spending without having to greatly reduce durable consumption. This feature of durables enables consumers to smooth consumption of non-durables such as food in response to negative income shocks. However, Browning and Crossley's (2009) discussion relies on the implicit assumption that consumers always hold sufficient durables to smooth out transitory income shocks. If this assumption is not satisfied for liquidity constrained consumers, they may have difficulties in consumption smoothing.[2]

The same argument holds for storable (non-durable) goods. Consumers can store goods for future consumption, which contributes to consumption smoothing in the same manner as holding durables. The key assumption of this argument is also the same as above. To smooth consumption, consumers need to have stockpiled a sufficient amount of storable goods before they experience a transitory shock. While there are no studies that formally examine whether this assumption holds in practice, a number of studies focusing on stockpiling behavior with regard to storable goods present results that are relevant to this issue. For example, Hendel and Nevo (2006*a*) show that lower-income households are more price sensitive than higher-income households, suggesting that stockpiling behavior by consumers does not depend on

[1] Chah, Ramey, and Starr (1995) and Attanasio, Goldberg, and Kyriazidou (2008) show that durable spending such as car purchases is subject to liquidity constraints.

[2] Attanasio and Weber (2010) note that more research should be conducted on the relationship between consumption smoothing and the timing of durable spending.

whether they are liquidity constrained, since lower-income households are more likely to face liquidity constraints. Therefore, determinants of stockpiling behavior other than liquidity constraints have been highlighted in the literature. Hendel and Nevo (2006*a*,*b*), for example, highlight the importance of heterogeneity in preferences and storage costs, while Boizot, Robin, and Visser (2001) incorporate fixed costs as well as storage costs into their model.

Are liquidity constraints irrelevant to stockpiling behavior? To answer this question, this paper focuses on Japan's consumption tax hike in April 2014. The consumption tax hike provides a useful case study in three respects. First, the consumption tax covers a wide variety of goods, which gives consumers an incentive to stockpile more goods than during promotional sales. As a result, it is more likely that consumers faced liquidity constraints before the tax hike than during regular promotional sales. Second, because many retailers increased their prices on the same day, the tax hike had little impact on relative prices, meaning that the problem of heterogeneity in brand preferences does not come into play. Third, the tax hike was announced by the Japanese government well in advance, so that all consumers had the same information about the future increase in prices.

By focusing on Japan's consumption tax hike, this paper provides two types of evidence suggesting that consumers' stockpiling behavior is affected by liquidity constraints. The first type of evidence is that some consumers did not reduce purchases of storable goods even after the tax hike. This finding is inconsistent with the prediction that consumers should have engaged in arbitrage, namely, that they should have increased purchases of storable goods before the tax hike and decreased them following the tax hike, since the tax hike was known in advance. The failure of these consumers to engage in such arbitrage can be explained by liquidity constraints. The second type of evidence is that a non-negligible fraction of consumers increased purchases of storable goods before the tax hike while reducing purchases of perishable goods. This finding suggests that these consumers had to sacrifice purchases of perishable goods to finance their stockpiling of storable goods under liquidity

constraints.

Based on these findings, this paper quantifies the effect of liquidity constraints on stockpiling behavior. An empirical issue that needs to be addressed in this context is how to identify liquidity constrained consumers. In previous studies such as Zeldes (1989), income is used as the key variable to examine whether consumers are liquidity constrained; however, this method cannot be applied in the analysis here. The reason is that income may be correlated with storage costs, which have been regarded as an important determinant of stockpiling behavior in existing studies such as Hendel and Nevo (2006*a*,*b*). To solve this problem, this paper proposes an innovative approach that uses the price paid by each consumer relative to the average price as an indicator of liquidity. On the one hand, the relative price is likely to be orthogonal to storage costs because it does not include aspects of quantity. On the other hand, the relative price reflects the fact that wealthier consumers typically buy higher quality goods at higher prices. Using this indicator in the regression analysis, this paper shows that a sizable fraction—at least 36 percent—of consumers are subject to liquidity constraints, and that liquidity constraints have a significant effect on consumers' purchases of both storable and perishable goods.

This paper is relevant to three research fields. The first field consists of analyses of consumers' dynamic behavior in the storable goods market when sales (temporary price reductions) occur. Boizot, Robin, and Visser (2001) were the first to model consumers' inventory problem in this situation. Using U.S. scanner data, Hendel and Nevo (2006*a*,*b*) show that consumers' dynamic reaction has a sizable effect on the estimation of demand.[3] Hendel and Nevo (2013) regard pricing patterns such as sales as a result of intertemporal price discrimination, and present a sellers' model where consumers are heterogeneous with respect to their storage technology. This paper also considers heterogeneity in storage technology as well as liquidity, and estimates the impact of each on stockpiling behavior.

[3]For Japan, Abe and Tonogi (2010) and Sudo, Ueda, and Watanabe (2014), using scanner data, find that the quantities of products sold during sale periods are considerably larger than during non-sale periods.

The second research field to which this study is related analyzes the consumption response to Japan's consumption tax hike. Regarding the consumption tax hike in 2014 as a negative income shock that decreased consumers' lifetime resources, Cashin and Unayama (2016*a*) examine the permanent income hypothesis.[4] They find that most of the Japanese households they focus on are not liquidity constrained. They report that the fraction of hand-to-mouth households in their sample is about 10 percent.[5] While Cashin and Unayama (2016*a*) use real expenditures on non-storable non-durable goods in their baseline analysis, this paper focuses on consumer inventories using records of storable goods purchases, to which less attention has been paid.

The third research field to which this paper is related examines the differences in prices paid by households. Aguiar and Hurst (2007) show that older households pay lower prices for identical goods and analyze the relationship between prices paid by households and their shopping time. Moreover, Broda, Leibtag, and Weinstein (2009) show that poorer households pay lower prices than richer households for identical goods, probably because poorer households are more likely to buy goods on sale. A similar mechanism is at work in this paper; that is, after the tax hike, some consumers can consume goods they stockpiled before the tax hike, while others have to purchase goods at the higher price. Thus, differences in consumers' dynamic reaction lead to the difference in prices paid by consumers.[6]

The remainder of the paper is organized as follows. In the next section, I provide a brief overview of Japan's consumption tax hike that took effect in April 2014. Section 3 describes the data used for the analysis and provides evidence that some consumers failed to engage in arbitrage around the time of the tax hike. Section 4 then presents a simple model

[4]There was another consumption tax hike in Japan in 1997 as well. Using this episode, Cashin and Unayama (2016*b*) estimate the intertemporal elasticity of substitution, since the tax hike at that time was compensated for by cuts in income tax rates.

[5]This result is very similar to that obtained by Hara, Unayama, and Weidner (2016), who report that the share of hand-to-mouth households in Japanese data is approximately 13 percent.

