博士論文

Inflation Dynamics, Consumption, and Monetary Policy
（インフレ動態、消費、金融政策）

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Chapter 1

Overview

1.1 Introduction

Over the past 20 years, microdata has been used to analyze inflation dynamics in a number of studies. For example, Bils and Klenow (2004), Klenow and Kryvtsov (2008), Nakamura and Steinsson (2008), and Klenow and Malin (2010), using microdata, document the frequency and size of price changes and the hazard function of price adjustment. These studies present new facts on inflation dynamics based on microdata, which cannot be observed based on aggregated data.

There are at least two reasons for the prevalence of the use of microdata rather than aggregated data in the literature. The first reason is that many theories focusing on inflation dynamics incorporate sluggishness or stickiness of price adjustment into individual prices. To directly examine the validity of this setting, it is essential to observe micro price dynamics. The second reason is that the accessibility of microdata has been highly improved over the last two decades. In the past, several studies such as Carlton (1986), Cecchetti (1986), and Kashyap (1995), using magazines and retail catalogs, tried to observe a limited number of individual prices. In contrast, currently many studies use microdata underlying the Consumer

Price Index and Producer Price Index, as well as scanner data, leading to a much larger number of price observations. This dissertation adds more evidence to this literature.

The novelty of this dissertation compared to existing studies can be summarized as follows. First, this dissertation focuses on heterogeneity across economic agents such as firms and households. Specifically, Chapter 2 of this dissertation shows that price-setting behavior depends on firm heterogeneity, especially heterogeneity in terms of the number of products sold by each firm. Similar results are shown by several, but a limited number of studies, including Midrigan (2011), Alvarez and Lippi (2014), Bhattarai and Schoenle (2014), and Pasten and Schoenle (2016). Chapter 3 shows that household stockpiling behavior in response to intertemporal price changes depends on household heterogeneity in terms of liquidity constraints and storage costs. While the importance of storage costs has been pointed out by Hendel and Nevo (2006a, b), the relevance of liquidity constraints is first examined in this chapter. Chapter 4 focuses on how prices payed by individuals differ depending on their ages. It shows that households around the retirement age experience the lower rate of inflation than working-age households. While Aguiar and Hurst (2007) and Kaplan and Menzio (2015) examine the differences in prices paid for identical goods across households, differences in the set of goods purchased and in the expenditure share for each of goods across households have not been considered; this chapter, taking these components into account, shows generational inequality in inflation rates.

Second, this dissertation empirically examines the responses of firms and households to policy shocks that stem from the government and the central bank. In this sense, I use policy shocks as natural experiments. Specifically, Chapter 2 focuses on an environment where a consumption tax hike affected firms' effective mark-ups over costs, and examines to what extent price stickiness was weakened. Similar empirical analysis has been conducted by Gagnon, Lopez-Salido, and Vincent (2012) and Karadi and Reiff (2018); however, these studies focus exclusively on the validity of menu cost models, whereas this chapter provides evidence for both information rigidity and menu costs. Chapter 3 focuses on an environment where households had a strong incentive to stockpile storable goods before the consumption tax hike, and quantifies the effect of liquidity constraints on household stockpiling. There are no earlier studies that empirically examine stockpiling behavior in response to a unique tax change that simultaneously increased prices of most consumer goods. Chapter 4 quantifies the effect of one's retirement on the rate of inflation she faces. One's decision on when to retire is unrelated to policy measures; however, the mandatory retirement age is planned to be increased in Japan, where population aging raises a serious question on the nation's growth, so that the result of this chapter is potentially related to policy making. Chapter 5 examines the effect of the announcement on future monetary policy measures on inflation expectations in a period of economic downturn due to the Great Depression. While Cecchetti (1992) and Hamilton (1992) focus on the same period, these studies do not examine the effect of policy measures on expectations.

Third, this dissertation focuses on the Japanese economy. Many earlier studies that analyze price stickiness focus on the U.S., with a few exceptions such as Gagnon (2009) focusing on Mexico and Alvarez et al. (2018) on Argentina. These countries experienced quite high inflation, which helps to test models for price stickiness. In contrast, Japan has faced substantial disinflation or moderate deflation over the past 20 years, which presents a different aspect of inflation dynamics. This dissertation, using the economic environment of Japan that differs from other countries, empirically documents price-setting behavior of firms as well as purchasing behavior of households.

1.2 Structure

Chapter 2, "Menu Costs and Information Rigidity: Evidence from the Consumption Tax Hike in Japan", using scanner data, examines firms' price-setting behavior in response to

Japan's consumption tax hike in 2014. The main findings are twofold. First, more than half of tax-excluded prices remained unchanged after the tax hike. Second and more importantly, the tax hike made tax-excluded price less sticky than in the previous year. The second finding suggests that firms had to revise posted price to pass through the tax hike to prices, so that they incurred menu costs. This finding is similar to the finding obtained by Hobijn, Ravenna, and Tambalotti (2006) that the introduction of the euro made prices more flexible. In addition, this chapter shows that firms selling more products were more likely to change tax-excluded prices after the tax hike. This finding cannot be explained by saying that stickiness of tax-excluded prices was due to the absence of shocks. Rather, this finding suggests that firms face information rigidity when changing tax-excluded prices.

Chapter 3, "Liquidity Constraints, Storage Costs, and Consumer Stockpiling", using scanner data with consumer IDs, examines consumer stockpiling behavior before Japan's consumption tax hike. The main findings can be summarized as follows. First, there are some consumers that purchase storable goods even after the tax hike, although the tax hike was anticipated in advance. Second, a non-negligible fraction of consumers increased purchases of storable goods before the tax hike, while reducing purchases of non-storable goods. These findings suggest that liquidity constraints affected consumers' stockpiling behavior. To quantify the effect of liquidity constraints, this chapter proposes a new approach to use the price paid by each consumer as a proxy for liquidity. On the one hand, wealthier consumers typically buy higher quality goods at higher prices. On the other hand, the price paid should be uncorrelated with storage costs, which have been regarded as an important determinant of stockpiling in earlier studies such as Hendel and Nevo (2006a, b). Using this proxy for liquidity, this chapter shows that at least 36 percent of consumers faced liquidity constraints before the tax hike.

Chapter 4, "The Cost-of-Living Index over the Life Cycle", using scanner data with individual IDs, quantifies the differences in inflation rates faced by each individual. The main findings are twofold. First, individual price indexes based on Aguiar and Hurst's (2007) method show that older individuals who have retired pay higher prices for identical goods than working-age individuals. Second, once the differences in the set of goods purchased and the expenditure share for each of these goods across individuals are taken into account, individuals around the retirement age experience the lower rate of inflation than working-age individuals. These findings suggest that retired individuals do not search for discounts for a given good; instead, they substitute across goods to save on the cost of living.

Chapter 5, "Policy Shocks and Expectations: Japan's Experience during the Great Depression", using monthly and daily Japanese government bond yields, empirically evaluates the effect of various policy measures adopted in the period of economic downturn due to the Great Depression on expectations about inflation and future nominal interest rates. The main findings can be summarized as follows. First, all of announcement, news, and implementation of JGB underwriting by the Bank of Japan had no effect of raising inflation expectations. Moreover, nominal interest rates declined after the announcement. Second, the fact that Britain abandoned the gold standard in September 1931 led market participants to anticipate Japan's withdrawal from the gold standard and the subsequent yen depreciation, which brought a jump in interest rates. Third, the decisions on fiscal expansion raised interest rates.

Chapter 2

Menu Costs and Information Rigidity: Evidence from the Consumption Tax Hike in Japan

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Abstract

Feldstein (2002) assumes that consumption tax hikes are immediately passed through to prices, and argues that raising consumption taxes generates inflation. To test this argument, I examine firms' price-setting behavior after Japan's consumption tax hike in 2014. I find that the tax hike made tax-excluded prices less sticky than in the previous year. This fact suggests that firms incurred menu costs when changing tax-included prices, which contradicts Feldstein's assumption. This finding is similar to the finding obtained by Hobijn, Ravenna, and Tambalotti (2006) that prices became flexible after the adoption of the euro. Additionally, I provide evidence for information rigidity.

JEL codes: E31, E62, H32

Keywords: Unconventional fiscal policy, price stickiness, intensive and extensive margins, tax-included and tax-excluded prices, consumption tax pass-through

2.1 Introduction

When nominal interest rates hit the zero lower bound, conventional monetary policy will not work, meaning that new policies to stimulate the economy are needed. To solve this problem, Feldstein (2002) proposes a unique solution: raising consumption taxes and reducing labor income taxes. Raising consumption taxes would generate inflation in consumer prices, so that real interest rates would decline, while the reduction in the labor income taxes would neutralize the impact on the overall tax burden. This idea has been further explored by Correia et al. (2013), who argue that this tax policy could provide appropriate stimulus to achieve the first-best allocation even at the zero lower bound.

The argument by Feldstein (2002) and Correia et al. (2013) builds on the important assumption regarding firms' price-setting behavior. Specifically, they assume that tax-excluded prices—rather than tax-included prices—are sticky, so that consumption tax hikes are fully and immediately passed through to prices. However, this assumption is not uncontroversial, and Eggertsson and Woodford (2006), Gagnon, Lopez-Salido, and Vincent (2012), and Karadi and Reiff (2018), for example, argue that it is tax-included prices that are sticky, based on the observation that consumption taxes (value-added taxes, VAT) are usually included in posted prices. Therefore, in order to determine whether Feldstein and Correia et al.'s proposal would work in practice, it is important to know which of these views is correct.[1]

To this end, this paper examines firms' price-setting behavior in response to Japan's consumption tax hike in April 2014. The main findings of the paper are as follows. First, more than half of tax-excluded prices remained unchanged after the tax hike. This finding suggests that tax-excluded prices are sticky, which is consistent with the argument by Feldstein (2002) and Correia et al. (2013). Second and more importantly, tax-excluded prices were less sticky in the week after the tax hike than a year earlier. This finding suggests that the tax hike

[1]There are a number of studies examining how the burden of an increase in the consumption tax is distributed between consumers and firms (e.g., Carbonnier, 2007; Benedek et al., 2015). However, the focus of these studies is not on the degree of price stickiness.

affected the degree of stickiness of tax-excluded prices, so that firms incurred menu costs to revise posted prices that include taxes after the tax hike. This is not consistent with the assumption by Feldstein (2002) and Correia et al. (2013) and instead supports the view of Eggertsson and Woodford (2006), Gagnon, Lopez-Salido, and Vincent (2012), and Karadi and Reiff (2018).

These two findings cannot be explained by saying that *either* tax-included *or* tax-excluded prices are sticky. Rather, they suggest that *both* tax-included *and* tax-excluded prices are sticky. Specifically, this paper presents the hypothesis that tax-included prices are sticky due to menu costs. This hypothesis is suggested by Gagnon, Lopez-Salido, and Vincent (2012) and Karadi and Reiff (2018), based on the observation that posted prices usually include consumption taxes. Moreover, this paper also argues that tax-excluded prices are sticky due to information rigidity. Information rigidity is a rigidity that makes firms' information updating infrequent or requires firms to incur a cost of collecting information on the desired price, as noted by previous studies (e.g., Mankiw and Reis, 2002; Woodford, 2003, 2009; Zbaracki et al., 2004; Alvarez, Lippi, and Paciello, 2011).

To examine whether firms face menu costs and information rigidity, I focus on the price-setting behavior of multi-product firms. The effect of menu costs and information rigidity on multi-product firms' price-setting behavior has been analyzed in existing studies. For example, Midrigan (2011), Alvarez and Lippi (2014), and Bhattarai and Schoenle (2014) argue that firms selling more products change prices more frequently (but by smaller amounts). Their rationale for this argument is that once fixed menu costs are incurred, the firm can reset the price of all its products. Similarly, Pasten and Schoenle (2016) argue that in an environment where information updating is costly, firms selling more products have a stronger incentive to update information on shocks that are common across products, meaning that these firms change prices more frequently. They provide a rationale that is similar to the one used in the context of menu costs for this argument; once information on common shocks is updated, the firm can use such information to reprice all its products.

Based on these arguments, I provide theoretical predictions on how Japan's tax hike affected firms' price-setting behavior. Specifically, on the one hand, the tax hike provided an incentive for firms to incur menu costs to change tax-included prices across the board. Therefore, the extent that firms selling more products change tax-included prices more frequently should have been weakened by the tax hike. On the other hand, the tax hike was a shock that was uncorrelated with shocks to tax-excluded prices, so that firms' decision of whether they updated information on these shocks was not affected by the tax hike. In this sense, the argument that firms selling more products change tax-excluded prices more frequently should have been satisfied.

This paper tests these predictions by analyzing the relationship between the number of products sold and the probability of price changes at the time of the tax hike and in the previous year, respectively. This paper provides evidence supporting these predictions, which means that firms face both menu costs and information rigidity when they adjust prices.

The closest study to this study is that by Hobijn, Ravenna, and Tambalotti (2006), who examined the impact of the introduction of the euro on firms' price-setting behavior. They argue that firms incurred menu costs when switching to the euro, so that prices in some sectors such as restaurants and cafes increased sharply at that time. Similarly, this paper argues that firms incurred menu costs when changing tax-included prices after the tax hike, so that tax-excluded prices were less sticky than in the previous year. Compared to their study, this study provides two additional observations regarding firms' price-setting behavior. First, this paper analyzes the change in both the probability and size of price changes after the tax hike, while Hobijn, Ravenna, and Tambalotti (2006) focus only on the increase in the probability of price adjustment after the euro adoption.[2] Second, this paper shows that firms selling more products were more likely to adjust tax-excluded prices after the tax hike.

[2]The probability and size of price changes are sometimes called the extensive and intensive margins, respectively. See Caballero and Engel (2007) for more detailed descriptions.

This observation suggests that tax-excluded prices are sticky due to information rigidity, even though firms incurred menu costs to revise posted prices after the tax hike. Similarly, Hobijn, Ravenna, and Tambalotti (2006) provide conjecture that information rigidity might have prevented firms from adjusting prices after the euro adoption; however, they did not provide evidence for their conjecture.

The remainder of the paper is organized as follows. The next section provides a brief overview of Japan's consumption tax hike and describes the data used for the analysis. Section 2.3 then presents several observations regarding firms' price-setting behavior in response to the tax hike, which suggest that both tax-included and -excluded prices are sticky. Section 2.4 focuses on multi-product firms' price-setting behavior and provides evidence that firms face both menu costs and information rigidity. Section 2.5 checks the robustness of the results. Finally, Section 2.6 provides concluding remarks.

2.2 Background

This section describes the salient features of Japan's consumption tax hike in 2014 as well as the data used for the analysis.

2.2.1 Brief Overview of Japan's Consumption Tax Hike

Consumption tax (value-added tax) was first introduced in Japan in 1989. The consumption tax covers a wide variety of goods, including food, necessities, durables, and services, and was initially set at 3 percent. The consumption tax rate was subsequently raised 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.

Since firms are encouraged to include the consumption tax in posted prices, consumption tax hikes are likely to affect firms' effective mark-ups over costs.[3] This means that consumption tax hikes provide an incentive for firms to reset prices.

However, consumption tax hikes do not necessarily force firms to reset prices. For example, when Japan's consumption tax rate was increased from 3 to 5 percent in 1997, according to a survey by the Japan Chamber of Commerce and Industry, more than half of small and medium-sized enterprises did not fully pass through the tax hike to their prices. This result indicates that even though the tax hike affected firms' effective mark-ups over costs, firms could not change prices given that their rivals did not change prices, which can be explained by coordination failure across firms. To address this issue, the Japanese government introduced a law in June 2013 stating that pass-through of the tax hike in April 2014 would be excluded from the application of antitrust laws.[4] This law allowed firms to form cartels to pass on the tax hike to prices, so that Japan's experience provides a useful case study to examine whether firms fully pass on consumption tax hikes to prices as suggested by Feldstein (2002) and Correia et al. (2013).

This is not the first study to use changes in the consumption tax rate in order to examine firms' price-setting behavior. Previous studies using VAT changes in other countries include, for example, Gagnon, Lopez-Salido, and Vincent (2012) focusing on Mexico and Karadi and Reiff (2018) focusing on Hungary. These studies show that the frequency of (tax-included) price changes increased in response to the tax hikes, which is consistent with menu cost models. However, they do not focus on the extent to which the assumption of full pass-through made by Feldstein (2002) and Correia et al. (2013) is satisfied.

[3]Although firms are not forced to quote tax-included prices in Japan, they are obliged to make efforts to do so.

[4]The official name of this law is "Act Concerning Special Measures for Pass-on of Consumption Tax."

2.2.2 Data

The data used for the analysis are daily scanner data collected by Nikkei. This dataset consists of sales records for a number of supermarkets in Japan, where typically food products and daily necessities are sold.[5] Since a barcode is printed on each of these products, they are distinguished by fairly detailed classifications. In addition, barcodes provide information about the product category (such as butter, yogurt, or shampoo) and the manufacturer of each product.

To observe firms' price-setting behavior, I focus on the period of two weeks centered on the day of the tax hike (April 1, 2014). The number of supermarkets for which observations during this period are available is more than 200, while the number of products sold in these supermarkets is approximately 170,000. For each of these products, the dataset includes both the turnover and the quantity sold at each retailer on a daily basis. Therefore, daily posted prices can be calculated as the turnover divided by the quantity sold.[6] The number of posted prices for which observations for April 1, 2014, for example, are available is approximately 1.1 million. Note that these posted prices exclude the consumption tax, since the turnover recorded in the dataset excludes the consumption tax.

The daily dataset provides high-frequency observations of prices. However, a potential concern is that these posted prices could be affected by daily promotional sales rather than the tax hike. To address this issue, I define the regular price at the retailer-product level before and after the tax hike as the modal price in the last week of March 2014 and in the first week of April 2014, respectively.[7] As a result, the number of regular price observations for each of these periods is approximately 2.4 million.

The data used in this paper have the advantage that they cover a much larger variety of products with different characteristics than previous studies. For example, Hobijn, Ravenna,

[5] Sales records for unprocessed food are excluded from the dataset.

[6] When the obtained price is not an integer, it is rounded to the nearest integer.

[7] Similarly, Abe and Tonogi (2010) define the regular price as the weekly mode of posted prices.

and Tambalotti's (2006) study of price stickiness after the adoption of the euro focuses only on the restaurant sector, so that prices analyzed in their study are fairly sticky. In contrast, this study analyzes price stickiness after the tax hike based on scanner data including a wide range of products, for which the degree of price stickiness varies.

2.3 Observations Regarding Firms' Price-Setting Behavior after the Tax Hike

This section presents three observations regarding firms' price-setting behavior in response to Japan's consumption tax hike in April 2014.

Observation 1: A sizable fraction of tax-excluded prices remained unchanged after the tax hike.

First, I examine the fraction of prices to which the tax hike was fully passed through. Recall that in the dataset prices are measured excluding taxes. Therefore, full pass-through of the tax hike means that prices remained unchanged, while incomplete or more than complete pass-through resulted in price changes (a decrease or increase, respectively).Thus, an item for which the difference between the regular price in the first week of April 2014 and the last week of March 2014 is no more than 1 yen is defined as one for which full pass-through was achieved.[8] Based on this criterion, the fraction of prices to which the tax hike was fully passed through is estimated to be 63 percent, while for the remaining 37 percent, the degree of pass-through was incomplete or more than complete.

A similar result is obtained when full pass-through is defined in relative terms instead of

[8] The reason for allowing a range of 1 yen rather than requiring prices to remain completely unchanged is that the regular price of an item before and after the tax hike may differ slightly due to rounding. That is, full pass-through of the tax hike from 5 to 8 percent may have resulted in decimal prices, so that retailers rounded these prices up or down. (Note that prices in yen have no decimals.)

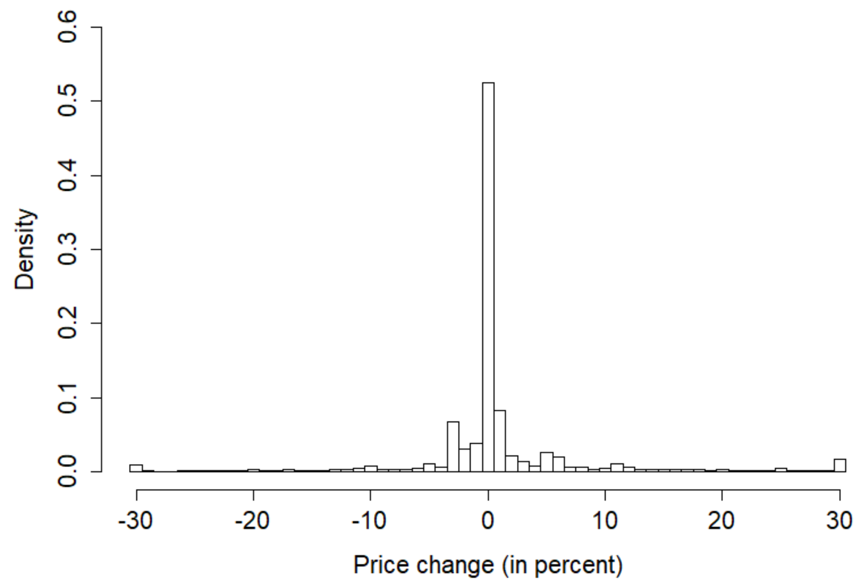

Figure 2.1: Distribution of price changes in April 2014

Notes: The price change is calculated as the percentage change between the regular price at the retailer-product level in the last week of March and the first week of April. Observations are grouped into bins of one percentage point. The bin including zero percent change ranges over the interval of [-0.5, 0.5). The number of observations is 2,384,954.

absolute terms. Figure 2.1 displays the distribution of price changes when these are calculated as the percentage change between the regular price in the last week of March and the first week of April. The figure shows that two pricing responses are particularly prevalent. First, more than half of all tax-excluded prices remained unchanged, while the remaining prices were revised either upward or downward. This suggests that the tax hike was fully passed through to the majority of prices, which is consistent with the argument by Feldstein (2002) and Correia et al. (2013). Second, a substantial fraction of prices decreased by about 3 percent, meaning that the tax-included prices of these items remained constant.

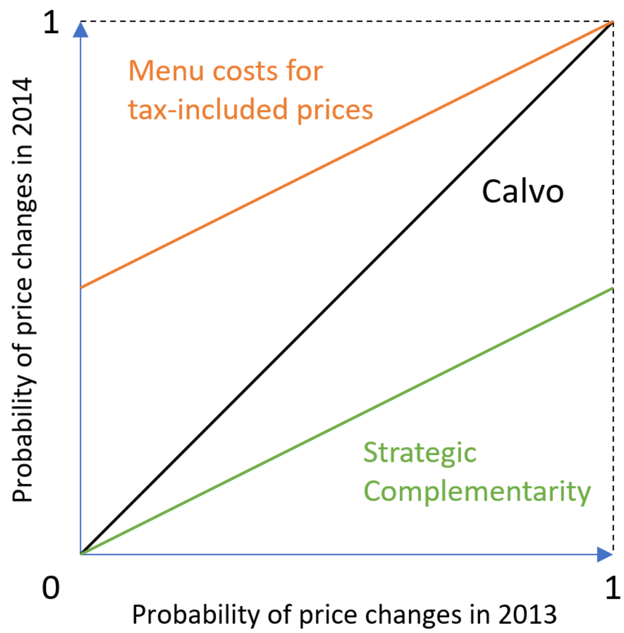

Figure 2.2: Prediction of hypotheses on price-setting behavior with and without a tax hike

Observation 2: The probability of price changes increased after the tax hike.

Second, I examine whether the probability of price changes was affected by the tax hike. To do so, I measure the probability of price changes at the product category level, because the degree of price stickiness is heterogeneous across product categories. Specifically, I calculate the empirical probability of price changes after the tax hike as follows. First, I construct a dummy that takes 1 if the regular price of an item sold at a retailer in April 2014 differs from that in March 2014 by more than 1 yen, and 0 otherwise. Second, I aggregate the turnover of items for which the dummy is 1 in each product category. Third, I divide this turnover by the turnover of all items in the product category. The value calculated is compared with the corresponding value a year earlier, so that seasonal effects do not come into play.[9]

[9]The year-on-year comparisons are based on sales records for retailers for which observations are available in both years.

Figure 2.2 illustrates the theoretical prediction of different hypotheses on price-setting behavior with and without a tax hike. This figure shows three predictions. First, if firms set their price in a time-dependent manner as described by Calvo (1983), the probability of price changes for each product category is constant over time. This means that the scatter plot of the probability of price changes will look like the 45 degree line in the figure. Second, when firms post tax-included prices, they have to incur menu costs to pass through the tax hike to prices. This suggests that the probability of price changes would be higher in 2014 when the tax hike took effect, than 2013, which is described as the orange line in Figure 2.2.[10] Finally, if strategic complementarity is relevant for pricing behavior, the tax hike might have worked as a coordination device. This means that firms increased their price by the exact amount implied by the tax hike, so that the probability of (tax-excluded) price changes would be lower in 2014 than 2013. This is drawn as the green line in the figure.

The result is shown in Figure 2.3(a). The figure shows that the probability of price changes increased in response to the tax hike in April 2014 for most of the categories. This result is not consistent with the assumption by Correia et al. (2013) that tax-excluded prices are set as in Calvo (1983) and instead is consistent with the argument by Gagnon, Lopez-Salido, and Vincent (2012) and Karadi and Reiff (2018) that firms incur menu costs when changing tax-included prices.

Since price changes can be divided into price increases and decreases, I construct similar dummies for price increases and decreases separately and plot the probabilities in Figures 2.3(b) and 2.3(c), respectively. Figure 2.3(b) clearly indicates that the probability of price increases rose in April 2014. On the other hand, in Figure 2.3(c), no systematic rise in the probability of price decreases in April 2014 can be observed. A caveat related to this figure is that the probability of price decreases in April 2014 might be biased. Specifically, given that a certain fraction of prices including taxes remained constant as seen in Figure 2.1, these

[10] Note that if firms post tax-excluded prices, the tax hike would be flexibly passed through to prices, meaning that the tax hike had no effect on the probability of price changes.

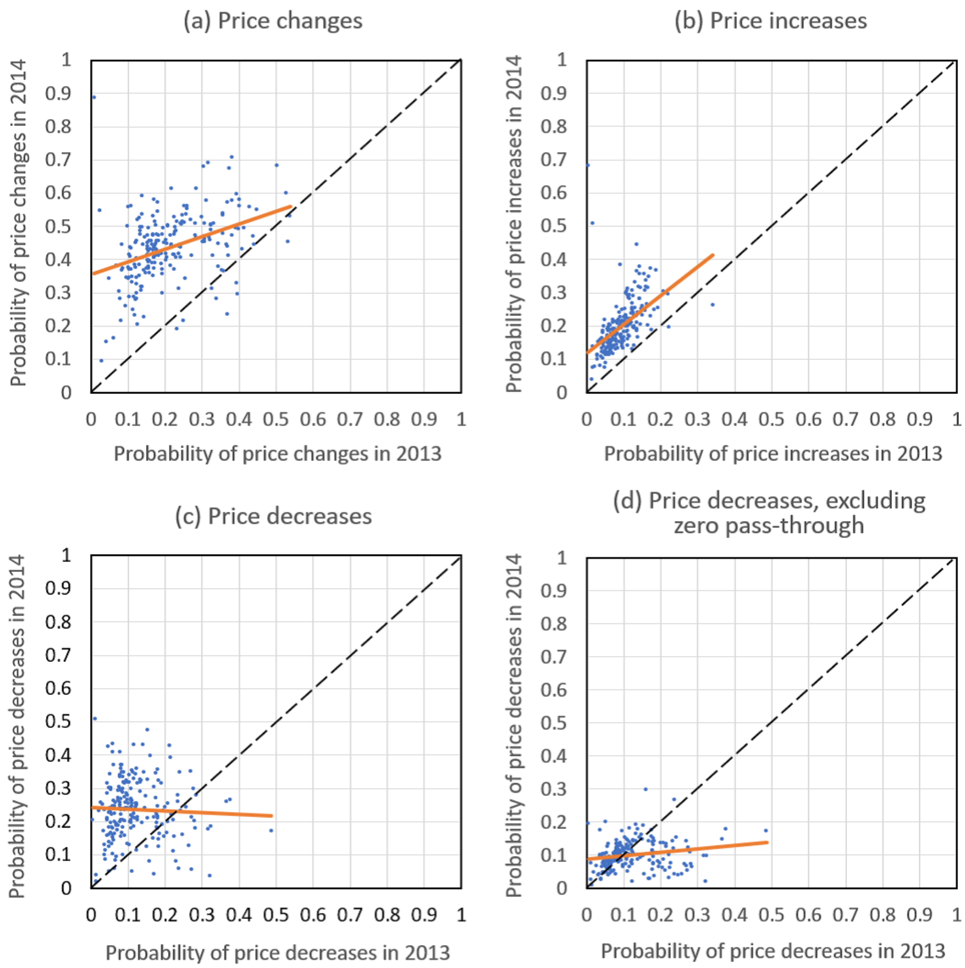

Figure 2.3: Probability of price changes for each product category

Notes: I calculate the empirical probability of price changes as the turnover share of items for which the regular price was changed in April in each product category. See text for more details. The orange line denotes the OLS fitted line, while the black dashed line denotes the 45 degree line.

prices were revised downward excluding taxes. Such a pricing response does not mean that the firm actively changed its price. To address this issue, I define price decreases in April 2014 in a narrow sense as prices that were decreased excluding taxes and were changed including taxes. (Note that a change in tax-included prices means that the degree of pass-through of the tax hike differed from zero.) Then I calculate the turnover share of items for which this condition is satisfied in each product category, which is displayed in Figure 2.3(d).

Observation 3: The size of price changes decreased after the tax hike.

Third, I examine the effect of the tax hike on the size of price changes. Again, I measure the size of price changes at the product category level to address heterogeneity in price stickiness. Specifically, I calculate the size of price changes after the tax hike in two steps. First, based on the dummy constructed above, I restrict the sample to items for which the dummy is 1. Second, I take the weighted average of the absolute value of price changes of these items in each product category, where the weight is the turnover share.

Figure 2.4(a) compares this value with the corresponding value a year earlier at the product category level. The figure suggests that the size of price changes decreased in the wake of the tax hike in April 2014 for most categories. Again, these price changes are divided into price increases and decreases, and the size of increases and the size of decrease are displayed in Figures 2.4(b) and 2.4(c), respectively. The figures indicate that the size of both price increases and decreases declined in April 2014. However, the latter result might be biased due to the same concern that the firm kept prices including taxes constant, instead of trying to revise prices excluding taxes downward, as noted in the measurement of the probability of price decreases. I therefore calculate the size of price decreases that are defined in a narrow sense as prices were decreased excluding taxes and were changed including taxes, which is shown in Figure 2.4(d). In this figure, the reduction in the size of price decreases in April 2014 is less clear than in Figure 2.4(c).

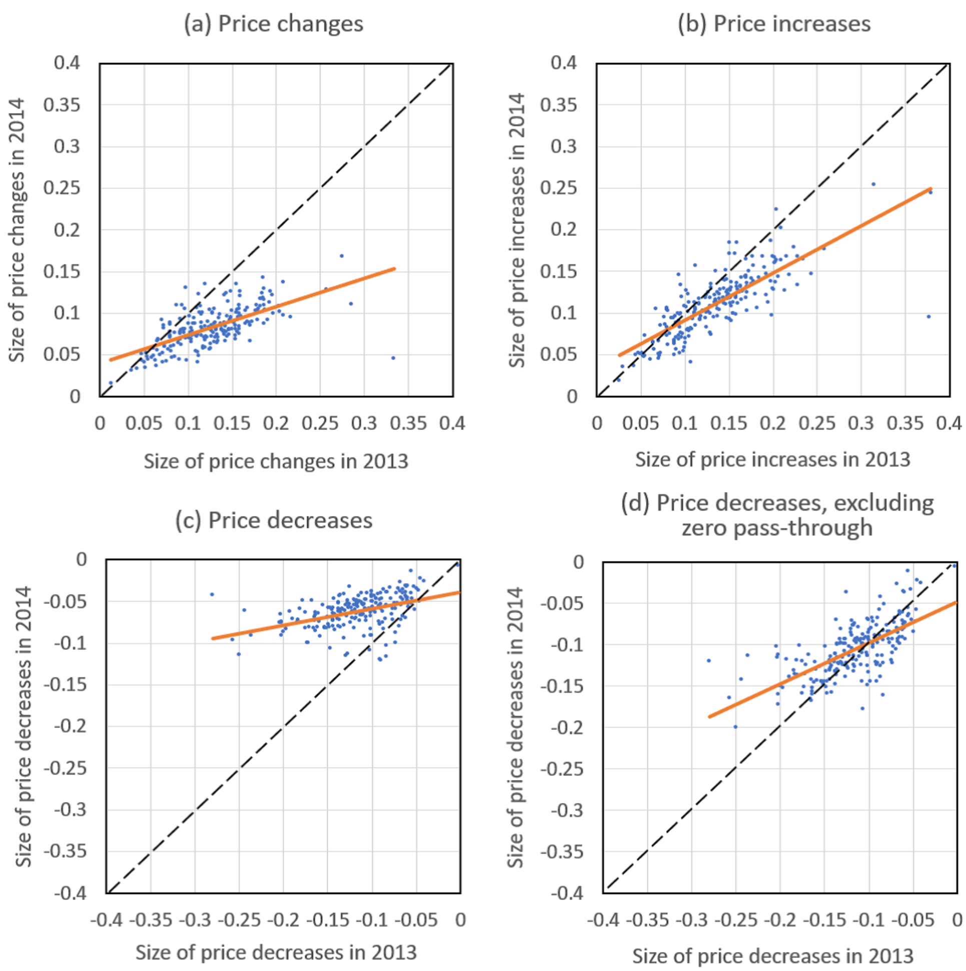

Figure 2.4: Size of price changes for each product category

Notes: I calculate the size of price changes as the turnover-weighted average of the absolute value of price changes of items for which the regular price was changed in April in each product category. See text for more details. The orange line denotes the OLS fitted line, while the black dashed line denotes the 45 degree line.

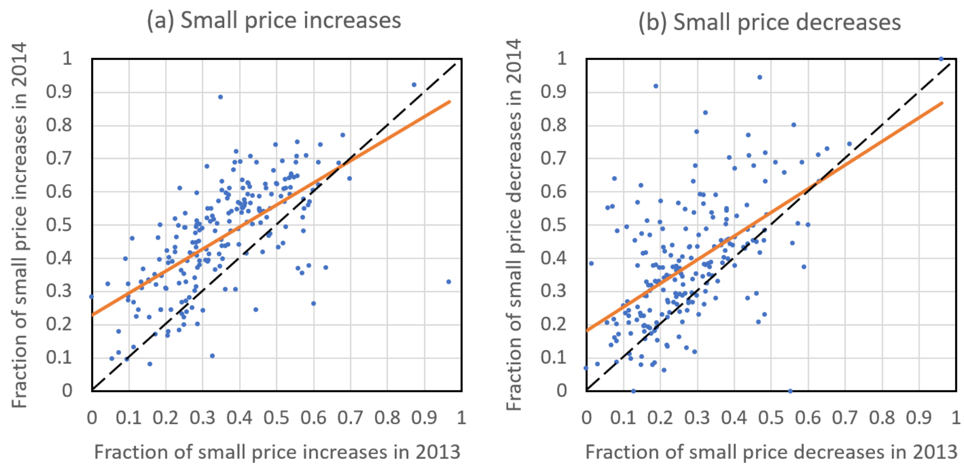

Figure 2.5: Fraction of small price changes in each product category

Notes: The fraction of small price increases and decreases is displayed. For an explanation of the way the figures are obtained, see the main text. The orange line denotes the OLS fitted line, while the black dashed line denotes the 45 degree line.

To explore why the size of price changes decreased in April 2014, I calculate the fraction of small price increases (decreases) in the following way. First, I restrict the sample to items for which prices increased (decreased) by more than 1 yen. Second, I calculate the mean size of price increases (decreases) across items within each product category in April 2013. Third, following Midrigan (2011) and Bhattarai and Schoenle (2014), I define price increases (decreases) as small if they are less than the half of the mean price increase (decrease). Finally, I aggregate the turnover share of items for which price increases (decreases) were small in each product category in April 2013 and April 2014.[11]

The results are displayed in Figures 2.5(a) and (b). They show that the fraction of small price increases and decreases rose in the wake of the tax hike in April 2014 for most categories, although the degree of the rise in the fraction of small price decreases varies across product categories. This finding suggests that firms incurred fixed menu costs to revise tax-included prices after the tax hike, because they post prices including taxes. The fact that

[11] For price decreases, I exclude prices that remained constant including taxes in the calculation.

firms incurred menu costs resulted in adjustment of tax-excluded prices as well, in spite of the small difference between their current price and the desired price.

2.4 Price-Setting Behavior of Multi-Product Firms after the Tax Hike

The observations in the previous section can be summarized as follows. First, a sizable fraction of tax-excluded prices remained unchanged after the tax hike. Second, tax-excluded prices were less sticky after the tax hike than in the preceding year in that the probability of price changes increased, while the size of price changes decreased.[12]

The first finding suggests that tax-excluded prices are sticky, while the second finding suggests that the tax hike affected the degree of price stickiness, so that tax-included prices are sticky as well. To account for these two findings, this section considers the sources of price stickiness in more detail. Specifically, this section provides a hypothesis that tax-included prices are sticky due to menu costs, while tax-excluded prices are sticky due to the cost of information gathering. To test this hypothesis, this section empirically examines price-setting behavior of firms that sell multiple goods.

2.4.1 Menu Costs: Theoretical Prediction

A number of existing studies point out that when firms are subject to menu costs, their price-setting behavior crucially depends on the number of products each firm sells. For example, Midrigan (2011) and Alvarez and Lippi (2014) argue that small price changes can be generated by multi-product firms but not by single-product firms. Their theoretical assumption for this

[12]The previous section also showed that these results are driven by changes in the probability and size of price increases rather than price decreases. This asymmetry might reflect macroeconomic conditions in Japan, which has experienced about two decades of deflation or stagnating prices, so that firms may have refrained from increasing prices for a long time.

argument is that once fixed menu costs are incurred, the firm can reset the price of all its products. This assumption is supported by empirical evidence. Lach and Tsiddon (1996, 2007), for example, show that the timing of price adjustments of different goods sold by the same firm are highly synchronized,[13] while Bhattarai and Schoenle (2014) show that firms selling more products change prices more frequently but by smaller amounts.

The key idea of these studies is that the cost of changing prices is lumped together. In this situation, multi-product firms adjust some prices that are nearly optimal due to the need to revise other prices that are far away from the optimal price. However, this is not the case for single-product firms, because they will wait until the desired price sufficiently differs from the current price. As a result, firms' price-setting behavior is related to the number of products sold, which has been characterized as economies of scope in price adjustment by Midrigan (2011) and Alvarez and Lippi (2014).

Based on this argument, this subsection presents two theoretical predictions. First, I focus on whether firms face menu costs when changing their prices. Under the null hypothesis that firms do not face menu costs,[14] the number of products sold by each firm will be irrelevant to price-setting behavior. In contrast, under the alternative hypothesis that firms face menu costs, firms selling more products are more likely to change their prices but by smaller amounts. This prediction is examined based on the scanner data for April 2013.

Second, given that menu costs play a role in firms' price-setting behavior, I focus on the following question: Are menu costs relevant to either tax-included or tax-excluded prices? Without tax rate changes, the revisions of tax-included and tax-excluded prices perfectly coincide, so that this question cannot be addressed. The tax hike in April 2014 thus provides a useful case study. Further, as shown in Figure 2.1, the tax hike created two prevalent price responses: tax-included or tax-excluded prices are kept constant. I focus on these price responses to test the null hypothesis that menu costs are relevant to tax-excluded prices.

[13] Similar empirical evidence is provided by Levy et al. (1997) and Dutta et al. (1999).

[14] An example is that firms set prices in a time-dependent manner as in Calvo (1983).

Table 2.1: Top 10 firms with the largest number of products

Name	No. of products sold
Retailer A	4,728
Retailer B	2,231
Kao Corporation	1,773
Yamazaki Baking Co., Ltd.	1,591
Shiseido Company, Limited	1,261
Mitsubishi Pencil Co., Ltd.	1,243
Pilot Corporation	1,177
Kokuyo Co., Ltd.	1,007
Meiji Co., Ltd.	976
Kose Corporation	923

Notes: Number of products sold by each firm in April 2014 is reported.