[6]Feenstra and Shapiro (2003) point out that stockpiling by consumers could be a source of bias in the consumer price index.

featuring storage costs as the only source of consumer heterogeneity and empirically shows that stockpiling behavior may be driven by liquidity constraints instead of storage costs. Section 5 extends the model and quantifies the effect of liquidity constraints on stockpiling behavior. Finally, Section 6 provides concluding remarks.

2 Brief Overview of Japan's Consumption Tax Hike

This section explains the salient features of Japan's consumption tax hike used as a case study here.

Consumption tax (value-added tax) in Japan was introduced in 1989 in order to cover social security expenditure. The initial consumption tax rate at the time of introduction was 3 percent. The consumption tax was subsequently increased to 5 percent in 1997 and then to 8 percent in 2014. The main reasons given by the government were the need to reduce the government deficit and to sustain the social security system.

Japan's consumption tax covers a fairly wide range of goods, including food, necessities, durables, and services.[7] In addition, unlike in European countries, where a reduced tax rate is applied to certain goods, Japan's consumption tax consists of a single flat rate. This means that the tax hike provided consumers with an incentive to engage in intertemporal substitution by "frontloading" purchases before the tax hike, but did not provide any incentives to substitute across goods. That is, the tax hike provided consumers with an incentive to stockpile various goods, which means that some consumers were likely to face liquidity constraints.

The increase in the consumption tax rate from 5 to 8 percent took effect on April 1, 2014. The *Nihon Keizai Shimbun*, Japan's leading business newspaper, reported that many retailers changed their prices on that day. This means that unlike promotional sales, which

[7] See Cashin and Unayama (2016*b*) for a list of exemptions.

lead to intratemporal substitution effects as consumers buy more of a particular good or buy more at a particular store at temporarily reduced prices, the consumption tax hike did not give rise to intratemporal effects.

Another important aspect is that consumers were able to anticipate the tax hike in advance. On October 1, 2013, Japan's Prime Minister Shinzo Abe declared that the tax hike would be implemented on schedule, in April 2014. Therefore, the timing of the tax hike was publicly known beforehand. Japan's consumption tax hike thus provides an ideal setting to measure intertemporal substitution with uniform expectations. In contrast, as highlighted by Aguiar and Hurst (2007), promotional sales are not publicly known in advance and mean that individual households face different prices.

Another study focusing on Japan's consumption tax hike in 2014 is that by Cashin and Unayama (2016*a*). They regard the announcement of the tax hike in October 2013 as a permanent income shock and test the permanent income hypothesis using monthly household-level panel data. They find that non-durable consumption significantly decreased in response to the announcement, which is consistent with the permanent income hypothesis. However, they also find last-minute demand for non-durable goods just before the tax hike. While they argue that this phenomenon can be explained by the strong complementarity between durables and non-durables, I show that this purchasing behavior may also be explained by consumer heterogeneity.

3 Data and Facts

This section describes the data used for the analysis and provides several facts suggesting that stockpiling behavior may be affected by consumer heterogeneity.

3.1 Data

The data used for the analysis are daily scanner data provided by IDs Co., Ltd., a Japanese marketing company. The dataset consists of sales records for more than 300 supermarkets from April 2011 to October 2014,[8] and products are distinguished by fairly detailed classifications called i-codes, which can be matched with barcodes widely used in Japan. More importantly, the dataset includes consumer identifiers. Consumers register their information to obtain a member's card for each store chain. Because consumers have an incentive to show their member's card when shopping,[9] a substantial fraction of the transactions are recorded with information about buyers. It is therefore possible to track the expenditure records as well as the prices and quantities of each product bought by the same consumers.

To observe consumer stockpiling behavior, I choose the records for cup noodles. Cup noodles are storable for months, which makes them suitable for the analysis here. In addition, cup noodles are usually sold in one-meal portions, reducing the possibility of measurement error. Because the IDs data do not include information about the unit (size, weight, or length) of each product, I count the quantity sold at the product level.[10]

The scanner data include rich information about consumers' purchasing behavior; however, one concern is that some consumers may make purchases at other retailers. Since such consumers' purchasing decision will be influenced by purchases that are not included in the data, care needs to be taken in designing the sample. To address this issue, the analysis focuses on *regular customers*. A regular customer is defined as someone who bought cup noodles at only one particular store in the data at least once in each quarter from 2011Q2 to 2014Q1 and purchased cup noodles again at least once after the consumption tax hike.[11]

[8] In fact, the dataset starts in 2010, but the number of consumers whose information is available before April 2011 is very small.

[9] For example, some stores offer coupons when a customer's purchases reach a certain value.

[10] Sometimes cup noodles are sold as a bundle, and in that case a barcode printed on the package instead of each cup will be scanned, so that the measurement of the quantity purchased will be imprecise. However, in Japan, cup noodles are sold separately in most cases.

[11] Some customers of a store may attempt to buy cup noodles in other stores at a lower price. Since such

Table 1: Sample statistics for 2013

	Min	1st Q	Median	3rd Q	Max
Expenditure on cup noodles (yen)	375	2,558	4,095	6,616	123,620
Quantity purchased (no. of cups)	4	25	39	63	1,048
Purchase frequency (no. of days)	4	13	19	30	359
Store visit frequency (no. of days)	5	88	142	214	365
No. of different cup noodle products purchased	1	11	16	24	120

Note: The table shows sample statistics for 2013 for 57,600 consumers who purchased cup noodles every quarter before the tax hike and purchased cup noodles again at least once following the tax hike. In each row, annual values are presented. Purchase frequency is defined as the number of days per year on which cup noodles were purchased. Store visit frequency is defined as the number of days per year a consumer visited a store.

In other words, I select the combination of consumers and retailers engaged in repeated transactions.

The sample consists of 57,600 regular customers making purchases at 339 stores. Although these customers make up only 2.6 percent of all customers at these stores, they account for 17.3 percent of all sales of cup noodles. Table 1 presents descriptive statistics for these regular customers for 2013. The table indicates that even across regular customers, expenditure on cup noodles varies widely. The median expenditure per year (before taxes) of regular customers on cup noodles is 4,095 yen, and the median quantity of cup noodles bought per year is 39 cups. The distribution of these variables has a fat tail, with a maximum that is about 30 times larger than the median. The table also shows the frequency of cup noodle purchases and store visits, where the purchase frequency is the number of days per year that a customer bought cup noodles, while the store visit frequency counts the number of days per year that a customer visited the store and bought something (not only cup noodles but any item). Finally, the table shows the number of different products (i-codes) within the cup noodle category that regular customers bought.

behavior might generate bias in the measurement of stockpiling behavior, customers who bought cup noodles at more than one store are removed from the sample.