Under the null hypothesis, it is *tax-excluded* prices that firms selling more products are more likely to change (not tax-included). In contrast, under the alternative hypothesis that menu costs are relevant to tax-included prices, it is *tax-included* prices that firms selling more products are more likely to change.[15] These predictions are examined in the next part.

2.4.2 Menu Costs: Empirical Tests

To examine the prediction discussed above, I calculate the number of products sold by each manufacturer. Focusing on the number of products sold by each manufacturer is useful in that the number of products sold has a larger variation across manufacturers than across retailers.[16] Table 2.1 lists the top 10 firms in Japan in terms of the number of products sold. As can be seen, the two top firms actually are retailers selling their own-brand products rather than manufacturers.[17] These retailers have several store brands, so that they are recorded

[15] In most cases, keeping tax-excluded prices constant implies tax-included price changes, and vice versa. However, for quite low-priced goods, it is possible to keep both prices constant.

[16] While Midrigan (2011) empirically shows that firms face economies of scope in price adjustment based on retailer scanner data, Bhattarai and Schoenle (2014) obtain similar results using micro-data underlying U.S. producer (i.e., manufacturer) prices.

[17] While names of these retailers are known to me, the data provider (Nikkei) does not allow me to disclose information regarding the source of their scanner data.

Table 2.2: Number of products sold and the probability and size of price changes in April 2013

	Probability	Size
1	0.14	0.17
2-9	0.14	0.17
10-99	0.17	0.14
100-999	0.25	0.13
1000-	0.31	0.11

Notes: The probability and size of price changes for a group of manufacturers with a different number of products are reported. See text for how the numbers in this table are constructed.

as the producer of a large number of products, even though they outsource manufacturing of these products to other firms. I exclude the products of these two retailers in the analysis below, since it is impossible to know the “true” producer of these products based on the scanner data. The top manufacturers in terms of the number of products sold are Kao Corporation (a chemicals and cosmetics company), Yamazaki Baking (a food company), Shiseido (another cosmetics company), and Mitsubishi Pencils (a company making pens and pencils).

Below, I empirically examine the two predictions described in the previous subsection step by step.

#1 Do firms face menu costs when changing prices?

The first prediction is examined in Table 2.2, where I calculate the probability of price changes as follows. First, I construct a dummy that takes 1 if the price of an item sold at a retailer in April 2013 differs from that in March 2013 by more than 1 yen, and 0 otherwise. Second, I aggregate the turnover of items for which the dummy is 1 in each manufacturer. Third, I divide this turnover by the total turnover of each manufacturer. Finally, I divide manufacturers into 5 groups based on the number of products sold and take the mean of the turnover share for each group. Similarly, I calculate the size of non-zero price changes for each group as follows. First, I restrict the sample to items for which the dummy is 1. Second, I take the weighted average of the absolute value of price changes of these items produced by each manufacturer, where the weight is the turnover share. Table 2.2 shows that in April 2013 manufacturers selling more products were more likely to change prices, but by smaller amounts.

To more precisely quantify the role of economies of scope in price adjustment, I conduct the following two estimations. First, I estimate the following logit model:

$$Pr(I^0_{i,r} = 1, 0 | X_{i,r} = x) = \Phi(\beta X_{i,r}), \tag{2.1}$$

where $I^0_{i,r}$ denotes an indicator variable that takes 1 if the price of item i sold at retailer r changed and 0 otherwise. $X_{i,r}$ is a vector consisting of the following three types of explanatory variables. The first is the log of the number of products sold by manufacturer m that produces product i, $\log_{10} N_m$. The second is a set of dummy variables for product categories, since the degree of price stickiness varies across product categories. The third is a set of dummy variables for retailers to control for the influence of retailers' attitude to price revisions.[18]

The second equation I estimate using ordinary least squares is as follows:

$$Size^0_{i,r} = \gamma X_{i,r} + \epsilon^0_{i,r}, \tag{2.2}$$

where $Size^0_{i,r}$ denotes the size of the price change for item i sold at retailer r, given that the price was changed. Again, $X_{i,r}$ includes the number of products sold by the manufacturer as well as dummy variables for product categories and retailers.

These equations are estimated based on observations in April 2013 and the estimation results are presented in Table 2.3. This table shows that there is a clear positive correlation

[18] Note that including dummies for all categories and retailers results in perfect collinearity. To avoid this, I include an intercept while omitting two dummies: one for a category and one for a retailer.

Table 2.3: Estimation results on economies of scope in price adjustment in April 2013

	Probability (1)	Size (2)
$\log_{10} N_m$	0.0131	-0.0064
	(0.0006)	(0.0005)
R^2	0.09	0.15
Observations	1,845,880	376,883

Notes: Standard errors in parentheses. Categories and retailers for which the number of observations is quite small are omitted when estimating the logit model. Column (1) reports the marginal effect of a one unit change in the number of products sold on the probability of price change around the mean of $X_{i,r}$. Column (2) reports the estimated coefficient on the number of products sold.

between the number of products a manufacturer sells and the probability of price changes in April 2013. Moreover, this table indicates that there is a negative correlation between the number of products sold and the size of price changes. These results clearly reject the null hypothesis that firms do not face menu costs when changing their prices and accept the alternative hypothesis.

These results are in line with the findings obtained in previous studies. Bhattarai and Schoenle (2014), for example, show that firms selling more products change prices more frequently but by smaller amounts. The estimation results obtained here are qualitatively similar to their finding.

#2 Are menu costs relevant to either tax-included or tax-excluded prices?

To examine the second prediction, I focus on the price observations in April 2014 when the tax hike took effect. I restrict the sample to prices that were kept constant after the tax hike in terms of tax-included or tax-excluded prices (or both). Then I estimate the logit model that is essentially the same as Equation (2.1). The only modification is that $I_{i,r}^0$ is replaced with the indicators as follows: an indicator that takes 1 if the *tax-excluded* price changed and 0 otherwise, and the other indicator that takes 1 if the *tax-included* price changed and 0

Table 2.4: Estimation results on economies of scope in price adjustment in April 2014

	Tax-excluded (1)	Tax-included (2)
$\log_{10} N_m$	0.0004	0.0063
	(0.0003)	(0.0002)
R^2	0.22	0.26
Observations	1,518,950	1,518,950

Notes: Standard errors in parentheses. Categories and retailers for which the number of observations is quite small are omitted when estimating the logit model. Columns (1) and (2) report the marginal effects of a one unit change in the number of products sold on the probability of price change around the mean of $X_{i,r}$.

otherwise.

The estimation results are reported in Table 2.4. This table shows that there is a positive correlation between the number of products a manufacturer sells and the probability of *tax-included* price changes, while there is no significant correlation between the number of products sold and the probability of *tax-excluded* price changes. This result clearly rejects the null hypothesis that firms selling more products are more likely to change tax-excluded prices and accepts the alternative hypothesis.[19]

The result obtained in this part is consistent with the argument in previous studies. For example, Gagnon, Lopez-Salido, and Vincent (2012) and Karadi and Reiff (2018) argue that menu costs are relevant to tax-included prices since posted prices include taxes. This study provides supporting evidence for their argument in light of economies of scope in price adjustment, which has been pointed out by Midrigan (2011) and Alvarez and Lippi (2014).

[19] Although the explicit statistical test is not conducted, Tables 2.3 and 2.4 indicate that the relationship between the number of products sold and the probability of price changes is weaker in 2014 than 2013. This result might suggest that the tax hike was a large aggregate shock, so that the majority of firms incurred menu costs to revise tax-included prices, as argued by Karadi and Reiff (2018).

2.4.3 Information Rigidity: Theoretical Prediction

The results obtained in the previous subsection indicate the following. First, firms face menu costs when changing prices. Second, menu costs are relevant to tax-included prices. These findings suggest that if menu costs are the only source of price stickiness, firms that changed tax-included prices should have been able to adjust their prices without constraint. However, this is not the case. Recall that more than half of tax-excluded prices remained unchanged after the tax hike, as shown in Figure 2.1. This observation suggests that firms faced another friction when adjusting tax-excluded prices.

This paper presents the hypothesis that this friction is information frictions. The notion that firms face information frictions when adjusting prices has been explored by a number of existing studies. For example, Mankiw and Reis (2002) propose a theoretical framework called the sticky information model where firms update information only infrequently, while Woodford (2003) constructs an incomplete information model where firms receive a noisy signal and update their belief sluggishly.[20] Based on these theoretical models, Coibion and Gorodnichenko (2015) empirically show that the degree of information rigidity is heterogeneous across macroeconomic variables and argue that firms' incentive to update information depends on the precision of the signal. Their argument helps us understand why firms postponed adjusting tax-excluded prices after the tax hike while they quickly changed tax-included prices. This is because the tax hike differs from other shocks in that firms received a precise signal provided by the government.[21]

To examine whether firms face information rigidity when adjusting prices, it is useful to focus on the relationship between the number of products sold by each firm and price-setting behavior again. Pasten and Schoenle (2016), for example, argue that in an environment where

[20] The infrequent and noisy update of information can be interpreted as the result of the cost of gathering or processing information on the optimal price. Such an interpretation has been theoretically argued by Woodford (2009) and Alvarez, Lippi, and Paciello (2011) and empirically examined by Zbaracki et al. (2006).

[21] Specifically, the Japanese government made a clear announcement in October 2013, stating that the tax hike from 5 to 8 percent would be implemented in April 2014.

Table 2.5: Number of products sold and the probability and size of price changes in April 2014

	Probability	Size
1	0.20	0.16
2-9	0.22	0.15
10-99	0.26	0.14
100-999	0.33	0.13
1000-	0.33	0.12

Notes: The probability and size of price changes for a group of manufacturers with a different number of products are reported. See text for how the numbers in this table are constructed.

information gathering is costly, firms selling more products have a stronger incentive to collect information on common shocks, meaning that these firms change prices more frequently. Based on this argument, under the null hypothesis that firms do not face information rigidity, the number of products sold by each firm is irrelevant to the probability of price changes. In contrast, under the alternative hypothesis that firms face information rigidity, firms selling more products are more likely to change prices.[22] The next part examines this prediction based on the scanner data for April 2014.

2.4.4 Information Rigidity: Empirical Test

To examine the prediction above, I again focus on the price observations in April 2014. I restrict the sample to prices that were changed in terms of tax-included prices, so that menu costs had already been incurred for these prices. Then the prediction is examined in Table 2.5, where the probability and size of price changes are calculated in the same manner as in Table 2.2. Table 2.5 shows that in April 2014 manufacturers selling more products were more likely to change tax-excluded prices, but by smaller amounts.

[22] As in the case of menu costs, it might be predicted that under the null hypothesis the size of price changes does not depend on the number of products sold, while under the alternative hypothesis firms selling more products change prices by smaller amounts. However, this prediction might need additional assumption on the variance of common and idiosyncratic shocks.

Table 2.6: Estimation results on economies of scope in information updating in April 2014

	Probability (1)	Size (2)
$\log_{10} N_m$	0.0325	-0.0047
	(0.0007)	(0.0004)
R^2	0.08	0.12
Observations	1,961,611	582,822

Notes: Standard errors in parentheses. Categories and retailers for which the number of observations is quite small are omitted when estimating the logit model. Column (1) reports the marginal effect of a one unit change in the number of products sold on the probability of price change around the mean of $X_{i,r}$. Column (2) reports the estimated coefficient on the number of products sold.

To quantify the impact of economies of scope in information updating, I estimate the logit model that is almost the same as Equation (2.1). A slight modification is that $I^0_{i,r}$ is replaced with the indicator that takes 1 if the *tax-excluded* price changed and 0 otherwise, conditional on non-zero change in the *tax-included* price. In addition, I estimate the equation that is essentially the same as Equation (2.2). Note that the sample is restricted to price observations that were changed in terms of both tax-included and tax-excluded prices. These equations are estimated based on the observations in April 2014.

The estimation results are shown in Table 2.6. This table shows that there is a clear positive correlation between the number of products a manufacturer sells and the probability of tax-excluded price changes in April 2014. Moreover, this table indicates that there is a negative correlation between the number of products sold and the size of price changes. These results clearly reject the null hypothesis that firms do not face information rigidity when adjusting their prices and accept the alternative hypothesis.

These results are in line with the findings obtained in previous studies. Zbaracki et al. (2004), for example, show that the cost of information gathering is substantial based on a case study of pricing process of a firm. This study adds more evidence for the cost of information gathering in light of economies of scope in information updating argued by

Pasten and Schoenle (2016).

2.5 Robustness

To check the robustness of the results, I conduct three additional analyses. First, I use a longer window length to construct the regular price. Second, I examine the potential effect of price points on firms' price-setting behavior. Third, I define price changes in relative terms instead of absolute terms. The main results are robust to all of these modifications.

2.5.1 Changing the Window Length

First, I examine whether the window length used to construct the regular price affects the main results. In the baseline analysis, I define the regular price as the modal price of the last week of March and the first week of April to focus on the effect of the tax hike. This is similar to the definition of the regular price adopted by Abe and Tonogi (2010), who use the weekly modal price as the regular price. However, other definitions have been used in previous studies to observe firms' price-setting behavior. For example, Eichenbaum, Jaimovich, and Rebelo (2011) define the reference price as the quarterly modal price. Based on these different definitions, Sudo, Ueda, and Watanabe (2014) point out that using a shorter window length leads to an increase in the measured frequency of price changes.

To check whether the baseline result is affected by the window length, I calculate the probability of price increases using longer window lengths. Specifically, I use a 2- and a 3-week window length, and the results are shown in Figures 2.6(a) and (b), respectively. The results are comparable to those in Figure 2.3(b), meaning that using a longer window length does not affect the finding that the probability of price increases rose in April 2014.[23]

[23] I do not use the modal price of the quarter before and after the tax hike as the regular price, because applying such a longer window might fail to pick up the effect of the tax hike.

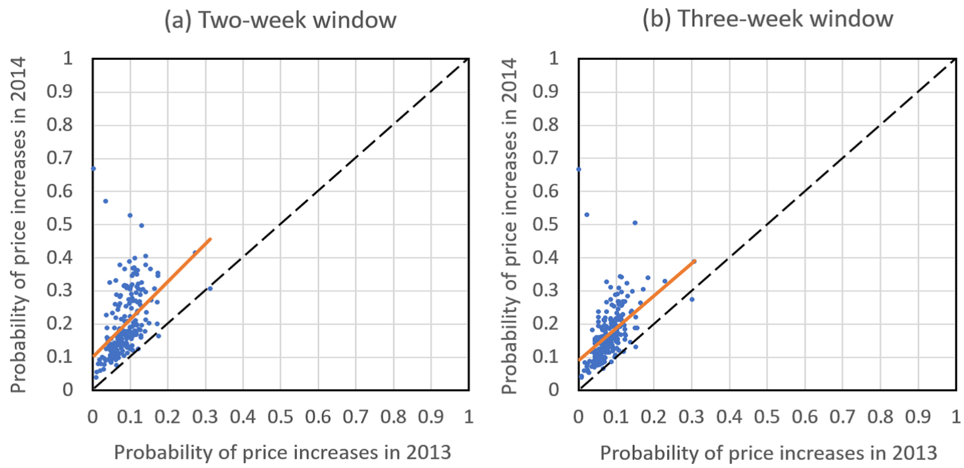

Figure 2.6: Probability of price increases using the longer window length

Notes: The probability of price increases is essentially calculated in the same way as in Figure 2.3(b). The only modification is that I use a 2- and a 3-week window to construct the regular price. The orange line denotes the OLS fitted line, while the black dashed line denotes the 45 degree line.

2.5.2 Price Points

Second, I check whether the main result is affected by the existence of so-called "price points." A number of studies, such as Kashyap (1995) and Levy et al. (2011), have noted that firms tend to set prices at particular levels that they believe maximizes the turnover.[24] This means that in the wake of the tax hike, firms may have adjusted prices by smaller amounts more intensively than in the preceding year, which may lead to biases in the measurement of the probability and the size of price changes.

To examine the effect of price points on firms' price-setting behavior, Figure 2.7 plots the distribution of the last digit of prices in March 2014. The figure indicates that "8" is the most frequent number in which prices end in the scanner data for Japan used in this study.[25] Taking this finding into account, it seems possible that some firms reset tax-included prices

[24]More formally, a price point represents a price where the marginal revenue curve is discontinuous, so that firms hesitate to exceed this. See Kashyap (1995).

[25]Levy et al. (2011) in their study using scanner data for the U.S. find that the most frequent number in which prices end is "9."

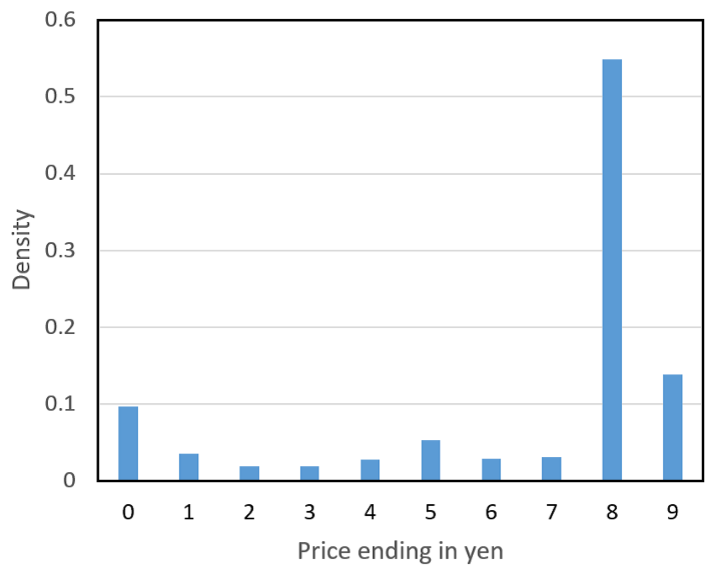

Figure 2.7: Distribution of the last digit of prices in March 2014

Notes: The figure shows the frequency of the last digit of tax-included prices in March 2014.

after the tax hike so that they end with "8."[26] To examine whether this kind of price-setting behavior affects the main findings in Section 2.3, Figures 2.8(a) and (b) plot the probability and size of price increases for items for which the price in April ended numbers other than "8." The figures indicate that the probability of price increases rose in April 2014, while the size of price increases declined, suggesting that the role of price points in firms' price-setting appears to have been limited.

2.5.3 Price Changes Defined in Relative Terms

Third, I examine whether changing the definition of price changes affects the main result. Specifically, I define price changes in relative terms instead of absolute terms. So far, a price is regarded to have changed when the regular price in April differs from that in March by

[26] Another possibility is that after the tax hike, firms were reluctant to change prices that had already been set at price points. This means that the probability of price changes is biased downward while the size of price changes is biased upward, so that the results are conservative.

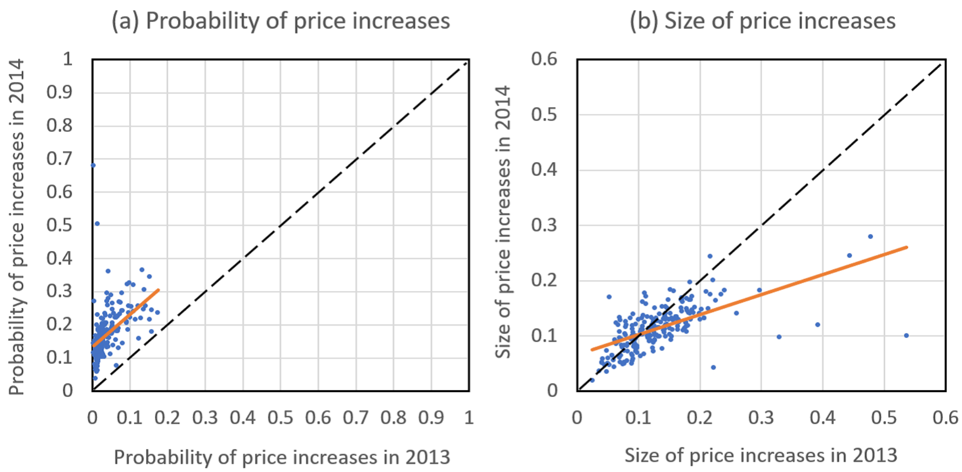

Figure 2.8: Probability and size of price increases excluding price points

Notes: The probability and size of price increases are essentially calculated in the same way as in Figures 2.3(b) and 2.4(b). The only modification is that I exclude price increases for items for which the price ended in "8" in both April 2013 and April 2014. The orange line denotes the OLS fitted line, while the black dashed line denotes the 45 degree line.

more than 1 yen. However, this could potentially result in downward biases in the probability of price change for low-priced items. As an example, consider an item which was priced at 20 yen in March. If the price of this item was raised by 1 yen in April, this would be equivalent to a price increase of 5 percent, which is quite substantial. However, when price changes are identified in absolute terms—i.e., that they need to exceed 1 yen—this would not be regarded as a price change.

Therefore, to address this issue, I identify price changes in terms of whether the percentage change of the regular price in April was more than plus or minus 0.5 percent. Similarly, I identify (tax-excluded) price changes in terms of whether the percentage change of the regular price in April 2014 was more than 3.5 percent or less than 2.5 percent. Based on these definitions, I repeat the estimation of the logit model and regression equation in the previous section. The results are shown in Table 2.7 and are very similar to the baseline results in Tables 2.3, 2.4, and 2.6.[27] Specifically, this table shows that firms selling more products are

[27]Note that when price changes are defined in relative terms, keeping the tax-excluded prices constant

Table 2.7: Estimation results on economies of scope in price adjustment and information updating

	Tax-excluded price changes		Tax-included price changes
	Probability	Size	Probability
	(1)	(2)	(3)
Observations for April 2013			
$\log_{10} N_m$	0.0169	-0.0047	
	(0.0006)	(0.0004)	
R^2	0.07	0.11	
Observations	1,845,880	458,536	
Observations for April 2014			
$\log_{10} N_m$	0.0488	-0.0035	0.0034
	(0.0007)	(0.0003)	(0.0002)
R^2	0.09	0.10	0.28
Observations	2,021,007	856,154	1,267,266

Notes: Standard errors in parentheses. Categories and retailers for which the number of observations is quite small are omitted when estimating the logit model. In columns (1) and (2), the sample for April 2014 is restricted to prices that were changed in terms of tax-included prices. In column (3), the sample is restricted to prices that were kept constant in terms of tax-included or tax-excluded prices. Columns (1) and (3) report the marginal effects of a one unit change in the number of products sold on the probability of price change around the mean of $X_{i,r}$. Column (2) reports the estimated coefficient on the number of products sold.

more likely to change prices by smaller amounts in April 2013 and April 2014, suggesting that firms face menu costs and the cost of information gathering, respectively. Moreover, firms selling more products are more likely to change tax-included prices, suggesting that it is *tax-included* prices that are relevant to menu costs.

2.6 Concluding Remarks

This paper examined firms' price-setting behavior in response to Japan's consumption tax hike in April 2014. The main findings of the paper can be summarized as follows. First, a sizable fraction of tax-excluded prices remained unchanged after the tax hike. Second, the

implies tax-included price changes, and vice versa.

probability of (tax-excluded) price changes increased after the tax hike, while the size of price changes decreased. These findings cannot be explained by saying that *either* tax-included *or* tax-excluded prices are sticky. This paper therefore argued that *both* tax-included *and* tax-excluded prices are sticky. Specifically, this paper argued that tax-included prices are sticky due to menu costs, while tax-excluded prices are sticky due to information rigidity. To support this argument, the price-setting behavior of multi-product firms was examined.

The results obtained in this paper provide two policy implications. First, they suggest that Feldstein's (2002) proposal to use a consumption tax hike to generate inflation should be effective, although the feed-through of such a tax hike would likely only be partial. The analysis using Japan's consumption tax hike in 2014 showed that although most prices were raised by an amount equal to or greater than the tax hike, not all prices were raised, implying that tax-included prices are sticky, likely due to menu costs. Given that firms face menu costs when changing tax-included prices, the size of the tax hike needs to be large enough for firms to incur menu costs. However, Feldstein's proposal is to increase the consumption tax rate by 1 percentage point per quarter, which is smaller than the 3 percentage-point increase in Japan, meaning that the feed-through may be smaller.

Second, this paper showed that both tax-included and -excluded prices are sticky. Previous studies, such as Schmitt-Grohe and Uribe (2012), point out that the inflation target adopted by central banks depends on what kind of prices are sticky. Specifically, they consider which of quality-adjusted and nonquality-adjusted prices should be targeted, and conclude that prices that are sticky should be kept constant to avoid inefficient price dispersions. Taking their discussion into account, Japan's experience suggests that central banks should pay attention to both tax-included and -excluded prices.

Chapter 3

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.

3.1 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 (2006a) 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 (2006a, 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 (2006a, 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 (2006a, 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 (2016a) 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 (2016a) 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 3.3 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 3.4 then presents a simple model

[4]There was another consumption tax hike in Japan in 1997 as well. Using this episode, Cashin and Unayama (2016b) 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 3.5 extends the model and quantifies the effect of liquidity constraints on stockpiling behavior. Finally, Section 3.6 provides concluding remarks.

3.2 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 (2016b) 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 (2016a). 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.

3.3 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.

3.3.1 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 3.1: 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 3.1 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.[12] 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. Further discussion on the sample

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.

[12]Even if I omit the top 1 percent customers in terms of cup noodle purchases, the observations obtained in the below part are very similar.

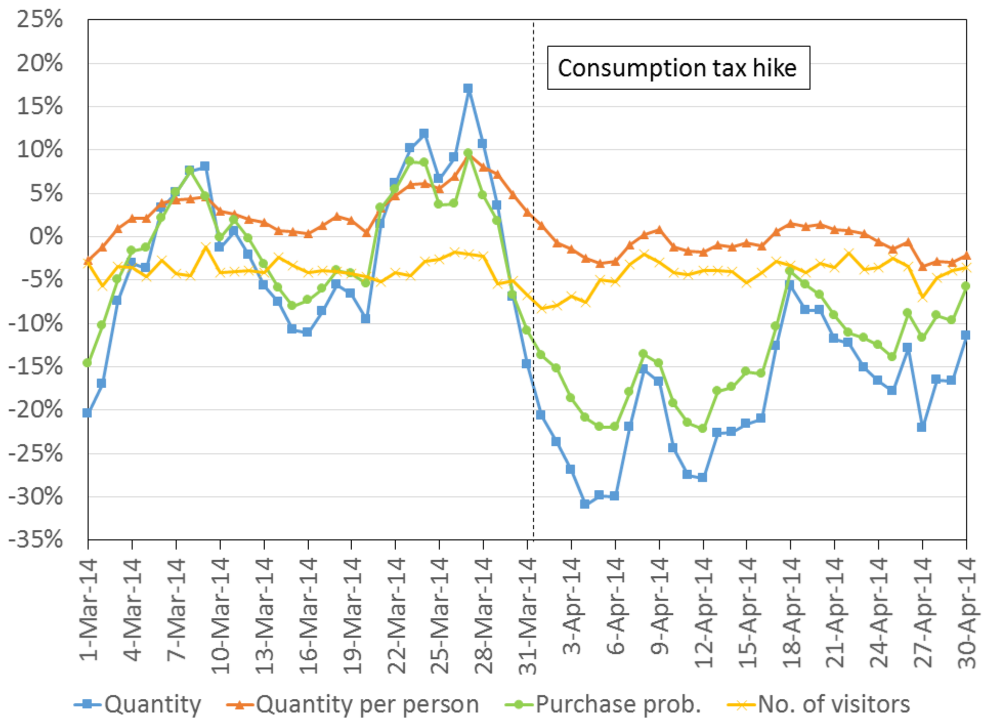

Figure 3.1: Quantity of cup noodles purchased

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.

selection can be found in Appendix.

3.3.2 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.[13] Figure 3.1 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

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

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 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,[14] indicating that consumers' store visit frequency was not affected by the tax hike.[15]

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

[15]Hendel and Nevo (2006b) 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.

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 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 (2006a, b). The next section explores this idea.

3.4 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.

3.4.1 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.[16] 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,

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

they continue to buy goods for consumption at the regular price, which involves no storage costs. In this case, the total costs are

$$c\frac{S^2}{2} + (p - \epsilon)S + p(T - S). \tag{3.1}$$

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

$$S = \begin{cases} T & (T < \epsilon/c) \\ \epsilon/c & (T \geq \epsilon/c) \end{cases}. \tag{3.2}$$

This basic model is useful for assessing consumer-specific storage costs. As can be seen, Equation (3.2) 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.

3.4.2 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 (3.2), 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.[17]

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 3.2 provides an illustration of

[17] 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.

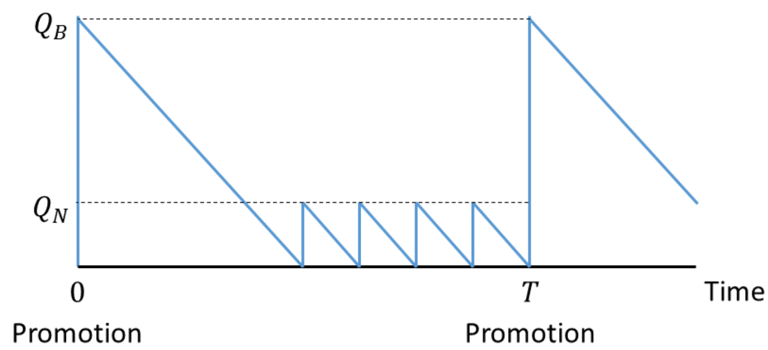

Figure 3.2: Dynamics of inventory holdings

the estimation procedure. The horizontal axis shows the time between two promotions, one 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 3.2. 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.

3.4.3 Analysis

In this part, I examine the relationship between storage costs and purchasing behavior. Using storage costs, I split consumers into five groups and plot the mean quantity (year-on-year log rate of change) of cup noodles purchased in March 2014 in the upper panel of Figure 3.3.[18] 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 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. The upper panel of Figure 3.3 therefore also shows expenditure on less storable or perishable goods including fresh vegetables and fruits, raw meat and fish, and delicatessen.[19] 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, this panel shows that although the error band is relatively wide, expenditure on perishable goods is also positively correlated with the inverse of storage costs, indicating that consumers with lower

[18] 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.

[19] 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.

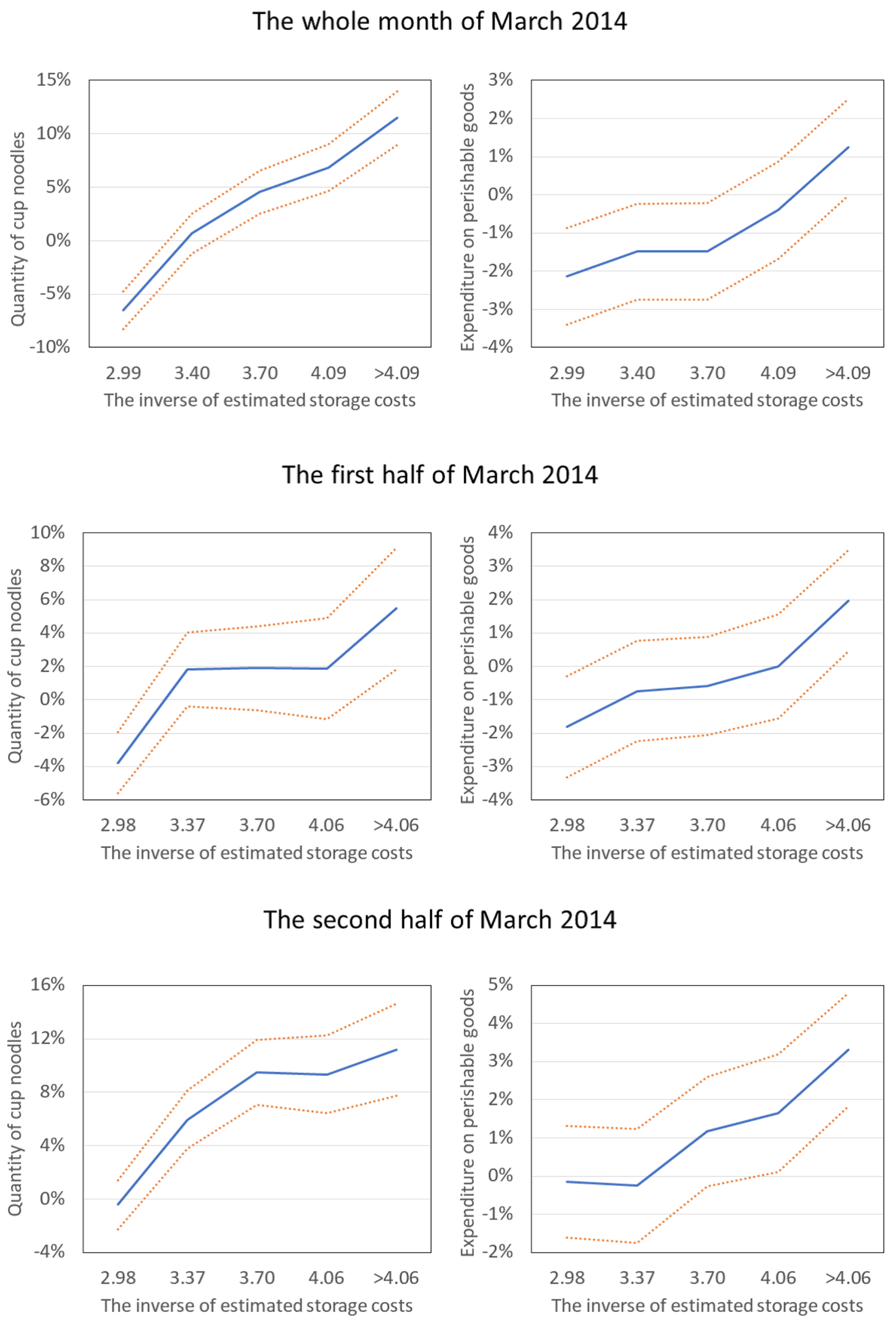

Figure 3.3: Storage costs and purchasing behavior

Note: Consumers are divided into five groups using the inverse of storage costs. Quintiles are defined based on consumers who bought perishable goods in both March 2013 and March 2014. In the upper panel, 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. Similarly, the middle and lower panels are constructed. The dotted lines denote 95 percent bands that are computed as $\pm 1.96\times$ std. error across consumers.

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.

One might argue that since perishable goods can be stored for a week or two, this finding does not reject the consumer inventory model featuring storage costs only. To address this concern, the middle and lower panels of Figure 3.3 show purchasing behavior in the first and second half of March 2014, respectively. In the first half of March 2014, consumers would not have an incentive to stockpile perishable goods, so that storage costs should have been insignificant determinant of purchases of perishable goods. However, the middle panel shows that consumers with lower storage costs tended to spend more on perishable goods.

Another notable result displayed in Figure 3.3 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 3rd quintile increased purchases of cup noodles by about 5 percent while reducing purchases of perishable goods by about 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.

3.5 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.

3.5.1 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 3.1.

Analogous to the notation used in Section 3.4.1, 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 $\eta S_{\text{VAT}}^2/2$.[20] Adding this term to Equation (3.1) yields the total cost function before the tax hike:

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

[20] 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 3.1 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.

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

$$S_{\mathrm{VAT}} = \begin{cases} Y & (Y < \frac{\tau}{c+\eta}) \\ \frac{\tau}{c+\eta} & (Y \geq \frac{\tau}{c+\eta}) \end{cases}, \tag{3.3}$$

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

The extended model has two notable features. First, as Equation (3.3) 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 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 (2006a, 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.

3.5.2 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 (3.3). 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.[21] 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

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

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.

3.5.3 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 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 3.2 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

Table 3.2: 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.

2013 and March 2014 are available,[22] 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 (3.4) to quantify the effect of liquidity constraints looks as follows:

$$\ln q_i = \beta_0 + \beta_1(p_i - \gamma)_- + \beta_2(p_i - \gamma)_+ + \beta_3 \ln s_i + \beta_4 \ln v_i + \beta_5 D_i + \beta_6 \ln q_i^{ctrl} + u_i, \tag{3.4}$$

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 in 2013 as an indicator of adjustment costs,[23] 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

[22]In addition, the sample is restricted to consumers aged between 20 and 90.
[23]It is likely that consumers with smaller adjustment costs visit stores more frequently.

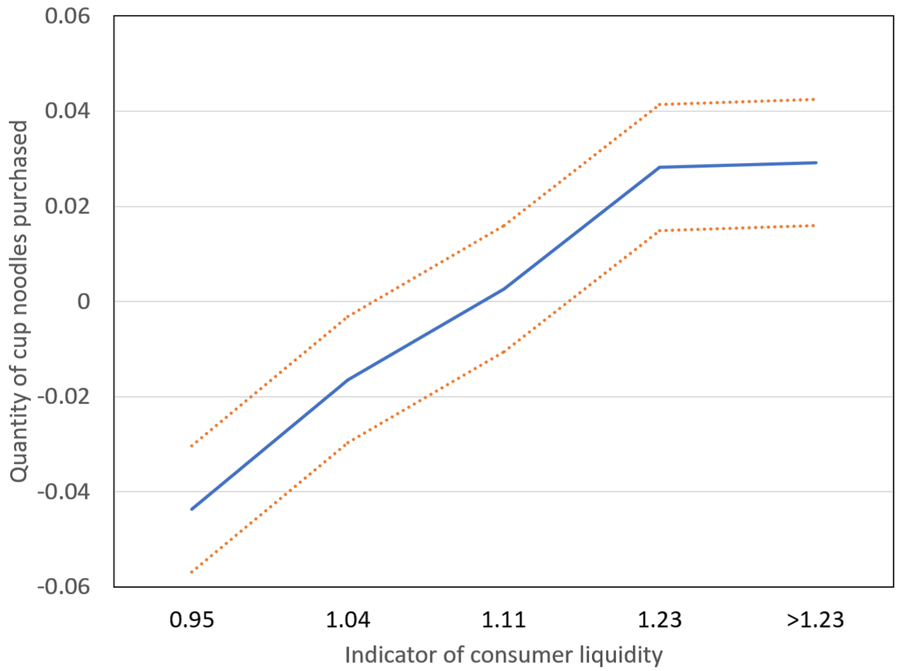

Figure 3.4: Consumer liquidity and quantity purchased

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. The dotted lines denote 95 percent bands that are computed as $\pm 1.96\times$ std. error across consumers.

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 3.4, 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 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.

3.5.4 Results

The kink regression results are shown in the first column in Table 3.3. First, using least squares estimation, the threshold value, γ, is estimated to be 1.16 and its standard error is 0.07. The 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.[24] Third, the coefficient on the positive part of the liquidity indicator, β_2, is not statistically significant.

[24] 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.

Table 3.3: 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.

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 3.2, 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 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 3.4.2 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.[25] 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 3.3 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.

To explore which of the explanatory variables have the largest impact on purchasing behavior, I calculate standardized coefficients, which are presented in Table 3.4. 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.[26] 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

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

[26] See Schroeder, Sjoquist, and Stephen (1986) for a detailed explanation.

Table 3.4: 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 $(p_i - \gamma)_-$.

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 (3.3), 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.

3.5.5 Discussion

The result obtained in the previous subsection is in line with the findings of previous studies. For instance, Hendel and Nevo (2006b) 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 (2006a) 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

Table 3.5: 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.

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 (2006a) 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

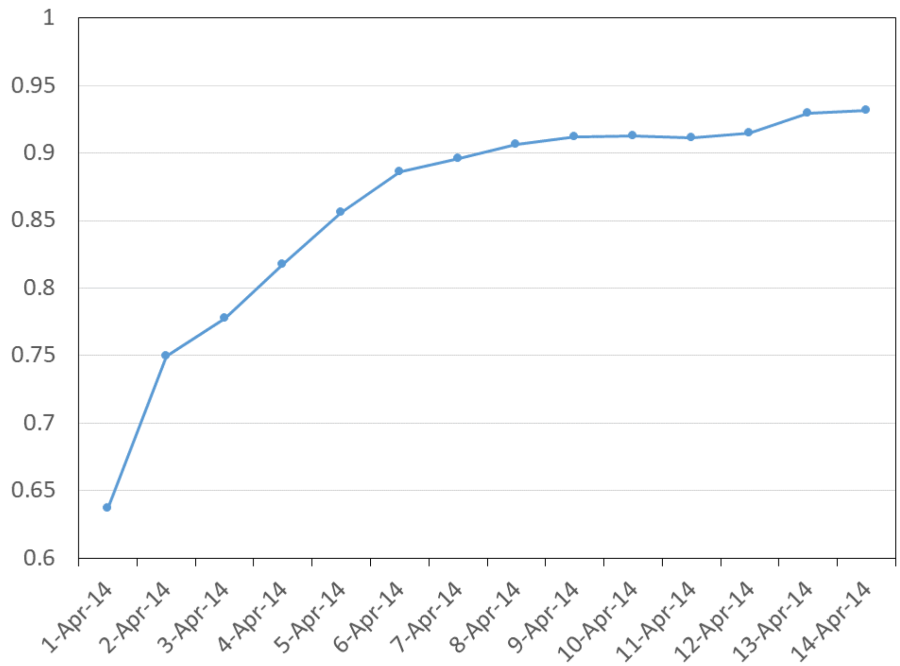

Figure 3.5: Ratio of purchase probabilities

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

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 3.5 and are very similar to the baseline results in the first column in Table 3.3.