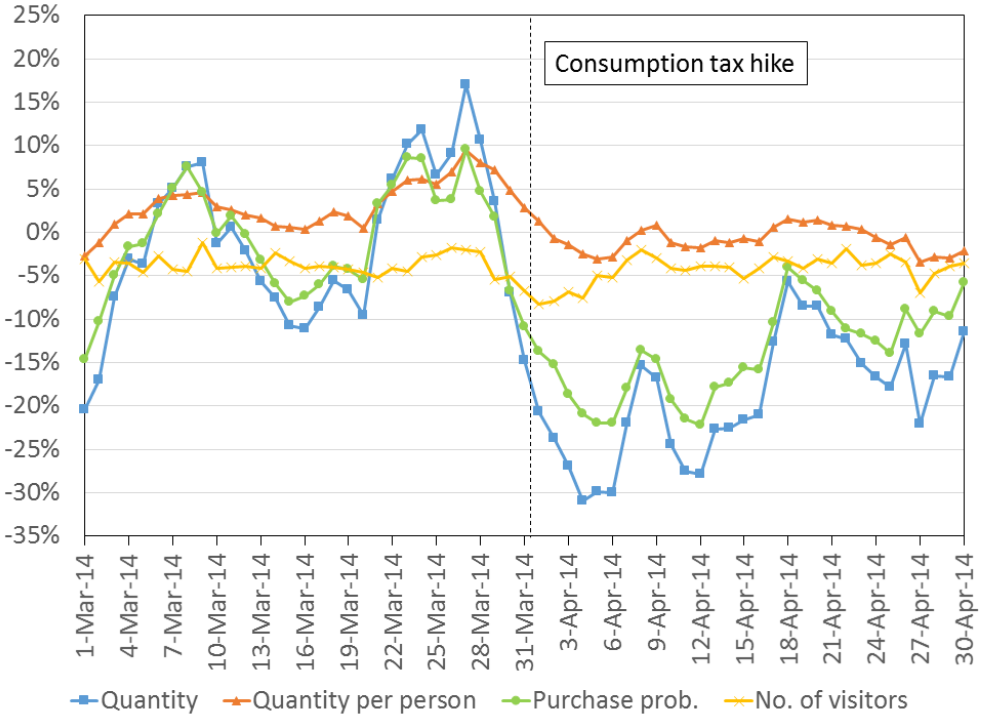

Figure 1: Quantity of cup noodles purchased

Note: The figure shows year-on-year rates of change (calculated as log rates of change; one-week moving averages). Changes in quantity are decomposed into changes in the quantity per person, the purchase probability, and the number of visitors.

3.2 Facts

I aggregate the quantity of cup noodles purchased by regular customers. I focus on the quantity to analyze stockpiling behavior, because the expenditure on cup noodles may reflect fluctuations in their price.[12] Figure 1 shows developments in purchases of cup noodles around the time of the implementation of the consumption tax hike (April 1, 2014). In the figure, the blue line with squares shows the year-on-year rate of change (calculated as the log rate of change; one-week moving average) in the quantity of cup noodles purchased. The line indicates that purchases jumped just before the consumption tax hike and then fell sharply following the tax hike. In sum, aggregate developments indicate that consumers engaged in

[12]In fact, using the expenditure on cup noodles instead of the quantity does not substantially change the following results.

stockpiling, which is what one would expect with regard to storable goods.

Next, I decompose changes in the quantity purchased into three components: changes in the quantity per person conditional on purchase (represented by the orange line with triangles), the probability of purchase conditional on store visit (represented by the green line with circles), and the number of visitors (represented by the yellow line with x marks). Representing these components by X_t, $Prob_t$, and V_t, where each variable is the year-on-year rate of change (log rate of change), quantity Q_t can be decomposed as follows:

$$Q_t = X_t + Prob_t + V_t.$$

This decomposition provides three interesting observations regarding consumers' stockpiling behavior around the time of the tax hike.

First, the last-minute demand before the tax hike consists of increases in both the quantity purchased per person and the likelihood that individuals would purchase cup noodles (purchase probability). That is, consumers did not visit stores more frequently, but they were more likely to purchase more cup noodles. Second, the subsequent decline in demand is mainly due to a decrease in the purchase probability and not a decline in the quantity purchased per person. In other words, the response before and after the tax hike was asymmetric. Third, the number of store visitors fluctuates less than the other two components,[13] indicating that consumers' store visit frequency was not affected by the tax hike.[14]

The asymmetric reaction before and after the tax hike is a notable finding. It suggests that there are at least two types of consumers. The first type are those who stocked up

[13]Because I observe the same pairs of consumers and retailers throughout, the number of visitors may be downward biased.

[14]Hendel and Nevo (2006*b*) in their model assume that the store visit frequency is exogenously given. Their rationale for this assumption is that each of the products is a minor component of overall household needs, implying that the need for these products does not lead to a store visit. The finding that there was little change in consumers' store visit frequency at the time of the tax hike provides support for this assumption, suggesting that the across-the-board price increases brought about by the tax hike did not lead consumers to substantially alter their shopping habits in terms of the frequency with which they visited stores.

before the tax hike and did not purchase any cup noodles in the month after the tax hike even though they visited retailers (in other words, the likelihood that such consumers bought cup noodles declined). The other type are consumers that did not stock up on goods at all and continued to buy as usual even after the tax hike (so the quantity purchased per person did not decline). As mentioned, all consumers knew about the consumption tax hike in advance. Therefore, Hendel and Nevo's (2013) assumption that there are storers and non-storers also seems to apply to the episode examined here.

What is the source of the difference in stockpiling behavior across consumers? A straightforward explanation is heterogeneity in storage costs, as argued by Hendel and Nevo (2006*a*,*b*). The next section explores this idea.

4 Consumer Stockpiling in an Economy with Storage Costs

This section contains three parts. First, I employ a simple model to show that the quantity purchased partly includes information about storage costs. Next, using this feature, I propose an empirical procedure to gauge each consumer's storage costs. Third, I show some results suggesting that storage costs alone cannot explain consumers' purchasing behavior and that liquidity constraints may potentially play a large role.

4.1 Model

I begin by discussing the consumer inventory model developed by Boizot, Robin, and Visser (2001) in which the price of a storable good is assumed to change deterministically. In their setting, time is continuous. The duration of price promotions (sales) is non-random and is denoted by T. The regular price is p, and the promotional price is $p - \epsilon$. In other words, when a promotion occurs, ϵ is discounted from the regular price. Boizot, Robin, and Visser

(2001) assume that each consumer consumes a constant quantity per time unit, and that the consumption rate is normalized to unity, so that consumption for a very short interval, dt, is also denoted by dt. In addition, they incorporate storage costs reflecting the fact that the space for storage is limited. The cost of storage is proportional to the amount of stocks held by a consumer. When the amount stored by a consumer is x, the cost of storage a consumer pays for the interval dt is expressed as $cx\ dt$.

Since storage incurs a cost, one would assume that by the time the next price promotion occurs, consumers' stockpile of a good from the previous promotion should have fallen to zero. Consumers' problem therefore is how much to stockpile when a price promotion occurs. Boizot, Robin, and Visser (2001) examine this inventory decision made by consumers and show that consumers can adopt two strategies. First, when a promotion occurs, consumers can buy exactly T units of the product all at once and stop purchasing the product while prices are not discounted. Put differently, consumers adopting this strategy buy the goods consumed between two adjacent promotions all at once.[15] In this case, storage costs are

$$\int_0^T cx\ dx = c\frac{T^2}{2}.$$

Adding the expenditure on goods purchased, the total costs are given by

$$c\frac{T^2}{2} + (p - \epsilon)T.$$

The other strategy is to stockpile amount $S(< T)$. Those who follow this strategy can consume the goods purchased at the promotional price until their stock runs out. After that, they continue to buy goods for consumption at the regular price, which involves no

[15]Note that since the rate of consumption is assumed to be unity, T units of the product will be consumed over T time units.

storage costs. In this case, the total costs are

$$c\frac{S^2}{2} + (p - \epsilon)S + p(T - S). \tag{1}$$

Consequently, the solution to the cost minimization problem is given by

$$S = \begin{cases} T & (T < \epsilon/c) \\ \epsilon/c & (T \geq \epsilon/c) \end{cases}. \tag{2}$$

This basic model is useful for assessing consumer-specific storage costs. As can be seen, Equation (2) implies that the quantity purchased at the promotional price partly includes information about storage costs, c. Based on these theoretical considerations, it is possible to estimate storage costs using scanner data.

4.2 Estimation of Storage Costs

The theoretical considerations in the previous subsection imply that there exist two types of consumers. The first type consists of consumers that buy only at discounted prices, since their storage costs are quite low. This means that it is not possible to extract storage costs from Equation (2), since the quantity purchased by such consumers simply reflects the interval. I address this issue by following Eichenbaum, Jaimovich, and Rebelo (2011) and calculating daily regular prices of a product sold at a retailer as the modal price in a quarter. Based on this measure, I exclude consumers who are categorized as the first type.[16]

The second type of consumers buy in both bargain and non-bargain periods. For these consumers it is possible to obtain the cost of storage. Figure 2 provides an illustration of the estimation procedure. The horizontal axis shows the time between two promotions, one

[16]Specifically, I calculate the exclusion criterion as follows. I first obtain the daily expenditure record of a consumer for cup noodles. I then calculate the hypothetical expenditure if the same basket was purchased at regular prices. If the former value is less than the latter for all days, the consumer is excluded.

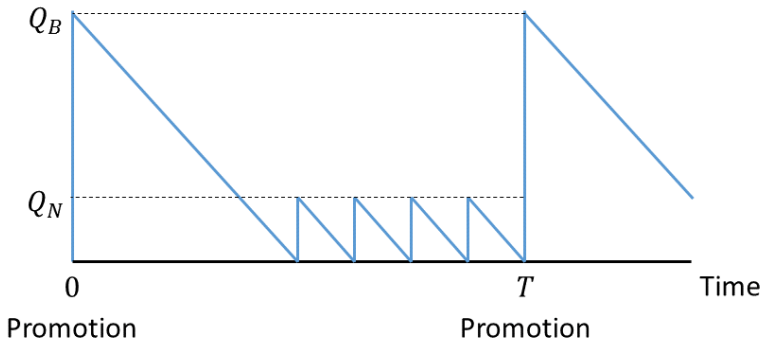

Figure 2: Dynamics of inventory holdings

at time 0 and the next at time T. Consumers make one purchase at the promotional price at time 0 and several smaller purchases (four purchases in the illustration here) between the two sales at the regular price. The quantities purchased in the two cases are denoted by Q_B and Q_N, respectively. To extract storage costs, a straightforward way would be to divide Q_B by Q_N to normalize individual taste effects. However, because purchases in non-bargain periods in practice are not continuous but infrequent, Q_B/Q_N would mismeasure storage costs.

To address this problem, I calculate the duration between purchases in non-bargain periods. Under the assumption that the quantity consumed is constant over time, the quantity purchased is proportional to the duration while consumers consume the product, as shown in Figure 2. Therefore, $Q_N/(Q_B \times 1 + Q_N \times 4)$ is the quantity ratio associated with the duration between purchases in non-bargain periods. Using this ratio, I obtain the quantity consumed per time unit and divide Q_B by this value.

Provided that the size of discounts is homogeneous across consumers, the indicator corresponds to the inverse of consumer-specific storage costs. In the empirical analyses below, I set Q_B and Q_N as the 90th and 10th percentiles of the daily quantity purchased of cup noodles in 2013, respectively. If the quantity is greater than or equal to Q_B, I regard that

purchase as being a purchase conducted during a sales promotion.

4.3 Analysis

In this part, I examine the relationship between storage costs and purchasing behavior. Using storage costs, I split consumers into ten groups and plot the mean quantity (year-on-year log rate of change) of cup noodles purchased in March 2014 in Figure 3.[17] We can observe that the quantity purchased is positively correlated with the inverse of storage costs, indicating that consumers with lower storage costs increased purchases of storable goods before the tax hike. This suggests that the cost of storage likely is one important determinant of stockpiling behavior.

At the same time, the role of storage costs in stockpiling behavior can be examined in another way. For example, Boizot, Robin, and Visser (2001) demonstrate that their inventory model is more suited for the analysis of purchases of storable goods such as noodles and butter that can be stored for a long time—several months or more—than less storable goods such as fresh vegetables and fruits that can normally only be stored for a week or two. Based on their argument, I can test the consumer inventory model featuring storage costs by comparing purchases of long- and short-term storable goods. Figure 3 therefore also shows expenditure on less storable or perishable goods including fresh vegetables and fruits, raw meat and fish, and delicatessen.[18] These goods are less storable than cup noodles, so that it is expected that unlike in the case of purchases of cup noodles, storage costs should be an insignificant determinant of purchases of perishable goods. However, Figure 3 shows that although the relationship is not monotonic, expenditure on perishable goods is also positively correlated with the inverse of storage costs, indicating that consumers with lower

[17]The sample is restricted to consumers who bought cup noodles in both March 2013 and March 2014. Consumers that buy only at discounted prices are excluded.

[18]Because the scanner data do not include exact information about the quantity of unprocessed food purchased, I use the expenditure here. Again, the sample is restricted to consumers who bought perishable goods in both March 2013 and March 2014 and consumers that buy only at discounted prices are excluded.