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 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 3.5 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 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.

3.6 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.

Appendix: Comparing the Regular Customers with All Consumers in Scanner Data

In this appendix, I compare the distribution of regular customers with that of all consumers observable in the scanner data. Specifically, I examine the age and expenditure distributions in 2013, which are presented in Figure 3.6. This figure indicates the following. First, the left panel shows that the age distributions are similar to each other, especially for older consumers aged over 60. This suggests that the sampling process of regular customers is almost uncorrelated with the age of consumers. That said, the density of younger consumers is smaller for the distribution of regular customers, indicating that these consumers change the location where they purchase goods more frequently.

Second, the right panel compares the distributions of total expenditure in 2013 for regular customers and all consumers. It shows that although cup noodles are seemingly inferior goods, expenditure of regular customers tends to be larger. The reason would be that regular customers are required to repeatedly buy goods at stores in the dataset. The median of their total expenditure per month is approximately 29,000 yen, which is comparable to the mean of food expenditure in supermarkets per month, 30,360 yen, reported in the national survey in 2014 (National Survey of Family Income and Expenditure).

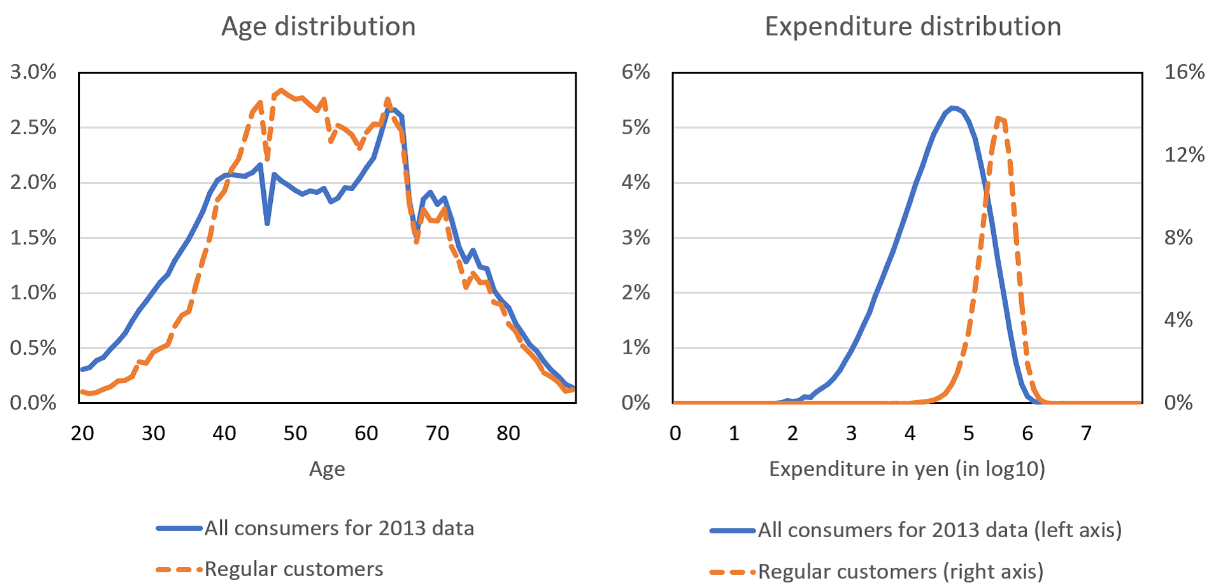

Figure 3.6: Distributions of age and expenditure in 2013

Note: The left panel shows the age distribution of regular customers and all consumers in 2013, while the right panel shows the total expenditure of regular customers and all consumers in 2013. The number of regular customers is 57,600, while the number of all consumers in 2013 is approximately 4.4 million. Among the all consumers, age information is available for 3.2 million consumers.

Chapter 4

The Cost-of-Living Index over the Life Cycle

I would like to thank Tsutomu Watanabe for fruitful discussions. Financial support from the Japan Society for the Promotion of Science (JSPS Grant Number: 16J09620) is gratefully acknowledged.

Abstract

Aguiar and Hurst (2007) show that older households who have retired pay lower prices for identical goods than younger households. However, the household-level price index they calculate has several problems in light of canonical index theories. To address these problems, this study adopts the alternative method and calculates the individual-level cost-of-living index using Japan's scanner data. The analyses show that individuals around the retirement age face the lower inflation rate than working-age individuals, and that increases in the frequency of shopping trips reduce the inflation rate. Moreover, individuals aged over 80 markedly reduce the frequency of shopping trips.

JEL codes: D12, E31

Keywords: Cost of living, shopping behavior, substitution

4.1 Introduction

Shopping behavior of each individual differs in various aspects—such as the set of goods purchased, the expenditure share of each of these goods, and the price at which each good is purchased. The differences in these aspects stem from each individual's deeper parameters, such as tastes, income, and employment status. The purpose of this paper is to quantify the impact of such differences on the cost-of-living index over the life cycle.

Differences in the cost-of-living index over the life cycle are important in light of three influential arguments in economics. First, differences in the cost-of-living index over the life cycle reflect the effect of shopping time on prices paid, which has been documented in exiting studies. For example, Aguiar and Hurst (2007) show that older households pay lower prices for identical goods than younger households, because older households should have retired and they can spare more time for shopping. This finding suggests that the cost-of-living index of older households will be lower than that of younger households.

Second, differences in the cost-of-living inflation over the life cycle can be regarded as an indicator of to what extent the assumption of the representative agent model holds, which provides important information especially for indexation of income payment programs. In most cases, income payment programs such as old-age pensions and the minimum wages are adjusted based on the consumer price index.[1] However, the statistical agency calculates the consumer price index assuming the representative agent model, meaning that heterogeneity across individuals is not taken into account. Given that the cost-of-living inflation faced by older people and/or low-paid workers differs from the aggregated cost-of-living inflation, indexation of income payments referring to each demographic is needed to maintain their purchasing power.

Third, differences in the cost-of-living inflation over the life cycle reflect, more broadly, differences in the cost-of-living inflation across individuals. Kaplan and Schulhofer-Wohl

[1] See ILO (2004) for this point.

(2017) provide empirical evidence for differences in the rate of inflation across individuals and argue that these differences are relevant to the real effect of monetary policy. Specifically, they argue that even if an individual observes the change in the rate of inflation, she faces information frictions that prevent her from knowing that either an idiosyncratic shock or an aggregate (monetary) shock caused that change, as argued by Lucas (1972) and King (1982).

Taking these arguments into account, this study reevaluates the effect of changes in employment status (especially retirement) on the cost-of-living index over the life cycle. Relatedly, Aguiar and Hurst (2007) have already examined the effect of one's retirement on prices paid for a given good through time allocation. The analyses in this study differ from those in Aguiar and Hurst (2007) in two respects. First, this study focuses on Japanese individuals, while Aguiar and Hurst (2007) focus on U.S. individuals. Since population aging is more severe in Japan than in the U.S., the fraction of individuals around the retirement age is larger in Japan, meaning that it will be easier to observe the impact of retirement on the cost-of-living index.

Second, this study employs a traditional method to measure the cost of living. Specifically, this study modifies the method suggested by Aguiar and Hurst (2007) in the following sense. First, while Aguiar and Hurst (2007) pool individuals before and after retirement and observe the differences in prices paid for identical goods, their analysis does not consider heterogeneity in individual tastes. To address this issue, this study focuses on prices the same individual pays for a given good in different time periods. By assuming that individual tastes do not change over time, this study compares individuals who experience retirement with those who do not experience such an event, which enables us to quantify the impact of retirement on the cost-of-living index allowing for heterogeneity in individual tastes. Second, while Aguiar and Hurst (2007) examine differences in prices paid taking the shopping basket as given, their analysis overlooks the aspect that each individual makes decision on what to buy. Taking this aspect into account, this study examines the effect of intertemporal variation in the shopping basket on the cost-of-living index following the method proposed by Feenstra (1994).

The main findings of the paper can be summarized as follows. First, older individuals in Japan pay higher prices—rather than lower prices—for identical goods, which is not consistent with the finding obtained by Aguiar and Hurst (2007). This finding suggests that older individuals face higher travel costs when shopping, so that searching for low-priced goods sold at distant stores does not pay.[2] Second, individuals around the retirement age (65 years old) experience the lower cost-of-living inflation than younger working-age individuals. This finding suggests that retired individuals in Japan do not search for discounts for a given good; instead, they engage in substitution across goods to reduce the cost of living.

There are two strands of literature related to this study. The first strand documents the difference in price movements faced by individuals over the life cycle with the motivation similar to this study. For example, Hobijn and Lagakos (2005) and Hobijn et al. (2009) show that the expenditure share for each good varies over the life cycle, so that social security benefits should be indexed to inflation faced by older individuals. In addition, Aguiar and Hurst (2007) and Kaplan and Menzio (2015) argue that prices paid for a given good varies over the life cycle, especially depending on each individual's employment status, so that shopping time affects prices paid.

The second strand of literature has documented differences in prices paid by individuals using data or methodology similar to those employed in this study. As an example, Kaplan and Schulhofer-Wohl (2017) measure the inflation rate at the household level using scanner data in U.S. However, the inflation rate they calculate does not reflect the fact that the shopping basket of each household differs over time. This issue is addressed in Argente and Lee (2017), who document differences in the cost-of-living inflation across income groups

[2] A study related to this issue is Allcott et al. (2018), who examine the effect of so-called "food deserts"—areas with low availability or high prices of foods—on consumers' purchasing behavior. They argue that Americans can go to a distant supermarket even though they live in food deserts; however, this discussion does not necessarily holds for older Japanese individuals, who substantially reduce the frequency of shopping trips as they age.

during the great recession. They argue that higher-income households reduced the quality of goods purchased for this period and experienced the lower rate of inflation, but they do not focus on differences in the cost-of-living inflation over the life cycle. In addition, Abe and Shiotani (2014) and Diamond, Watanabe, and Watanabe (2018), using scanner data in Japan, analyze differences in prices paid for a given good, but they do not focus on the cost of living.

The remainder of the paper is organized as follows. The next section overviews the data used for the analysis. Section 4.3 reviews the price index proposed by Aguiar and Hurst (2007) and discusses potential problems regarding their methodology. Section 4.4 provides the calculation method of the alternative cost-of-living index, which is empirically examined in Section 4.5. Section 4.6 employs reduced-form analysis and quantifies the impact of increases in the frequency of shopping trips on the cost-of-living index. Finally, Section 4.7 concludes.

4.2 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 a number of supermarkets from April 2011 to October 2014,[3] and products are distinguished based on 13- or 8-digit barcodes called Japanese Article Number (JAN) codes, which are widely used in Japan.[4] More importantly, the dataset includes individual identifiers. To obtain a member's card for each store chain, each individual registers his/her information such as the gender and the date of birth. Because individuals have an incentive to show their member's card when shopping,[5] 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

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

[4] Sales records for unprocessed foods and unclassified products are removed from the sample.

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

Table 4.1: Number of observations for January 2012

Variable	Number of obs.
Stores	349
Individuals	1,238,455
Barcodes	76,626

quantities of each product bought by the same individuals.

To construct the cost-of-living index, this paper uses the data for the period of January 2012 and January 2013. The sample is restricted to individuals aged 20-89, who made purchases at stores in the dataset in both months. Table 4.1 presents the number of stores, individuals, and products (barcodes) observable in the scanner data for January 2012. The table shows that even in a month, purchases of a large number of (approximately 1.2 million) customers are recorded in the sample. This study focuses on the pairs of individuals and stores observable in this period, for which the number of observations is 1,359,982.[6]

Precisely, the data used in this study are store scanner data, which differ from the data analyzed in previous studies such as Aguiar and Hurst (2007), Kaplan and Schulhofer-Wohl (2017), and Diamond, Watanabe, and Watanabe (2018). In these studies, household scanner data have been used. There are both an advantage and a disadvantage to use store scanner data compared to using household scanner data. The advantage is that the number of observable individuals is much larger for store scanner data. As shown in Table 4.1, purchases of about 1 million customers are recorded in the store scanner data, while the household scanner data used in Kaplan and Schulhofer-Wohl (2017) tracks purchases of only 50,000 households. The disadvantage of using store scanner data is that purchases in stores that are not covered in the dataset cannot be observed, while household scanner data can track all purchases of a given household.

[6] The reason for focusing on the pairs of individuals and stores is that Aguiar and Hurst (2007) show that the frequency of shopping trips per store varies over the life cycle, while the number of different stores does not.

Table 4.2: Dispersion of individual-level (household-level) inflation rates

	IDs data	DWW (2018)	KS (2017)
Interquartile range			
Laspeyres	5.17	4.83	7.33
Fisher	5.18	4.87	7.13
Paasche	5.20	5.19	7.37
Tornqvist	5.20	4.78	
90th percentile minus 10th percentile			
Laspeyres	16.25	11.65	15.87
Fisher	16.09	11.91	15.32
Paasche	16.33	13.00	15.83
Tornqvist	16.11	11.41	

Notes: Dispersion of rates of inflation at the individual (household) level is reported. This study, using IDs data for January 2012 and January 2013, report the dispersion of individual-level inflation rates. Diamond, Watanabe, and Watanabe (2018) and Kaplan and Schulhofer-Wohl (2017) report the average of the dispersion of household-level inflation rates, calculated at the quartely frequency.

In Table 4.2, I compare the dispersion of individual-level inflation rates with the counterparts calculated in Kaplan and Schulhofer-Wohl (2017) and Diamond, Watanabe, and Watanabe (2018). While the data used in this study differ from those in previous studies as discussed, the values reported in Table 4.2 are surprisingly similar.

4.3 Previous Method to Calculate the Price Index

This section first reviews the methodology to calculate the individual-level price index proposed by Aguiar and Hurst (2007) and applies this methodology to Japan's data. Second, this section discusses several potential problems about this price index in light of canonical index theories.

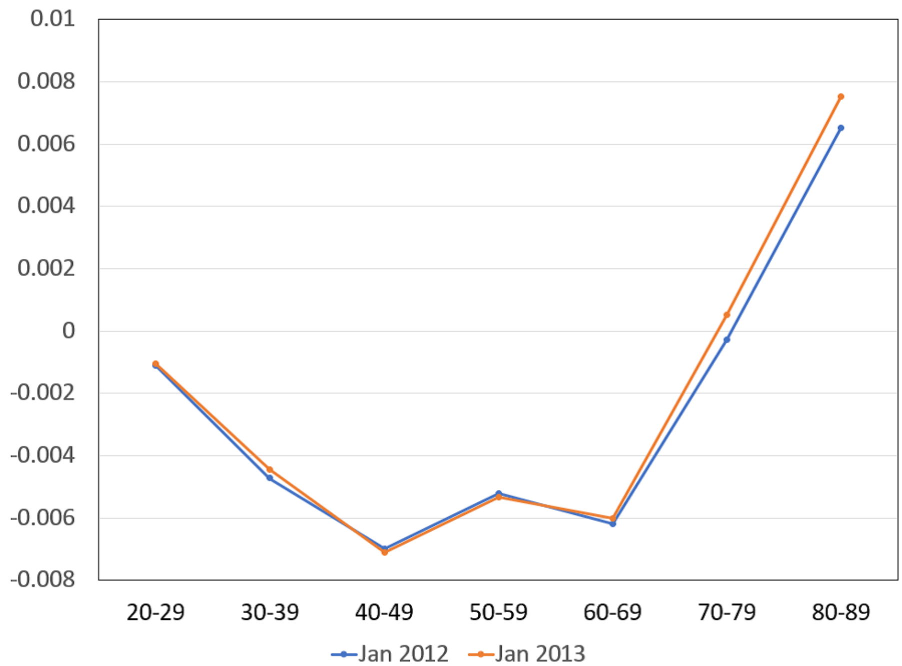

Figure 4.1: Aguiar and Hurst's (2007) price index

Notes: The figure plots Aguiar and Hurst's (2007) price index over the life cycle. The price index is calculated as follows. First, I calculate the individual-level price index following the method proposed by Aguiar and Hurst. Specifically, I calculate the price paid for a certain good by a given individual and the price paid for that good on average, and take the weighted average of these price ratios across goods. Second, I take the logarithm of the price index and take the mean for each age group.

4.3.1 Review and Application of Aguiar and Hurst's (2007) Price Index

To calculate Aguiar and Hurst's price index for a given individual, one needs essentially two prices for each product: the price paid by the individual in question and the average price paid by all individuals. Based on these prices, one can obtain Aguiar and Hurst's price index as the weighted average of the price ratios, with the weight as the expenditure share of each good within the basket of goods purchased by the individual.

Following their methodology, I calculate the price index in January 2012 and January 2013 for each individual based on the scanner data in Japan. I take the logarithm of the individual-level price index and take the mean for each age group, which is shown in Figure

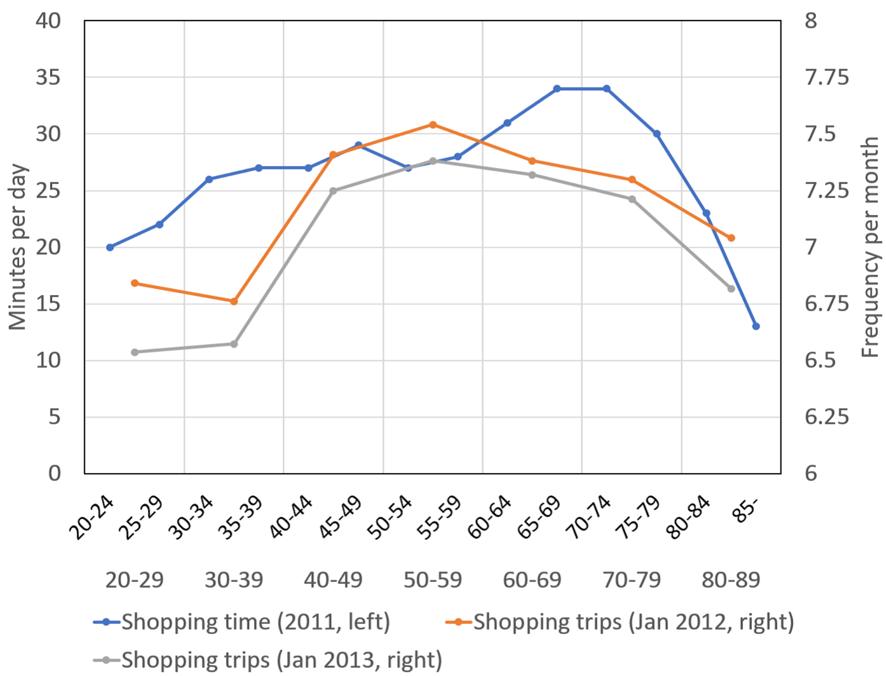

Figure 4.2: Shopping behavior over the life cycle

Notes: Shopping time is measured as the weekly average of time spent on shopping (per day), which is taken from the national survey, "Survey on Time Use and Leisure Activities," conducted by Statistics Bureau, Ministry of Internal Affairs and Communication. Shopping trips are measured as the frequency of transactions between individuals and stores (per month) based on IDs data.

4.1. This figure shows that for working-age individuals (in their 20s to 50s), the price index is slightly decreasing or nearly flat. In contrast, for non-working age individuals (in their 60s to 80s), the price index is clearly increasing.