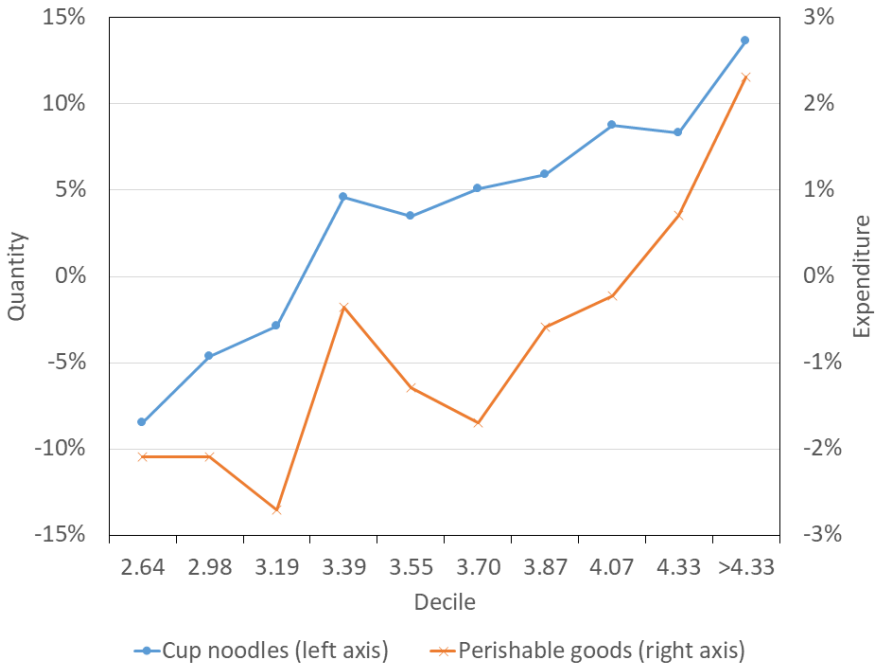

Figure 3: Storage costs and purchasing behavior

Note: Consumers are divided into ten groups using the inverse of storage costs. Deciles are defined based on consumers who bought perishable goods in both March 2013 and March 2014. For each consumer group, I take the mean of year-on-year rates of change (calculated as the log rates of change) in the quantity of cup noodles purchased in March 2014. Also, I take the mean of year-on-year rates of change (calculated as the log rates of change) in expenditure on perishable goods in March 2014.

storage costs increased purchases of perishable goods as well as storable goods before the tax hike. This finding is difficult to reconcile in the consumer inventory model incorporating storage costs only.

Another notable result displayed in Figure 3 is that a non-negligible fraction of consumers increased purchases of cup noodles before the tax hike while reducing purchases of perishable goods. For example, consumers around the 5th decile increased purchases of cup noodles by 5 percent while reducing purchases of perishable goods by more than 1 percent. This suggests that some consumers could not afford to buy both cup noodles and perishable goods before the tax hike, so that they were forced to sacrifice purchases of perishable goods. This kind of purchasing behavior can be explained as a result of optimization under liquidity

constraints, provided that the benefit from arbitrage in cup noodles exceeds the cost of reducing consumption of perishable goods. In the next section, I therefore turn to analyses of the role of liquidity constraints in stockpiling behavior.

5 Consumer Stockpiling in an Economy with Liquidity Constraints and Storage Costs

This section describes an extended inventory model incorporating liquidity constraints and provides a new methodology to empirically identify liquidity constrained consumers. After that, the effect of liquidity constraints on consumer stockpiling behavior is quantified using regression analysis.

5.1 Extended Model

Boizot, Robin, and Visser (2001) analyze how the quantity of goods purchased and the duration of purchases depend on current and past prices of goods rather than on heterogeneity in consumer characteristics. I therefore extend their model step by step and attempt to describe differences in stockpiling behavior due to consumer heterogeneity. Specifically, I incorporate three components into their model as a source of heterogeneity: liquidity constraints, storage costs, and travel (adjustment) costs. While the first two components have already been mentioned, travel costs represent an additional potentially important determinant of stockpiling behavior, since the frequency of store visits varies substantially across consumers as shown in Table 1.

Analogous to the notation used in Section 4.1, T_{VAT} and S_{VAT} are employed to refer to the duration of the price change and the amount of goods stockpiled. Because the tax hike is a permanent shock, T_{VAT} is so long that S_{VAT} should depend on storage costs, c, and the size of the tax hike, τ. Moreover, I incorporate adjustment costs reflecting differences in

travel costs into the model as a source of heterogeneity. I assume that adjustment costs are quadratic in the quantity purchased and are expressed as $\eta S_{\text{VAT}}^2/2$.[19] Adding this term to Equation (1) yields the total cost function before the tax hike:

$$c\frac{S_{\text{VAT}}^2}{2} + (p-\tau)S_{\text{VAT}} + p(T_{\text{VAT}} - S_{\text{VAT}}) + \eta\frac{S_{\text{VAT}}^2}{2}.$$

Next, the tax hike means that prices of a large range of goods increase across the board. This implies that, compared to regular discount sales, consumers potentially stockpile on a much wider scale, suggesting that they are more likely to face liquidity constraints. Liquidity thus can be regarded as another source of heterogeneity, with the extent of stockpiling subject to the exogenous level of liquidity available before the tax hike, Y. The level of stockpiling before the tax hike is given by

$$S_{\text{VAT}} = \begin{cases} Y & (Y < \frac{\tau}{c+\eta}) \\ \\ \frac{\tau}{c+\eta} & (Y \geq \frac{\tau}{c+\eta}) \end{cases}, \tag{3}$$

where Y, c, and η are consumer-specific parameters.

The extended model has two notable features. First, as Equation (3) shows, liquidity constraints have an effect on the quantity purchased before the tax hike. For those who are liquidity constrained, the level of available liquidity is a key determinant of their stockpiling behavior. Second, this model also includes those who are not liquidity constrained and hence can stockpile as much as they like, subject to storage and adjustment costs. These unconstrained consumers more substantially substitute over time than constrained consumers, so that unconstrained consumers are more likely to postpone making purchases after the

[19] While Boizot, Robin, and Visser (2001) introduce fixed costs, doing so—as shown by Caballero and Engel (1999)—generates lumpy behavior; on the other hand, convex costs simply restrain increases in quantity. Table 1 shows that approximately 75 percent of regular customers visit a store on more than 90 days a year, so that on average they visit a store at least once every four days. In this sense, lumpy behavior in stockpiling by consumers is likely to be limited.

tax hike, which may reflect the fact that the probability that consumers made purchases following the tax hike declined.

Although these extensions to the model are quite moderate, their implications are potentially substantial. The largest difference from existing models is the introduction of liquidity constraints. While the original model by Boizot, Robin, and Visser (2001) considers consumers' cost minimization problem, Hendel and Nevo (2006*a*,*b*) construct a model in which utility is linear in consumption of a numeraire (which they refer to as the outside good). These models ignore the role of liquidity constraints and implicitly assume that consumers' income does not affect their stockpiling behavior. In contrast, the model presented here explicitly takes liquidity constraints into account and describes both constrained and unconstrained consumers' stockpiling decisions.

5.2 Methodology to Identify Liquidity Constrained Consumers

This part explains how I distinguish liquidity constrained consumers from unconstrained ones. In previous studies, a key variable used to examine whether consumers are liquidity constrained is income. For example, Zeldes (1989), using family-level panel data, shows that the annual growth rate of food consumption is significantly linked to lagged income and based on this finding, he argues that a certain proportion of consumers are liquidity constrained. However, the method he employed cannot be applied to the analysis of stockpiling behavior. The reason is that income may be correlated with storage costs, which should be a determinant of stockpiling behavior of unconstrained consumers as shown by Equation (3). Therefore, the fact that income and stockpiling behavior are linked does not necessarily provide evidence that some consumers are liquidity constrained, since it might pick up the role of storage costs.

To solve this problem, in this paper I calculate the price each consumer paid relative to the average price as an indicator of liquidity. This indicator reflects the fact that wealthier

consumers typically purchase higher quality goods at higher prices.[20] On the other hand, more importantly, this indicator may be orthogonal to storage costs because the relative price does not include aspects of quantity. Consequently, the relationship between the relative price and stockpiling behavior implies that liquidity constraints are binding, and vice versa.

Specifically, the relative price is calculated as the expenditure-weighted average of prices across product categories compared to the average price paid for goods in each category. This indicator is constructed as follows. Let p_i^k and e_i^k denote the price and expenditure paid by consumer i to purchase good k. Then, the price consumer i paid for goods in category c can be defined as

$$p_i^c = \sum_{k \in c} \omega_i^k p_i^k,$$

where $\omega_i^k = e_i^k / \sum_{k \in c} e_i^k$. Using this, the relative price paid by consumer i to purchase goods in various categories can be written as

$$p_i = \sum_c \omega_i^c (p_i^c / \bar{p}^c),$$

where $\omega_i^c = \sum_{k \in c} e_i^k / \sum_c (\sum_{k \in c} e_i^k)$ and $\bar{p}^c$ denotes the average price paid by consumers who purchase goods in category c. I calculate the consumer-level relative price using the purchasing records for all goods except for perishable goods in the entire year 2013.

5.3 Regression

This part describes how to quantify the effect of liquidity constraints on stockpiling behavior using regression analysis. I choose the quantity of cup noodles purchased in March 2014, just before the tax hike, as the indicator of stockpiling behavior. While the extended model does not explicitly focus on individual taste effects, such effects may exist in practice and should

[20] Similar arguments can be found in Bils and Klenow (2001) for durables and Broda and Romalis (2009) for non-durables.

Table 2: Controlling for the taste effects

	(1) March 2013	(2) Annual
Coefficient	0.405	0.710
	(0.005)***	(0.005)***
Adj. R^2	0.158	0.325
Obs.	36,640	36,640

Note: Standard errors in parentheses. Each column presents the result of ordinary least squares regression of the quantity purchased in March 2014 on the control variable and an intercept. *** denotes significance at the 1 percent level.

be eliminated from this indicator. There are two candidates to control for taste effects: the quantity purchased in March 2013, and the quantity purchased in the entire year 2013. While the former considers monthly seasonal effects as well as taste effects, the latter is a more stable indicator of tastes.

Table 2 shows the result of regressing the quantity purchased in March 2014 on the control variable and an intercept in each case. Both the dependent and control variables are in logarithm. The sample is restricted to consumers for which observations for both March 2013 and March 2014 are available,[21] and consumers that buy only at discounted prices are excluded. The adjusted R^2 indicates that controlling for the annual amount is preferable to controlling for the monthly amount. Thus, in the analyses below, I use the quantity purchased in the previous year as the control variable.

The regression equation (4) to quantify the effect of liquidity constraints looks as follows:

$$\begin{aligned} \ln q_i = \beta_0 + \beta_1 (p_i - \gamma)_- + \beta_2 (p_i - \gamma)_+ + \beta_3 \ln s_i \\ + \beta_4 \ln v_i + \beta_5 D_i + \beta_6 \ln q_i^{ctrl} + u_i, \end{aligned} \tag{4}$$

where p_i represents the consumer-specific relative price. Other explanatory variables are s_i denoting the inverse of storage costs, v_i representing a consumer's frequency of store visits

[21] In addition, the sample is restricted to consumers aged between 20 and 90.

in 2013 as an indicator of adjustment costs,[22] and D_i denoting a dummy for consumers that have retired. The parameters of interest are β_1 to β_5 and γ. Note that γ denotes the threshold value which divides the explanatory variable into negative and positive parts as discussed by Hansen (2017). To describe this, I use the following notation: $(a)_- = \min[a, 0]$ and $(a)_+ = \max[a, 0]$. Since both constrained and unconstrained consumers are included in the sample, the estimate of the threshold provides useful information about the fraction of consumers subject to liquidity constraints.

Let me explain the theoretical predictions for the other parameters above. The prediction with regard to liquidity constraints is that $\beta_1 > 0$ and that β_2 may not be different from zero, since these two coefficients represent the effect of liquidity constraints on stockpiling of liquidity constrained and unconstrained consumers, respectively. Next, β_3 and β_4 represent the influence of storage and adjustment costs, and since s_i and v_i are negatively correlated with each of the corresponding costs, β_3 and β_4 are expected to be positive. Finally, β_5 represents the potential effect of time use, that is, the fact that older consumers who had retired may have had more time on their hands to stockpile goods before the tax hike than working-age consumers.

Before proceeding to the regression results, let us examine the relationship between relative prices and consumers' stockpiling behavior. In Figure 4, consumers are divided into five groups based on the relative price they paid in 2013. The figure shows the mean of the quantity of cup noodles purchased by each group in March 2014 after controlling for taste effects. The figure indicates that as liquidity constraints become slacker, the amount purchased increases to some extent. Moreover, there appears to be a threshold around the fourth quintile.

To take the kink in the relationship between the relative price paid by consumers and their stockpiling behavior into account, I estimate the link between the two using a regression

[22] It is likely that consumers with smaller adjustment costs visit stores more frequently.