This finding is inconsistent with the finding obtained by Aguiar and Hurst (2007), who show that older households pay lower prices for identical goods using the U.S. scanner data. There are two possible reasons why the result for Japan is inconsistent with that for the U.S. The first reason is that shopping habits differ across Japan and the U.S. Specifically, it is possible that older Japanese individuals face non-negligible travel costs, so that only high-priced goods are accessible, especially for those who live in "food deserts"—areas with low availability of foods due to the absence of supermarkets.[7] To check this point, Figure

[7]This is in contrast with the circumstances in the U.S. documented by Allcott et al. (2018), who argue

4.2 shows the frequency of shopping trips in each age group. This figure shows that older individuals (especially in their 80s) shop less frequently than middle-age individuals. Figure 4.2 also shows that time spent on shopping for individuals aged over 80 is shorter than the counterparts for younger individuals.[8]

The other reason is that the calculation method of price index proposed by Aguiar and Hurst (2007) fails to capture the effect of retirement on prices paid. The next subsection discusses this point in more detail.

4.3.2 Potential Problems about Aguiar and Hurst's Price Index

Aguiar and Hurst's (2007) methodology to calculate the individual-level price index is simple and straightforward; however, there would be three potential problems regarding their methodology in light of canonical index theories.

First and most strikingly, even though Aguiar and Hurst (2007) compare prices paid for the same good across individuals, there is generally no guarantee that utility from consumption of the same good is equal across different individuals, due to heterogeneity in preferences. This means that the amount saved by taking advantage of discounts for a given good differs across individuals in terms of utility.

Second, while Aguiar and Hurst (2007) use the expenditure share of each good for the individual in question as the weight when calculating their price index, this treatment would mismeasure the cost-of-living index for each individual. Even if we shut our eyes to the first problem, a desirable price index should be based on the expenditure share of both the mean individual as well as the individual in question, as shown by earlier studies such as Sato

that American individuals are willing to travel long distances for shopping.

[8]In fact, shopping time and shopping trips in Figure 4.2 do not perfectly coincide. Specifically, for younger individuals aged 20-39 and older individuals aged 60-79, shopping time is relatively higher than shopping trips. There are two possible reasons for the difference. The first reason is that shopping time is an incomplete measure in that it does not include travel time spent on shopping. The second reason is that shopping time includes time spent on window shopping and online shopping, so that it can differ from the actual frequency of transactions in supermarkets.

(1976), Vertia (1976), and Diewert (1978).

Third, Aguiar and Hurst's (2007) method does not consider the fact that the shopping basket differs across individuals. As Aguiar and Hurst argue that individuals that more frequently visit stores can buy goods at lower prices, it is natural to consider that such individuals can substitute from high-priced goods to low-priced ones more intensively, which would lead to systematic differences in the set of goods purchased.

To address these potential problems regarding Aguiar and Hurst's price index, the next section provides an alternative methodology to measure each individual's cost of living.

4.4 Alternative Method to Calculate the Individual-level Cost-of-Living Index

This part describes how to calculate the cost-of-living index for each individual. To address three potential problems regarding Aguiar and Hurst' (2007) price index discussed above, this study proposes the solution as follows. First, this study constructs the index that focuses on changes in the cost of living over time for a given individual to allow for heterogeneity in preferences across individuals. By comparing the index for individuals that retire between the base period and the current period with the counterpart for other individuals, I can measure the effect of retirement on the cost of living. Second, this study includes the expenditure share of each good for both periods as the weight when calculating the index to correct the weight used by Aguiar and Hurst (2007). Finally, taking the fact that the set of goods purchased changes over time even for a given individual into account, I follow the method proposed by Feenstra (1994)—where the cost function is assumed to be the constant elasticity of substitution (CES) form—and evaluate this effect on the cost of living.[9]

[9] Feenstra's (1994) method has been used in a number of existing studies. For example, Ueda, Watanabe, and Watanabe (2018) apply this method to consider the effect of product turnover on the cost-of-living index, while Argente and Lee (2017) use this method to consider heterogeneity in the perceived quality of

The cost-of-living index can be defined as the minimum cost incurred by each individual to obtain a certain level of utility. Specifically, by imposing the CES functional form, I express the cost-of-living index of individual (or household) h over the changing set of goods as follows:

$$C^h(p^h(t), I_t^h) = \left(\sum_{i \in I_t^h} c_i^h(t) \right)^{1/(1-\sigma)} \tag{4.1}$$

where I_t^h denotes the set of goods consumed by individual h in period t, $c_i^h(t)$ represents the inverse of individual h's cost for good i in period t, which can be written as follows.

$$c_i^h(t) = b_i^h p_i^h(t)^{1-\sigma}, \tag{4.2}$$

where $p_i^h(t)$ denotes the price paid by individual h to purchase good i in period t, $p^h(t)$ is the correspoding vector, σ represents the elasticitiy of substitution which is assumed to be common across individuals. In addition, b_i^h expresses the quality of good i perceived by individual h, which is constant over time.

The CES functional form is useful in that it provides the following formula:

$$\frac{p_i^h(t) q_i^h(t)}{\sum_{j \in I_t^h} p_j^h(t) q_j^h(t)} = \frac{c_i^h(t)}{\sum_{j \in I_t^h} c_j^h(t)}, \tag{4.3}$$

where $q_i^h(t)$ denotes the quantity of good i purchased by individual h in period t. See Ueda, Watanabe, and Watanabe (2018) for the proof. In the scanner data used in this study, both the price and quantity purchased by each individual are observable, so that the left hand side of Equation (4.3) can be calculated.

Then, I can calculate a change in the cost-of-living index of individual h from period $t-1$

---

each product across income groups.

to t in the same way as in Feenstra (1994):

$$
\begin{aligned}
\frac{C^h(p^h(t), I_t^h)}{C^h(p^h(t-1), I_{t-1}^h)} &= \frac{\left[\sum_{i \in I_t^h} c_i^h(t)\right]^{1/(1-\sigma)}}{\left[\sum_{i \in I_{t-1}^h} c_i^h(t-1)\right]^{1/(1-\sigma)}} \\
= & \left[\frac{\sum_{i \in I_t^h} c_i^h(t)}{\sum_{i \in I_{t-1}^h \cap I_t^h} c_i^h(t)} \times \frac{\sum_{i \in I_{t-1}^h \cap I_t^h} c_i^h(t)}{\sum_{i \in I_{t-1}^h \cap I_t^h} c_i^h(t-1)} \times \frac{\sum_{i \in I_{t-1}^h \cap I_t^h} c_i^h(t-1)}{\sum_{i \in I_{t-1}^h} c_i^h(t-1)}\right]^{1/(1-\sigma)} \\
= & \left[\frac{\sum_{i \in I_t^h} p_i^h(t) q_i^h(t)}{\sum_{i \in I_{t-1}^h \cap I_t^h} p_i^h(t) q_i^h(t)} \times \frac{\sum_{i \in I_{t-1}^h \cap I_t^h} c_i^h(t)}{\sum_{i \in I_{t-1}^h \cap I_t^h} c_i^h(t-1)} \times \frac{\sum_{i \in I_{t-1}^h \cap I_t^h} p_i^h(t-1) q_i^h(t-1)}{\sum_{i \in I_{t-1}^h} p_i^h(t-1) q_i^h(t-1)}\right]^{1/(1-\sigma)} \quad (4.4)
\end{aligned}
$$

In this expression, the second term in Equation (4.4) calculates the change in c_i in the common set $I_{t-1}^h \cap I_t^h$, which is called the *matched sample*. Given that the quality of good i, b_i^h, does not change over time, this term can be obtained as follows.

$$
\left[\frac{\sum_{i \in I_{t-1}^h \cap I_t^h} c_i^h(t)}{\sum_{i \in I_{t-1}^h \cap I_t^h} c_i^h(t-1)}\right]^{1/(1-\sigma)} = \prod_{i \in I_{t-1}^h \cap I_t^h} \left(\frac{p_i^h(t)}{p_i^h(t-1)}\right)^{\omega_i^h(t)}, \quad (4.5)
$$

where the weight $\omega_i^h(t)$ is expressed as

$$
\omega_i^h(t) = \left(\frac{p_i^h(t-1) q_i^h(t-1)}{\sum_{j \in I_{t-1}^h \cap I_t^h} p_j^h(t-1) q_j^h(t-1)} + \frac{p_i^h(t) q_i^h(t)}{\sum_{j \in I_{t-1}^h \cap I_t^h} p_j^h(t) q_j^h(t)}\right) / 2, \quad (4.6)
$$

which is called the Tornqvist weight. As suggested by Diewert (1978), this weight tracks changes in the true cost-of-living index at the second order approximation.

The first and third terms in Equation (4.4) capture the effect of product entry and exit in individual h's choice set, respectively, on her cost-of-living index. Since the shopping basket of each individual varies over time, this formulation makes it possible to understand how substitution across goods affects the cost-of-living index of each individual.

4.5 Applications of the Individual-level Cost-of-Living Index

This section applies the method described in the previous section to Japan's scanner data to solve the three problems regarding Aguiar and Hurst's (2007) price index step by step. The first part modifies the weight only and compares the cost-of-living index across age groups. The second part, allowing for heterogeneity in preferences across individuals, compares the cost-of-living inflation across age groups. The third part, taking the intertemporal variation in the set of goods purchased by each individual into account, calculates the cost-of-living inflation based on Feenstra's (1994) method.

4.5.1 The Cost-of-Living Index across Age Groups

As the first step, this part calculates the cost-of-living index for each individual, using the weight described by Equation (4.6) to address the problem regarding the weight used in Aguiar and Hurst's (2007) price index. Based on the new weight, the cost-of-living index for the matched sample for the base period and current period can be calculated as the denominator and numerator in the right hand side of Equation (4.5), respectively.

By applying this calculation method to scanner data for January 2012 and January 2013, I obtain the cost-of-living index for these periods. The result is shown in Figure 4.3, where I take the mean of the individual-level index (in logarithm) for each age group. This figure shows that for working-age individuals (in their 20s-50s), the cost-of-living index is increasing. At the same time, for non-working age individuals (in their 60s-80s), the cost-of-price index is almost flat.

The result shown in Figure 4.3 is similar to that in Figure 4.1, in that both suggest that older (retired) Japanese individuals face higher prices, while these results differ in the location of the increasing slope. This means that in spite of the correction of the weight, the

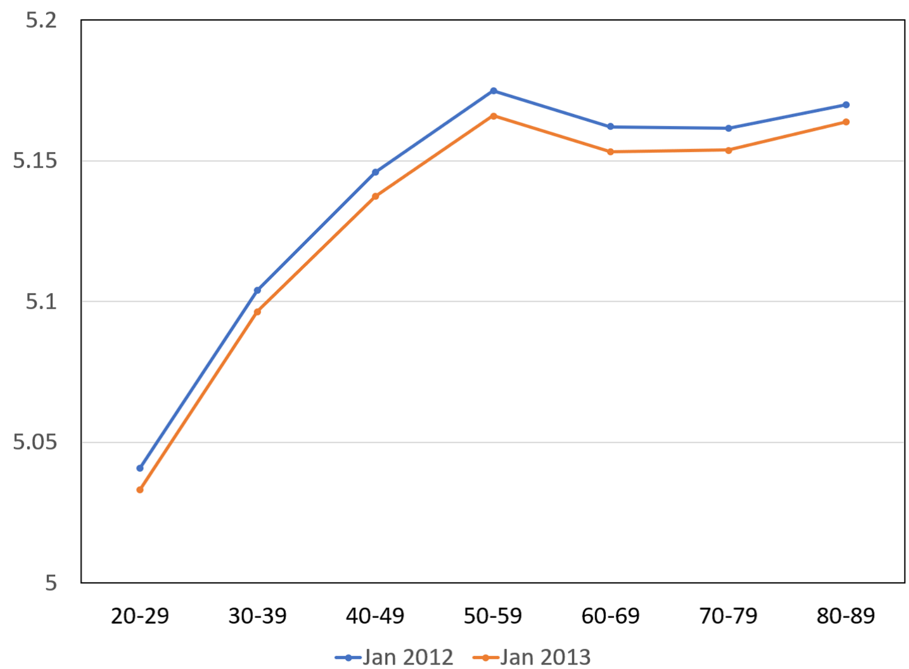

Figure 4.3: The cost-of-living indexes based on the matched sample

Notes: The figure plots the cost-of-living index over the life cycle. The cost-of-living index is calculated as follows. First, I calculate the individual-level index following the method described by the numerator and denominator in the right hand side of Equation (4.5). That is, I calculate the weighted average of the price paid for each good in January 2013 and January 2012. Second, in each month, I take the logarithm of the index and take the mean for each age group.

cost-of-living index does not precisely reflect the effect of retirement. I therefore move to the next unresolved problem, heterogeneity in preferences across individuals.

4.5.2 The Cost-of-Living Inflation across Age Groups

As the second step, this part allows for differences in utility from consumption of a given good across individuals. To do so, this part calculates the cost-of-living inflation—rather than index itself—from January 2012 to January 2013, which corresponds to Equation (4.5).

Why do we focus on the "inflation" rather than the "level" of the cost-of-living index? The reason is that inflation rates can measure the effect of retirement allowing for heterogeneity in preferences across individuals. Individuals will be splitted into two groups over time: those

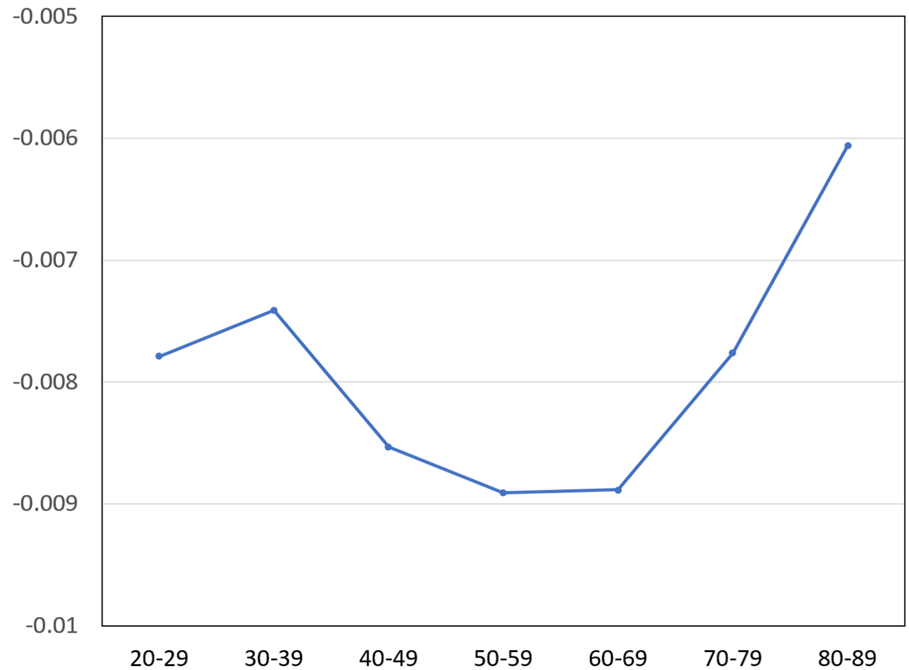

Figure 4.4: The cost-of-living inflation based on the matched sample

Notes: The figure plots the cost-of-living inflation based on the matched sample from January 2012 to January 2013 over the life cycle. The cost-of-living inflation is calculated as follows. First, I calculate the individual-level inflation rates following the method described by Equation (4.5). Second, I take the logarithm of the inflation rates and take the mean for each age group.

who retire during this period and those who do not. Inflation rates of the former group reflect the effect of retirement, while inflation rates of the latter group do not, so that the difference between these rates are meaningful. Crucially, these inflation rates are calculated at the individual level, meaning that heterogeneity in preferences across individuals does not play a role, while preferences of each individual are assumed be time-invariant.

The cost-of-living inflation over the life cycle is shown in Figure 4.4. As discussed, this figure shows the inflation rates rather than the level of the cost-of-living index, so that one needs to interpret the result more carefully. In this figure, the effect of retirement is included in the inflation rates faced by individuals around the retirement age (in their 60s), since the fraction of retired individuals increases as time passes. On the other hand, the inflation rates faced by working-age individuals (in their 20s to 50s) do not include such effects. Given this, we can observe that individuals around the retirement age experience the lower rate of inflation than younger individuals (especially in their 20s and 30s). This result is in contrast with that displayed in Figure 4.3, where retired individuals pay higher prices than younger individuals in terms of the cost of living. However, the inflation rate of 60s is almost the same as that of middle-age individuals, indicating that inflation rates based on the matched sample might not be ideal, since each individual changes the set of goods purchased over time. This issue will be discussed in the next subsection.

4.5.3 The Cost-of-Living Inflation with Shopping Basket Changes

As the final step, this part calculates the cost-of-living inflation for each individual based on the method proposed by Feenstra (1994), which captures the effect of intertemporal variation in the shopping basket. This effect may be important especially for Japan, because as noted by Ueda, Watanabe, and Watanabe (2018), the rate of product entry and exit is higher in Japan than that in the U.S., suggesting that individuals in Japan may be more accustomed to substitute across similar goods to lower the cost of living.

When applying Feenstra's (1994) method, there are two possible interpretations regarding the set of goods purchased by each individual. The first interpretation is that the set of goods purchased is equal to the choice set. This is consistent with the discussion by Feenstra that when the cost function is assumed to be the CES form, zero consumption of a good corresponds to the infinite price of that good, so that this good is not available. The other interpretation is that the shopping basket is only the subset of the choice set, meaning that goods that are not purchased can be included in the choice set. This can happen when not imposing the CES functional form. While both interpretations have advantages and disadvantages, under the latter interpretation the true choice set of each individual cannot be observed, so that this study adopts the former interpretation and calculates the cost-of-living inflation. This means that the choice set of each individual changes over time—that

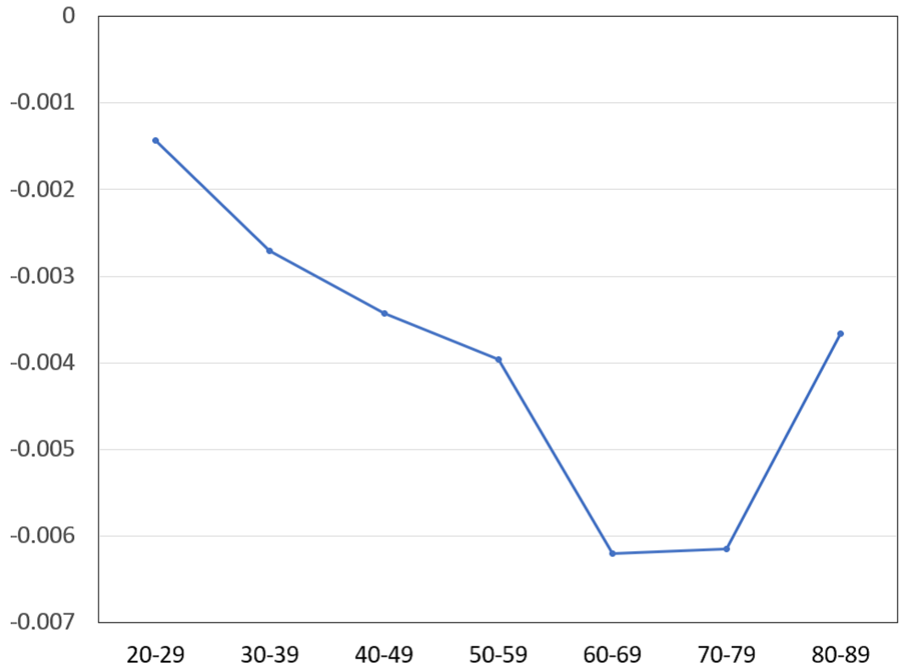

Figure 4.5: The cost-of-living inflation with shopping basket changes

Notes: The figure plots the cost-of-living inflation with shopping basket changes from January 2012 to January 2013 over the life cycle. The cost-of-living inflation is calculated as follows. First, I calculate the individual-level inflation rates following the method described by Equation (4.4). Second, I take the logarithm of the inflation rates and take the mean for each age group.

is, each individual *finds* new goods as time passes.[10]

Feenstra's (1994) calculation method is described as Equation (4.4), where the elasticity of substitution is set as $\sigma = 11.5$.[11] Following this method, the cost-of-living inflation for each individual is calculated and the mean is taken for each each age group, which is shown in Figure 4.5. This figure shows that for individuals around the retirement age (in their 60s), the cost-of-living inflation with shopping basket changes is clearly lower than that for working-age individuals (in their 20s to 50s). Compared to the result in Figure 4.4, the difference between the inflation rates for 60s and younger individuals is large. This suggests

[10] Precisely, the set of goods purchased by each individual can vary due to suppliers' behavior as well. Specifically, stores would change what they sell due to inventory control or product creation and destruction. To eliminate such effects, the products analyzed in this part are restricted to those that exist in each store over time.