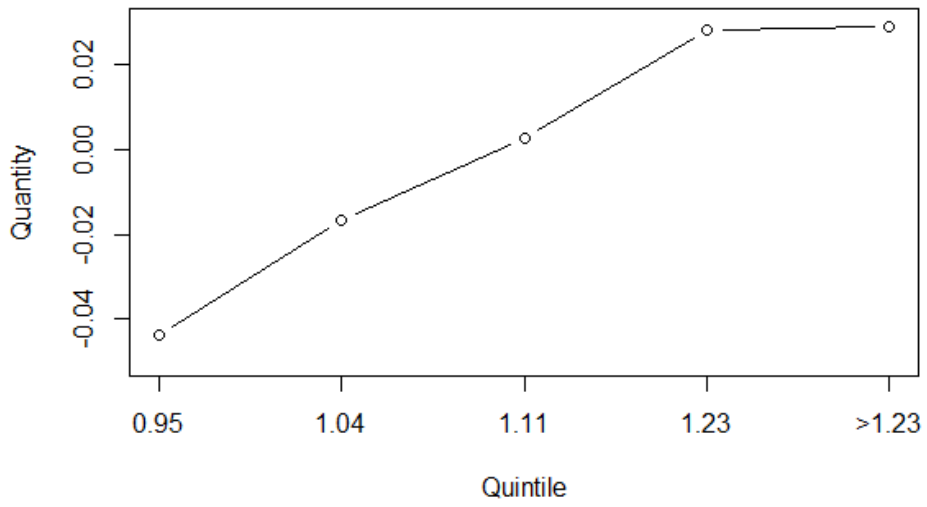

Figure 4: Consumer liquidity and quantity purchased

Note: Consumers are divided into five groups based on the relative price they paid in 2013. For each consumer group, I take the mean of residuals obtained by ordinary least squares regression of the quantity of cup noodles purchased in March 2014 on the control variable and an intercept.

kink model following the approach developed by Hansen (2017). Specifically, as seen in the figure, the threshold point is likely to be located around the fourth quintile. Therefore, I set the parameter space Γ for the threshold parameter to $\Gamma = [0.89, 1.36]$, so that at least 10 percent of the sample are placed in both the positive and the negative parts. Moreover, I evaluate the sum of squared errors function on a discrete grid with increments of 0.01. As shown by Hansen (2017), the regression kink model makes it possible to make inferences on the regression parameters.

5.4 Results

The kink regression results are shown in the first column in Table 3. First, using least squares estimation, the threshold value, γ, is estimated to be 1.16 and its standard error is 0.07. The

Table 3: Estimation results

	(1) Cup noodles	(2) Perishable goods
$(\text{Price})_-$	0.173	0.155
	(0.047)***	(0.026)***
$(\text{Price})_+$	0.006	-0.003
	(0.014)	(0.011)
Storage costs	0.097	0.014
	(0.007)***	(0.004)***
Frequency of visits	0.028	0.003
	(0.006)***	(0.006)
Retired dummy	0.027	0.002
	(0.008)***	(0.006)
Control	0.760	1.003
	(0.007)***	(0.004)***
Threshold	1.16	1.16
	(0.07)	(exogenous)
Adj. R^2	0.330	0.747
Obs.	36,640	36,411

Note: Standard errors in parentheses. The dependent and control variables in the first column are the quantities of cup noodles purchased in March 2014 and in the entire year 2013, respectively. In the second column, these are replaced with spending on perishable goods in each period. *** denotes significance at the 1 percent level.

point estimate and the lower bound of the 95 percent confidence interval for the threshold indicate that 70 percent and 36 percent of the consumers are subject to liquidity constraints, respectively. Second, the coefficient on the negative part of the indicator of liquidity, β_1, is positive and statistically significant at the 1 percent level.[23] Third, the coefficient on the positive part of the liquidity indicator, β_2, is not statistically significant. These results are consistent with the extended inventory model. Finally, the adjusted R^2 is almost the same as that in the second column in Table 2, which means that even though the indicator of liquidity is statistically significant, the relative price might be a poor indicator of liquidity.

These results have two implications. The first is that liquidity constraints have an impact

[23]Hansen (2017) notes that asymptotic confidence intervals may have poor coverage in small samples. However, the sample size here is sufficiently large for this not to be a problem.

on consumers' stockpiling behavior. Although the relative price might be a poor indicator of liquidity, the estimate of β_1 shows that liquidity is one of the sources of differences in stockpiling behavior. Second, a sizable fraction of consumers are subject to liquidity constraints. Since these consumers faced liquidity shortages, the results obtained here highlight another aspect of the regressive nature of the consumption tax, namely, that poorer consumers were unable to stockpile goods at lower prices before the tax hike. This indicates that the distributional effect of the consumption tax hike may be more serious when taking stockpiling into account than when not paying attention to such behavior.

Next, I turn to the rest of the kink regression results. First, the coefficient on the indicator of storage costs is significantly positive and highly robust. This result shows that the estimation procedure of storage costs in Section 4.2 makes sense. Second, whether consumers have retired or not has a significant effect on stockpiling, but the coefficient is relatively small. Third, the coefficient on the frequency of store visits is positive and statistically significant, implying that consumers visiting stores less frequently stockpile a smaller amount of goods. This result is different from the effect of fixed adjustment costs, which yield infrequent and lumpy adjustments as shown by Caballero and Engel (1999).

In the second column, expenditure on perishable goods is used as the dependent variable.[24] As in the first column, the coefficient on the negative part of the indicator of liquidity is again statistically significant, which is consistent with the conjecture that the purchasing behavior observed in Figure 3 can be explained by liquidity constraints. At the same time, the coefficient on the indicator of storage costs becomes much smaller but is still statistically significant. This result indicates that even though perishable goods are storable to some extent, purchases of perishable goods are less responsive to storage costs than storable goods. Finally, the coefficients on the frequency of store visits and the dummy for retired consumers are not statistically significant.

[24]The threshold is exogenously given by the estimated value.

Table 4: Standardized coefficients

	(1) Cup noodles	(2) Perishable goods
Liquidity	0.023	0.018
Storage costs	0.076	0.009
Frequency of visits	0.020	0.002
Retired dummy	0.015	0.001

Note: Each of the standardized coefficients, $\hat{b}_j$, is obtained as $\hat{b}_j = \hat{\beta}_j \times \sqrt{S_{jj}/S_{yy}}$, where $\hat{\beta}_j$ is the estimated coefficient on the j-th regressor, and S_{jj} and S_{yy} denote the variance of the regressor and the dependent variable, respectively. The first row uses the variance of $(p_i - \gamma)_-$.

To explore which of the explanatory variables have the largest impact on purchasing behavior, I calculate standardized coefficients, which are presented in Table 4. The standardized coefficients show how much the quantity purchased (expenditure) changes in response to a one-standard-deviation change in an explanatory variable holding all other variables constant.[25] The table shows that storage costs have the largest impact on consumers' stockpiling of cup noodles. Liquidity, the frequency of store visits, and whether a consumer is retired are less important determinants of stockpiling. On the other hand, in the case of spending on perishable goods, liquidity plays the most important role, while the other factors play only a small role.

One limitation of the analysis above is that it pools both constrained and unconstrained consumers. As indicated in Equation (3), whether liquidity constraints are binding depends on other consumer-specific parameters such as storage and adjustment costs, which may cause estimation errors. Nevertheless, the estimation results with respect to the threshold value suggest that a non-negligible fraction of consumers were subject to liquidity constraints before the consumption tax hike.

[25] See Schroeder, Sjoquist, and Stephan (1986) for a detailed explanation.

5.5 Discussion

The result obtained in the previous subsection is in line with the findings of previous studies. For instance, Hendel and Nevo (2006*b*) have shown that the frequency at which households buy items on sale is affected by storage costs even after controlling for income and work hours. Further, Hendel and Nevo (2006*a*) structurally estimate a consumer inventory model allowing for heterogeneous storage cost parameters and argue that the purchasing decision regarding what quantity of products to buy depends on these parameters. The impact of storage costs found above is consistent with their evidence. Moreover, the estimation result suggesting that retired consumers are more likely to engage in stockpiling is consistent with Aguiar and Hurst's (2007) finding that retired households are more likely to use coupons than working-age households, in that both suggest that retired households are more price sensitive. However, the result on liquidity is somewhat new. Although Hendel and Nevo (2006*a*) and Aguiar and Hurst (2007) note that lower-income households are more price sensitive, suggesting that liquidity constraints are not relevant to consumers' stockpiling behavior, in Japan's case, stockpiling behavior of liquidity constrained consumers is indeed restricted by the liquidity they have available. This paper also quantifies the effect of liquidity constraints on these consumers' stockpiling, taking other factors such as storage and adjustment costs into account.

To check the robustness of the results, I repeat the kink regression analysis but assume that the kink is exogenously given. Specifically, I set the threshold to the 60th percentile of consumer-specific liquidity indicators. The results are shown in Table 5 and are very similar to the baseline results in the first column in Table 3.

Next, it is worth considering whether we can derive any potential policy implications from the analysis of stockpiling behavior. Originally, the Japanese government had planned to raise the consumption tax rate further from 8 to 10 percent in April 2017, but the tax hike was postponed. One reason is that the tax hike in April 2014 resulted in substantial swings

Table 5: Robustness check

	(1)
	Cup noodles
$(\text{Price})_-$	0.190
	(0.040)***
$(\text{Price})_+$	0.011
	(0.014)
Storage costs	0.097
	(0.007)***
Frequency of visits	0.027
	(0.007)***
Retired dummy	0.028
	(0.008)***
Control	0.760
	(0.007)***
Threshold	1.11
	(exogenous)
Adj. R^2	0.330
Obs.	36,640

Note: Standard errors in parentheses. The dependent and control variables are the quantities of cup noodles purchased in March 2014 and in the entire year 2013, respectively. *** denotes significance at the 1 percent level.

in demand. Did the stockpiling behavior in early 2014 play a central role in this problem?

To answer this question, I examine the impact of the consumption tax hike in 2014 on demand through stockpiling. Figure 5 therefore compares the purchase probabilities of constrained and unconstrained consumers. Let us take a look at how this figure was constructed using the values for April 3, 2014, as an example. The fraction of consumers that purchased cup noodles from April 1 to April 3 among unconstrained consumers was 0.13, while the corresponding value for constrained consumers was 0.167. Dividing the former by the latter yields a ratio of 0.78, which implies that the fraction of unconstrained consumers who returned to a store after the tax hike within three days was 22 percent lower than that of constrained consumers. The figure shows that it took a week for the ratio to reach 0.9, and that the ratio gradually approached 0.95 two weeks after the tax hike. This finding

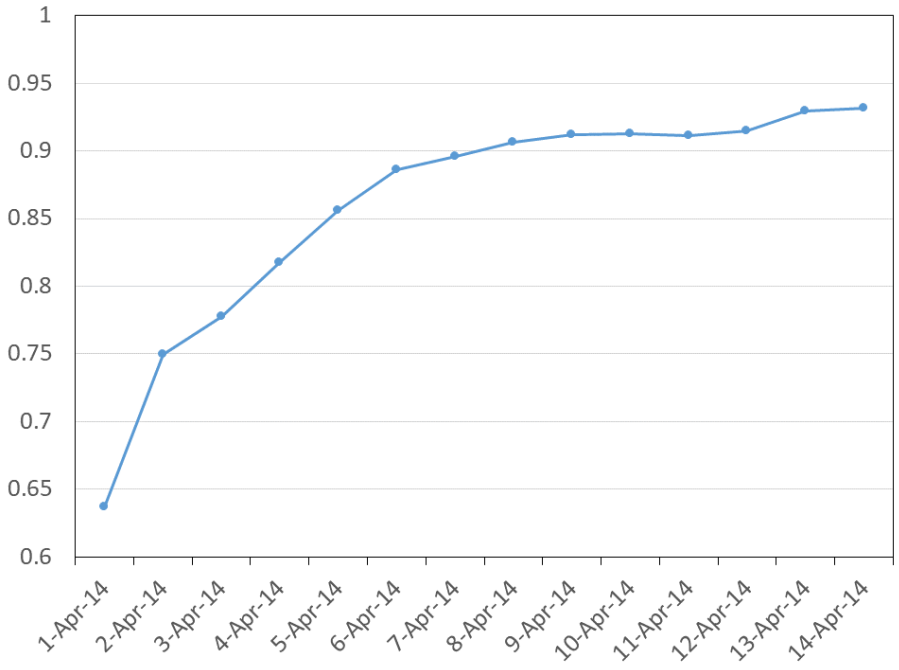

Figure 5: Ratio of purchase probabilities

Note: The figure shows the ratio of the purchase probability of unconstrained consumers after the tax hike divided by that of constrained consumers.

indicates that inventory holdings were adjusted rapidly and that the stockpiling behavior with regard to storable goods examined in this paper did not play a large role in the prolonged slump caused by the tax hike. The analysis here perhaps suggests that the large swings in demand were driven by purchases of durables such as cars and fridges rather than storable non-durables such as cup noodles, because purchases of durables are more infrequent.

6 Concluding Remarks

Stockpiling plays an important role in consumption smoothing. In this paper, I characterized consumer stockpiling behavior caused by Japan's consumption tax hike and explored the interaction between storable and perishable goods purchases through liquidity constraints. Using scanner data, the graphical analyses indicated that some consumers failed to engage

in arbitrage in response to the tax hike, and that a non-negligible fraction of consumers sacrificed purchases of perishable goods. The regression analysis showed that a sizable fraction of consumers face liquidity constraints and that for these consumers, both storable and perishable goods purchases are constrained by the liquidity they have available.

While the analysis in this paper relied on the deterministic price change caused by a tax hike, consumers also stockpile goods during regular promotional sales, leading to differences in the prices paid by consumers with different characteristics such as liquidity and storage costs. How such differences affect consumers' dynamic behavior and the implications for welfare are issues worth examining in the future.

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