[11] This number is based on the estimate of Broda and Weinstein (2010).

that individuals who have retired substitute across goods, rather than searching for a given good with lower prices to reduce the cost of living.[12]

4.6 Reduced Form Analysis

This section estimates the effect of retirement on the cost-of-living inflation based on reduced-form analysis. Specifically, following the price function estimation conducted by Aguiar and Hurst (2007), this section quantifies the effect of changes in the frequency of shopping trips on the cost-of-living inflation at the individual level. Figure 4.6 shows the log rate of change in the frequency of shopping trips from January 2012 to January 2013 (taking the mean for each age group). It is evident that the rate of change for individuals aged around 65 is higher than the counterpart rates for working-age individuals, while these rates are overall slightly negative.[13] This observation suggests that individuals aged around 65 are more likely to retire, so that they can increase time for shopping.

The regression equation looks as follows:

$$\ln \pi_h = \beta_0 + \beta_s \ln \left(\frac{s_h^{2013}}{s_h^{2012}} \right) + \sum_{k=1}^{K} \beta_k X_{k,h} + \epsilon_h, \tag{4.7}$$

where π_h denotes the cost-of-living inflation over a year for individual h. Both the inflation rates for the matched sample as well as those with shopping basket changes are used. s_h^y denotes the frequency of shopping trips of individual h during January of year y, and X_k denotes the kth variable that controls for shopping needs, which includes the number of barcodes purchased and the number of product categories, following Aguiar and Hurst (2007).

[12]To check the robustness of the results obtained in this section, I calculate the individual-level inflation rates from February 2012 to February 2013 as well. The main finding that individuals around the retirement age experience the lower rate of inflation than working-age individuals is unaffected.

[13]There are two possible reasons for why the overall rate of change in the frequency of shopping trips is negative. The first reason is that macroeconomic conditions changed for this period, so that individuals reduced their shopping frequency across the board. The other reason is that observing the fixed pairs of individuals and supermarkets results in the decline in the measured frequency of shopping trips.

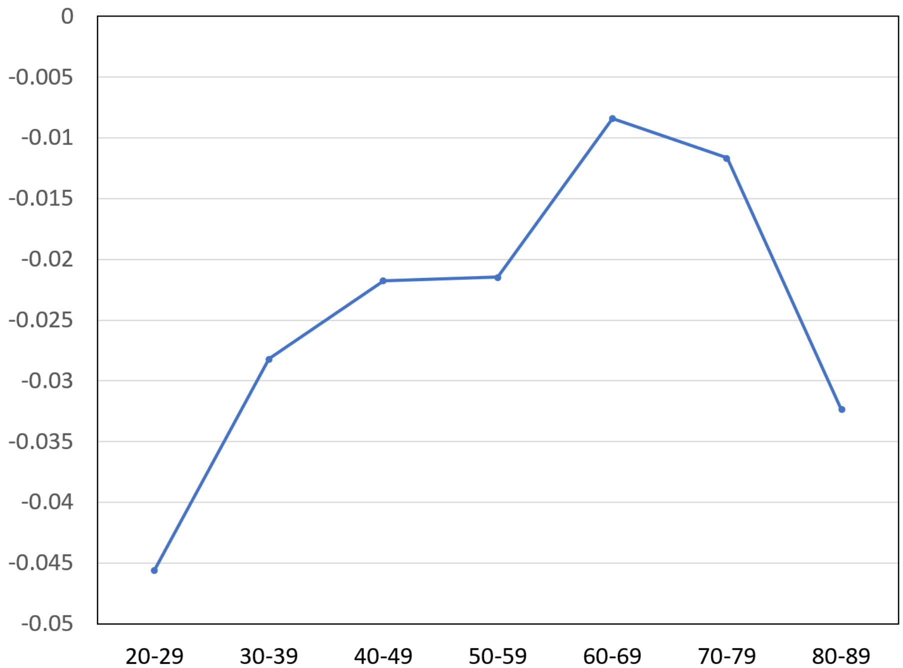

Figure 4.6: Changes in the frequency of shopping trips

Note: The figure plots the log rate of change in the freqency of shopping trips from January 2012 to January 2013 for each age group.

The regression results are shown in Table 4.3. Columns (1) and (3) show that increases in the frequency of shopping trips lower the rate of inflation, and that the impact is larger for the inflation rates with shopping basket changes. However, as discussed by Aguiar and Hurst, the OLS regression might have endogeneity problems. Columns (2) and (4) thus use seven age-category dummies as the instrument set and estimate the impact of changes in the frequency of shopping trips on inflation rates. These columns show that doubling the frequency of shopping trips lowers the inflation rates by 3 to 14 percent, which is comparable to Aguiar and Hurst's (2007) estimates of 7 to 19 percent.

Table 4.3: The elasticity of inflation rates with respect to shopping trips

	(1)	(2)	(3)	(4)
Estimated elasticity: β_s	-0.001	-0.034	-0.068	-0.135
	(0.000)	(0.010)	(0.000)	(0.013)
Shopping basket changes	No	No	Yes	Yes
Regression type	OLS	IV	OLS	IV
Instrument set	None	Age dummies	None	Age dummies

Notes: The results of regression of log inflation rates on log changes in shopping trips and controls for individual shopping needs are reported. For all columns, the estimated coefficient is statistically significant at the 1 percent level. The controls for shopping needs are the number of products and the number of product categories purchased. The F-statistic on the first stage for the instrument set in columns (2) and (4) is 414.5. The number of observations is 807,540.

4.7 Conclusion

This paper quantitatively evaluated the impact of the differences in prices paid and the expenditure share for each good on the cost-of-living index over the life cycle. This paper showed that older individuals, especially in their 70s and 80s, pay higher prices for identical goods, which is inconsistent with the finding by Aguair and Hurst (2007). To focus on the difference in expenditure shares across age groups, this paper calculated two inflation rates: one based on the matched sample, one with shopping basket changes. These inflation rates are lower for individuals around the retirement age than other age groups, suggesting that Japanese individuals who have retired save the cost of living by substituting across similar goods.

The analyses in this paper have at least two limitations. First, the sample period analyzed is limited, although the number of individuals is large. It is thus necessary to confirm that the main findings of the paper are robust to changes in the sample period. Second, focusing on individuals' shopping behavior in more detail should be useful. Specifically, focusing on whether individuals visit stores during daytime could be helpful to verify they have retired or not. This extention needs to be done in future work.

Chapter 5

Policy Shocks and Expectations: Japan's Experience during the Great Depression

This chapter is an English translation of the study originally written in Japanese, which was published in The Economic Review (Keizai Kenkyu) Vol. 68 No. 1 in January 2017. I would like to thank Masanao Itoh, Michihiro Kandori, Etsuro Shioji, Masato Shizume, Tomoyoshi Yabu, Yoshihiro Yajima, and Tsutomu Watanabe for helpful comments and recommendations of useful studies.

Abstract

The Japanese government implemented various policies in the early 1930s to deal with the economic downturn due to the Great Depression. To examine the impact of these policies on expectations about nominal interest rates and inflation, this study analyzes yield curves and forward rate curves and conducts event studies, using monthly and daily Japanese government bond yields estimated by the Nelson-Siegel model. The main findings of the paper are as follows. First, all of announcement, news, and implementation of JGB underwriting by the Bank of Japan had no effect of raising inflation expectations. Moreover, nominal interest rates declined in response to the announcement. Second, market participants anticipated Japan's withdrawal from the gold standard and the subsequent yen depreciation when Britain abandoned the gold standard in September 1931, which brought a jump in expectations of interest rates. Third, fiscal shocks raised expectations of interest rates, however, the effect was relatively small and not robust.

JEL codes: E31, E52

Keywords: The Great Depression, inflation expectations, fiscal and monetary policies by Korekiyo Takahashi, event study

5.1 Introduction

The purpose of this paper is to examine what kind of policies contributed to rises in expectations about future nominal interest rates and inflation rates, when Japan dealt with the deflationary period after 1929. The fact that the United States experienced the Great Depression in October 1929 as well as that Japan readopted the gold standard in January 1930 brought a sharp decline in the price level. However, Figure 5.1 shows that wholesale prices started to increase after 1931, and that retail prices stopped to decrease as well. In existing studies, the recovery of the Japanese economy has been regarded as the result of policy measures adopted by Minister of Finance Korekiyo Takahashi, who was appointed in December 1931 when the Rikken Seiyuukai Party cabinet was formed (e.g., Nakamura, 1994; Ide, 2006). Takahashi's policies were wide-ranging, including fiscal expansion, such as additional spending on infrastructure projects, a low interest rate policy, and abandoning the gold standard. Specifically, the depreciation of the yen after Japan's withdrawal from the gold standard was as high as 40 percent against the dollar and sterling, which contributed significantly to the recovery of the international competitiveness of the Japanese industry (see Figure 5.2), while the Manchurian Incident in September 1931 led to the expansion in military budget. It is important to investigate which of these factors contributed to the recovery of the Japanese economy.

Many studies focusing on the early 1930s have worked on interpreting historical documents, which is a standard way in economic history (Itou, 1989; Shizume, 2001). In contrast, this study uses econometric methods to quantitatively examine the effects of the policies, which is another way used in existing studies.[1] For example, Cecchetti (1992) applies econometric methods in a time-series analysis to a range of macroeconomic variables to find that deflation was anticipated in the United States before the Great Depression. However, Hamil-

[1] A survey of research using quantitative analysis methods relating to the Japanese economy before WWII identified studies by Harada and Sato (2012) and Umeda (2006).

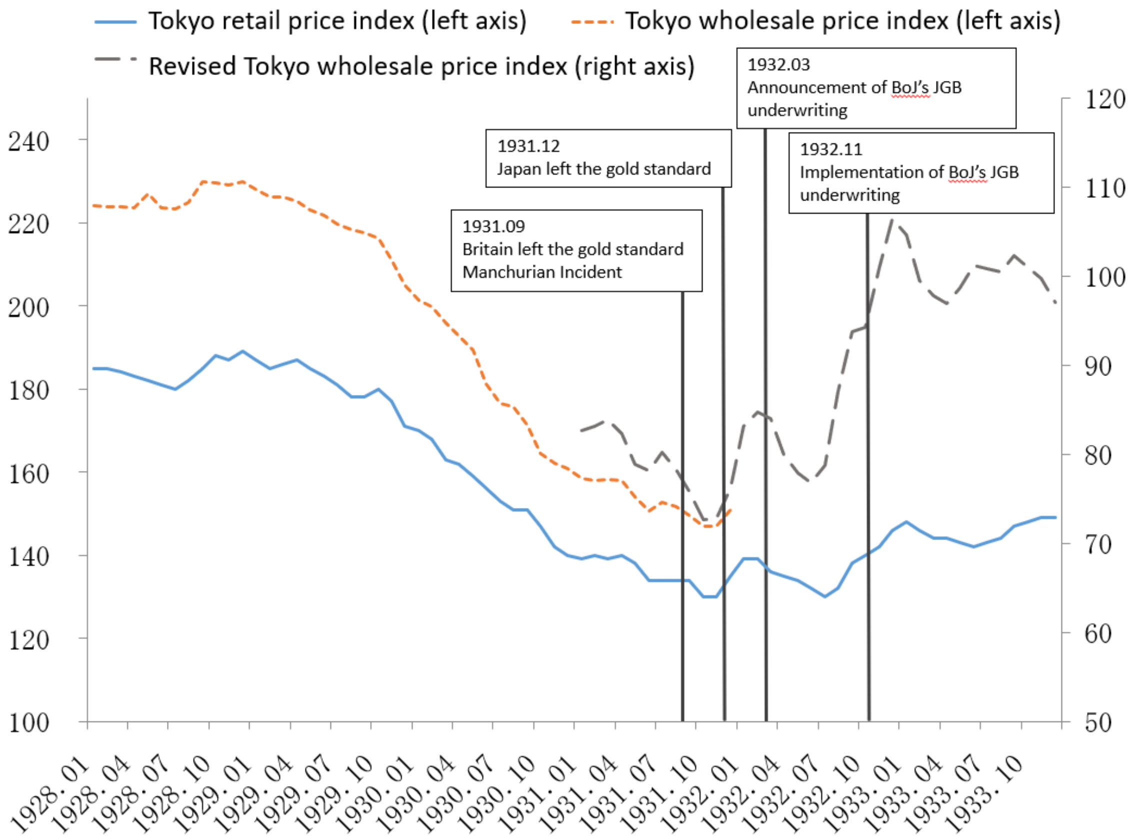

Figure 5.1: Price indexes

Source: Compiled by the Institute for Monetary and Economic Studies, Bank of Japan, and historical and commodity price statistics.
Tokyo retail price index base period: July 1914 = 100
Tokyo wholesale price index base period: October 1900 = 100
Revised Tokyo wholesale price index base period: 1933 = 100

ton (1992), using commodity futures prices, shows that deflation was not anticipated in the first half of the Depression, while it was anticipated in the second half.

As an example of existing studies focusing on the Japanese economy, Iida and Okada (2004) extend the method of Cecchetti (1992) to estimate inflation expectations and find significant rises in September 1931 and April 1932. They argue that the former coincided with Britain's withdrawal from the gold standard and the latter with the announcement of Japanese government bond (JGB) underwriting by the Bank of Japan (BoJ), allowing us to conclude that these policies were effective. However, Shizume (2009) employs the

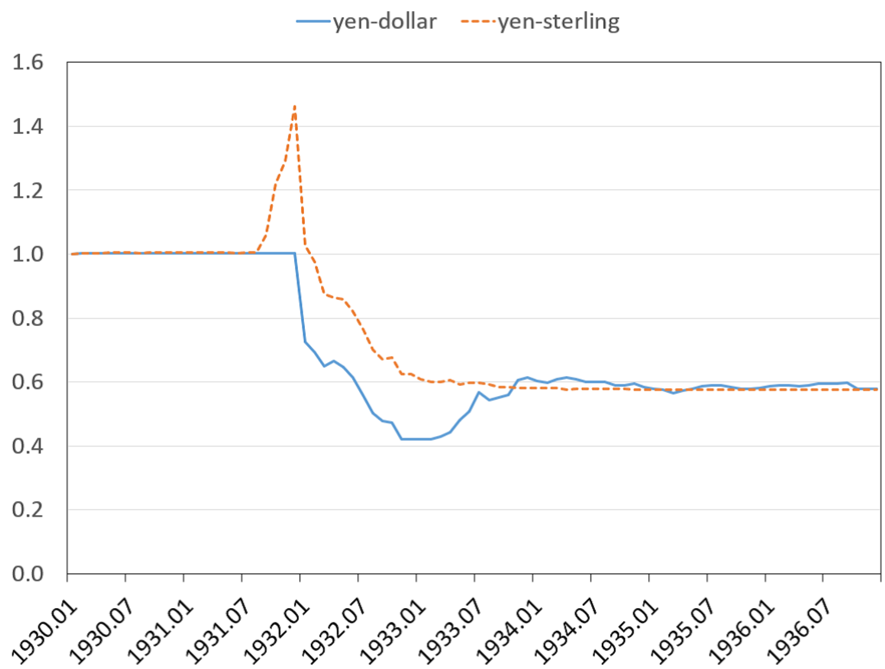

Figure 5.2: Standardized foreign exchange rates

Source: Compiled by the Institute for Monetary and Economic Studies, Bank of Japan, and historical and financial market-related statistics.
Base period: January 1930 = 1

principle component analysis of JGB yields and analysis based on commodity futures prices to show that inflation expectations were raised from the fall of 1931 until the end of the year, before receding in 1932. The conclusions of these studies are thus the same for 1931 but different for 1932, indicating that the consensus has not been built on the effectiveness of JGB underwriting by the BoJ (a form of monetary easing).[2]

Compared to these existing studies, this study has two notable features to estimate the effect of policies on expectations. First, I use JGB price data to construct time-series data for the risk-free interest rate, while Iida and Okada (2004) use interest rates that were probably subject to the risk premium. Second, I analyze both monthly and daily interest rate data, while Shizume (2009) use monthly data only. Daily data enable us to pick up high-frequency

[2]In addition, Naitou (2010) conducts a positive analysis by using monthly data for a variety of interest rates and finds no Fisher effect in the 1930s.

changes in interest rates based on the event study approach, while monthly data make it possible to visually note important changes in interest rates and inflation expectations.

The results obtained in this study are threefold. First, all of the announcement, news, and implementation of JGB underwriting by the BoJ had no effect of raising inflation expectations. Moreover, nominal interest rates declined in response to the announcement. Second, the abandonment of the gold standard by Britain and Japan (and the forecasts of such actions) caused significant expectations of higher interest rates. Third, decisions or statements about fiscal expansion led to expectations of higher interest rates. The second finding is consistent with the findings by Iida and Okada (2004) and Shizume (2009), whereas the first is inconsistent with Iida and Okada (2004) and is taken as supporting the result that was only conjectured by Shizume (2009). The third finding is less robust than the first two; however, it points out an effect not suggested in earlier studies.[3]

The remainder of this paper is organized as follows. Section 5.2 describes the data and interest rate calculation methods used in this study. Section 5.3 uses monthly data to visually present, and interpret, changes in the shape of the yield curve and forward rate curve. Section 5.4 uses daily data to conduct event studies that present the impact of the various policies more clearly. Section 5.5 concludes.

5.2 Background

This section contains three parts. The first part presents the price data used in this study and describes the interest rate calculation methods. The second part reviews the economic climate at the beginning of the 1930s as well as relevant policies and events. The final part compares the characteristics of the JGB yield indicator used in this study with that of the interest rate indicators adopted in previous studies to explain why the JGB yield is useful.

[3]While Okura and Teranishi (1994), Cha (2003), and Umeda (2006) find that fiscal expansion is effective, they barely discuss the relationship with expectations.

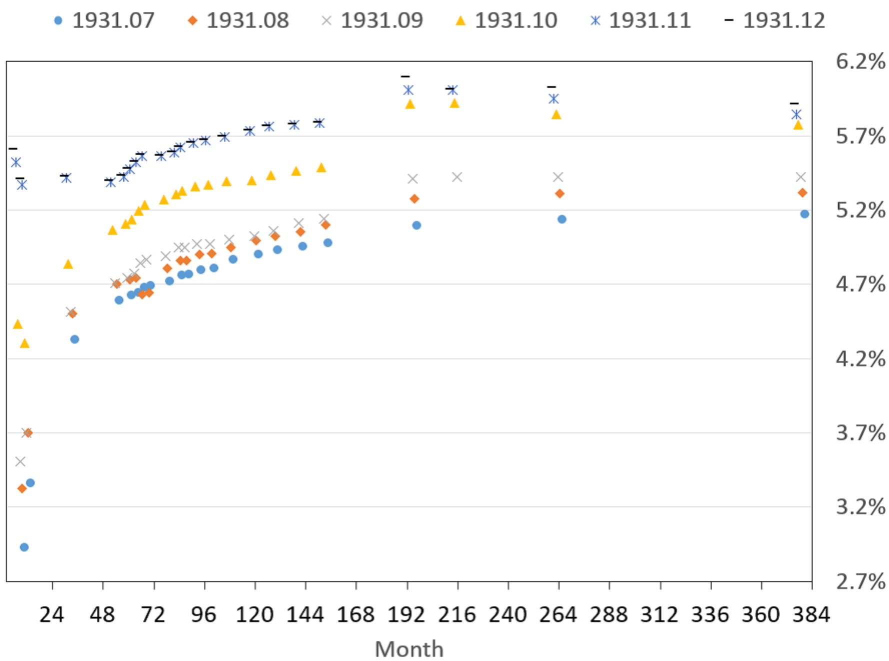

Figure 5.3: Examples of the calculated interest rates (horizontal axis: time until maturity)

5.2.1 Interest Rate Data and Calculation Methods

The data used in this study are monthly data for average JGB transaction prices found in the "Kokusai toukei nenpou (JGB statistics annual report)" published by the Financial Bureau of the Ministry of Finance and daily data for JGB indicative prices (as of midday) in the Tokyo Stock Exchange JGB daily market report issued by the Tokyo Stock Exchange. Among the bonds in these documents, the Ko-Go Five Percent Loan Bond and the Five Percent Exchequer Note (domestic bonds with coupon rates of 5 percent) were chosen, and their JGB yields were calculated.[4] However, concern about insufficient arbitrage gave rise to questions about the reliability of price data within two months of the redemption date, so that such data were excluded from the sample.

Specifically, the interest rate $R_{t,n}$ was calculated so that it satisfied Equations (5.1) and

[4]Obvious mistakes in the price data were corrected as far as possible.

(5.2):[5]

$$P_{t,n} = \sum_{j=t}^{n} \frac{CF_j}{(1+R_{t,n})^{\frac{j-t}{12}}} \tag{5.1}$$

$$P_{t,n} = \sum_{j=t}^{n} \frac{CF_j}{(1+R_{t,n})^{\frac{j-t}{360}}} \tag{5.2}$$

Here, $R_{t,n}$ is the annual yield to maturity in period t, $P_{t,n}$ the JGB transaction price or indicative price in period t, CF_j the cashflow in period j, and n maturity ($n \geq j$). In Equation (1), t, j, n are shown monthly and, in Equation (2), daily. Strictly speaking, in addition to Equations (5.1) and (5.2), it is necessary to take account of the number of days between delivery and first interest payment (accrued interest). However, the mathematical expression of this is cumbersome and thus it has been omitted. These interest rates correspond to spot rates. Figure 5.3 shows an example of interest rates calculated from monthly data with time until maturity on the horizontal axis, highlighting that these interest rates can fluctuate significantly on a monthly basis.

5.2.2 Overview of the Economic Policies and Events in the Early 1930s

Next, referring to reports on the domestic economy in Ginkou tsuushin roku, a banking industry journal available at that time, Table 5.1 shows the policies and events at the beginning of the 1930s (the major items are also shown in Figure 5.1). Severe deflation continued until the middle of 1931, during which time the gold standard was maintained under the Minseito Party cabinet. However, in September of that year, Britain abandoned the gold standard and the Manchurian Incident occurred, which had a large impact on the economic environment. In December, under the new Seiyuukai cabinet, Minister of Finance Takahashi

[5] For the calculation, the “Yield” function in Excel was used.

decided to abandon the gold standard, which instantly weakened the yen. Alongside making decisions and statements from December 1931 until the summer of 1932 about a budget bill incorporating additional spending on infrastructure projects and the cost of dealing with the Manchurian Incident, Takahashi also continued to make comments related to the JGB underwriting by the BoJ or the Deposit Section of the Ministry of Finance as a method of procuring the necessary funds as well as pursued a low interest rate strategy. Regarding the JGB underwriting by the BoJ, there was an initial statement in March 1932, followed by news reports related to concrete figures for the amount of the underwriting and the coupon, and actual implementation on November 25. In addition, a report by the Lytton Commission, set up in response to concern in the international community over the interests of Manchukuo, was published in October 1932 and attracted a great deal of attention. As a result of these various factors, Japanese deflation was rapidly eliminated and, from 1932, there was an underlying inflationary trend.

Table 5.1: Policies and events at the beginning of the 1930s

Policy decisions, events	Date	Brief description
Manchurian Incident	1931.9.18	10.30 pm, South Manchurian Railway explosion, exchange of fire
Britain abandons the gold standard	1931.9.21	The British cabinet announces the suspension of the gold standard
Gold standard political statement (1)	1931.10.3	Minister of Finance Junnosuke Inoue discusses the easing of finance
Gold standard political statement (2)	1931.10.10	Meeting of political and business leaders
		Junnosuke Inoue makes a statement defending the gold standard
Gold standard political statement (3)	1931.11.6	Agreement related to defending the gold standard
Gold standard political statement (4)	1931.11.10	Rikken Seiyuukai resolves to ban gold exports
Japan abandons the gold standard	1931.12.13	The Minister of Finance decides to ban gold exports again
Decision on fiscal expansion	1931.12.27	Cabinet decides 1932 financial year budget
Announcement of the BoJ JGB underwriting	1932.3.9	Discussion forum on current topics
Interest rate cut (1)	1932.3.11	The BoJ announces policy interest rate cuts
Decision on fiscal expansion (2)	1932.3.12	Proclamation of previous financial year budget implementation
Fiscal expansion statement (1)	1932.6.3	Takahashi decides to expand fiscal spending
Interest rate cut (2)	1932.6.7	Same as Interest rate cut (1)
Interest rate cut (3)	1932.8.17	Same as Interest rate cut (2)
Fiscal expansion statement (2)	1932.8.25	Same as Fiscal expansion statement (1)
Lytton Commission report	1932.10.2	Lytton Commission report published at 9 p.m.
Implementation of the BoJ JGB underwriting	1932.11.26	Ministry of Finance notification of JGB underwriting by the BoJ

5.2.3 Comparison of Interest Rate Data in This Study and Existing Studies

Besides the BoJ's lending rate (the so-called official discount rate) and private-sector banks' operational rates (term loan, bill discount, and call rates), available indicators of interest rates at that time included the deposit rate and the yield on marketable securities.[6] Iida and Okada (2004) and Hamori and Hamori (2000) use the term loan rate; however, this interest rate is associated with loans to private sectors and may reflect credit risks, making it particularly unsuitable for arguments involving expectations. Further, regarding call rates, interbank agreements make it difficult to view these as rates determined purely by the market (Oshima, 1936). For such reasons, it is desirable to use JGB yields. In the present study, the same calculation method as that used in Shizume (2009) is adopted. However, Shizume (2009) uses only monthly data, whereas this study aims to handle monthly and daily data at the same time.

5.3 Monthly Data Analysis

This section constructs yield curves and forward rate curves by applying the model proposed by Nelson and Siegel (1987) to monthly JGB yield data, allowing us to visually observe changes in interest rates (See Appendix for the detailed description of Nelson-Siegel model). In addition, this section provides interpretations of the movement of the curves based on the policies and events at that time.

First, the upper and lower panels of Figure 5.4 show changes in yield curves based on calculations of the spot rate from September 1931 to December 1931 and from February 1932 to April 1932, respectively. Notable increases in long-term interest rates are observable in October 1931 and in short-term interest rates a month later (increases up to 0.40 and

[6] On this point, see Shizume (2009).

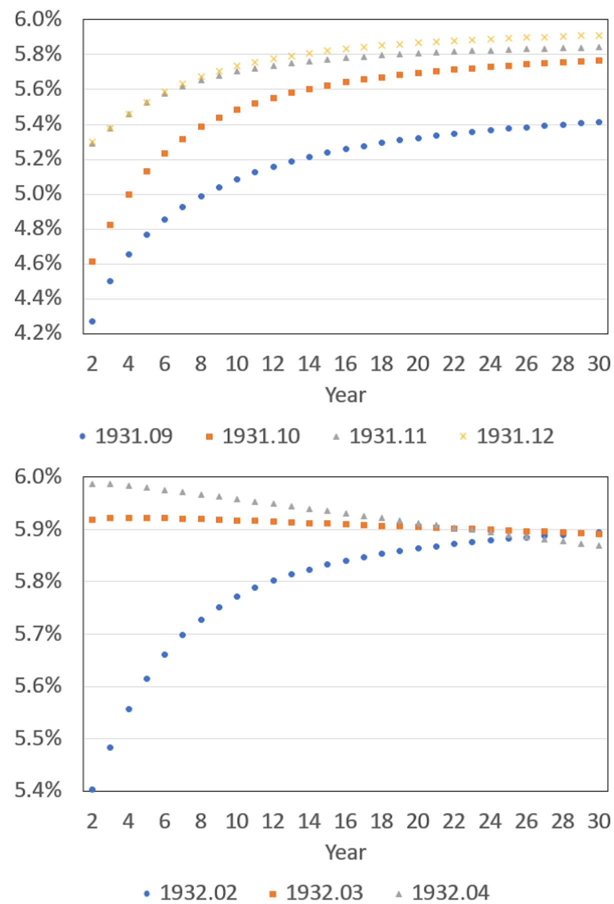

Figure 5.4: Spot rate values estimated (horizontal axis: time until maturity)

0.68 percentage points, respectively). Thereafter, an increase in short-term interest rates is observable in March 1932 (up to 0.51 percentage points) and the yield curve is almost flat.

Understanding the spot rate is intuitive because it directly corresponds to JGB prices. However, this interest rate is never more than the average rate until maturity, so that care needs to be taken. For example, the 10-year rate is the average expected rate of return when staying invested in a certain security for 10 years, and we could fail to identify any change in expectation that may occur at a specific time within that 10-year period (Svensson, 1995).

To address this issue, the panels of Figure 5.5 show the forward rates for one year n years ahead, based on the spot rates calculated above (only when $n \geq 2$). These rates include

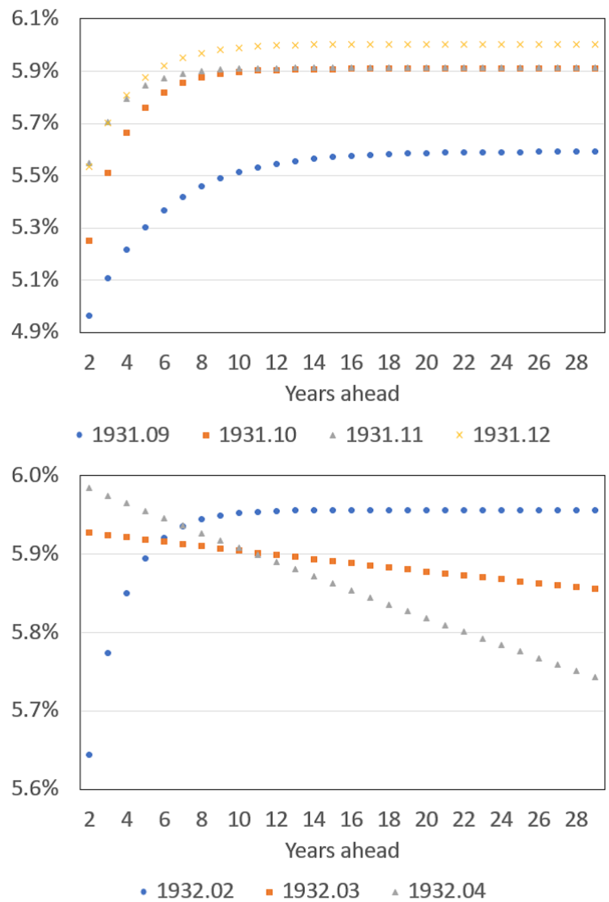

Figure 5.5: Forward rate values estimated (horizontal axis: n years ahead)

expectations of the rate of return in the year that starts n years ahead while excluding expectations of interest rate movements over the period of n years, enabling us to more accurately observe expectations. This figure shows, first, a notable rise (up to 0.46 percentage points) in October 1931 in the relatively long-term four-year forward rates, followed by a rise (up to 0.30 percentage points) in the short-term two- or three-year forward rates in November. These results are similar to those for the spot rates. In addition, in March 1932, although it is not as strong as with the spot rates, it is possible to see a rise in short-term forward rates (up to 0.28 percentage points) and the curve is again more or less flat. These changes are interpreted in relation to the events of the time in the following subsections.

5.3.1 October and November 1931

Table 5.1 shows that after Britain abandoned the gold standard at the end of September 1931, there was fierce debate in Japan in October and November about whether the nation should retain the gold standard. Umeda (2006) suggests that commodity prices in Japan at that time were heavily influenced by overseas commodity prices and exchange rates, implying that the Japanese economy was closely linked to foreign economies. Under such circumstances, the fact that Britain, an important economic power at the time, had abandoned the gold standard could also have dealt a strong blow to Japan.[7]

Based on the above, we now consider the large changes in the yield curve and forward rate curve in October and November 1931. In that period, the forward rate rose by as much as 0.46 percentage points. It is possible to interpret this result as the significant influence of Britain and Japan abandoning the gold standard in September and December 1931, respectively, and the relevant discourse, suggesting that the forecasts of yen depreciation led to higher nominal interest rates.

These considerations can be expressed as the following interest rate parity model:

$$i_t = \tilde{i}_t + E_t \log s_{t+1} - \log s_t \tag{5.3}$$

where i_t denotes domestic interest rates, $\tilde{i}_t$ denotes foreign interest rates, and s_t is the yen-based exchange rate in time period t. Based on Equation (5.3), when foreign interest rates $\tilde{i}_t$ are fixed, domestic rates it fluctuate according to (the forecasts of) movement in the foreign exchange rate. In other words, when Britain abandoned the gold standard, there were forecasts that Japan would follow suit, subsequently leading to a sharp yen depreciation.

[7]Indeed, the morning edition of the *Tokyo Asahi Shimbun* of September 22, 1931 carried a column by banker Norihiko Yatsushiro entitled "Hoka no shokoku mo tsuizui ka" (Will other countries follow suit?). In addition to mentioning that a ban on the export of gold may become a global trend, the article suggested that the huge gold holdings of the United States and the possibility that payments related to Japan's balance of international borrowing/lending could become excessive were fundamental problems.

Therefore, the shape of the curve changed before Japan *actually* abandoned the gold standard. In addition, the observed results that relatively long-term forward rates rose in October 1931 and short-term forward rates increased in November suggest that while Japan was expected to leave the gold standard four or five years after in the October of that year, Japan was forecast to withdraw from the gold standard sooner by the November (i.e., expectations changed between these two months).

However, when the monthly short-term domestic interest rates calculated in this study and foreign interest rates (the US commercial paper rate and British bill discount rate[8]) were used to find the forecast value for the forward exchange rate based on the interest parity model, no forecasts of yen depreciation in October and November 1931 were identified. This can be attributed to a rise in foreign interest rates at the time or an immediate-term move to yen appreciation against the sterling. However, this was a time when attention focused on the possibility of Japan following Britain in abandoning the gold standard, and it is reasonable to assume that forecasts of forward exchange rates were fluctuating daily. In addition, based on the assumption that the strength of the yen at that time was also a temporary move ahead of Japan leaving the gold standard, even if these monthly data did not suggest forecasts of yen depreciation, this does not represent grounds for overturning the interpretation just mentioned, and more detailed analysis is required.

5.3.2 March 1932

Next, we consider changes in the shape of the forward rate curve for March 1932. Looking again at Table 5.1, there was a notice of the intended JGB underwriting by the BoJ at that time; the impact of that policy thus needs to be examined and, for this purpose, it is useful

[8] Source: NBER, Macrohistory database http://www.nber.org/databases/macrohistory/contents/.

to consider the following Fisher equation:

$$i^* = r^* + \pi^* \tag{5.4}$$

where i^*, r^*, and π^* are, respectively, the steady-state short-term nominal interest rate, real interest rate, and rate of inflation.

Okina and Shiratsuka (2003), using Equation (5.4), describe β_0 (i.e., the long-term forward rate) in the Nelson-Siegel model as a combination of the expected inflation rate and expected growth rate, or as a proxy indicator of the expected nominal growth rate.[9] The same thought process is followed in the present study.

Because the JGB underwriting by the BoJ leads to an increase in money supply, a rise in short-term forward rates at that time can be interpreted as the result of a rise in the expected inflation rate. However, the scale of the rise in the March two-year forward rate, which we can confirm here, is smaller (up to 0.28 percentage points) than the change observed in October and November 1931. Changes in interest rates have been estimated in existing studies as well. For example, Iida and Okada (2004) show that the expected inflation rate increased by about 10 percentage points in September 1931 and about 15 percentage points in April 1932, while they also show that expected real interest rates at those times fell by around 10 percentage points. Following the Fisher equation, the sum of these two values is therefore the rate of change in the nominal interest rate. However, there is no clear consistency with the estimated result for the forward rate obtained in this section, and more detailed consideration of how to interpret this is required.[10]

[9] However, Okina and Shiratsuka (2003) suggest that it is necessary to consider the possibility of the impact of supply and demand factors in the financial markets on changes in forward rates.

[10] As an aside, there is scope for interpretations other than those mentioned so far in this paper. For example, the Manchurian Incident in September 1931, and the attendant expansion in public spending, may have caused these curve changes.

5.4 Daily Data Analysis

The previous section visually identified changes in the shape of the yield curve and forward rate curve by using monthly data. The aim of this section is to more precisely measure the effect of the various policies and events on interest rates. To this aim, Section 5.4.1 presents the hypotheses that describe how nominal interest rates fluctuate. Section 5.4.2 calculates interest rates by using daily data, presents a regression model to explain the changes in estimated interest rates, and conducts event studies. Section 5.4.3 presents the regression results and tests the hypotheses. Section 5.4.4 compares the findings of this study with those in earlier studies.

5.4.1 The Mechanism for Changes in Nominal Interest Rates

Table 5.2 classifies the policies and events in the period analyzed in this study (July 1931-December 1932), identified from Ginkou tsuushin roku (Bank communication record), Chugai shougyou shinpou (Current Nihon Keizai Shimbun), and the Tokyo Asahi Shimbun. Below, the hypotheses for how each policy and event affects interest rates are presented.

Based on Woodford (2003) and Oda and Muranaga (2003), I present an equation that corresponds to the Fisher equation (5.4) in an economy where prices are assumed to be sticky. I introduce the following definitions for nominal interest rates it and real interest rates rt, as the variables expressing the rate of deviation from long-term trends on a gross interest rate basis:

$$\hat{i}_t \equiv \log \frac{1+i_t}{1+\bar{i}}$$
$$\hat{r}_t \equiv \log \frac{1+r_t}{1+\bar{r}}$$

Their long-term trends are defined as

$$\begin{aligned} \bar{i} &\equiv \bar{r} + \bar{\pi} \\ \bar{r} &\equiv \sigma^{-1} g_A + \rho \end{aligned}$$

where $\bar{\pi}$ expresses the target inflation rate, σ the value of elasticity related to the intertemporal substitution of consumption, g_A the constant rate of technological progress, and ρ the time preference rate. By applying log linear approximation to the first-order condition of the optimization problem for consumption smoothing around the long-run equilibrium, I derive the following equations:[11]

$$x_t = E_t x_{t+1} - \sigma(\hat{i}_t - E_t \pi_{t+1} - \hat{r}_t^n) \tag{5.5}$$

$$\hat{r}_t^n \equiv \sigma^{-1}[(g_t - \hat{Y}_t^n) - E_t(g_{t+1} - \hat{Y}_{t+1}^n)] \tag{5.6}$$

where x_t is the output gap in period t defined as $x_t \equiv Y_t - Y_t^n$ and $E_t \pi_{t+1}$ is the expected inflation rate between period t and $t+1$. Equation (5.5) is regarded as a New Keynesian IS curve. Moreover, in Equation (5.6), $\hat{r}_t^n$ is the short-term natural interest rate (denoting the short-term change remaining after the elimination of long-term trends), g_t a demand shock, and $\hat{Y}_t^n$ the short-term change in the natural output. Next, when Equation (5.5) is rewritten with regard to $\hat{i}_t$,

$$\hat{i}_t = E_t \pi_{t+1} + \hat{r}_t^n - \sigma^{-1}(x_t - E_t x_{t+1}) \tag{5.7}$$

is obtained, and it is possible to explain the change in nominal interest rates by using factors on the right-hand side of Equation (5.7). In addition, when a first-order Taylor expansion

[11] For details of the derivation, see Woodford (2003).

regarding Y_t^n is conducted around the steady state, Equation (5.8) is obtained:

$$\hat{Y}_t^n = \frac{\sigma^{-1} g_t + \omega q_t}{\sigma^{-1} + \omega} \tag{5.8}$$

Here, ω expresses the elasticity value of the real marginal cost of a producer's output and q_t a supply shock.

Equations (5.6)-(5.8) are the model used to explain the change in interest rates. Equation (5.7) expresses the IS curve related to changes in nominal interest rates and Equations (5.6) and (5.8) express the influence of a demand shock on the short-term equilibrium. A notable feature of the formulation of Equations (5.6)-(5.8) is that they pick up changes in nominal interest rates flexibly. First, this formulation allows the incorporation into the model of the short-term effect of a demand shock, which the Fisher equation (5.4) was unable to handle. In addition, in the Fisher Equation (5.4), the effect of monetary policy is in principle completely absorbed within the change in the expected inflation rate, which means that the real interest rate perfectly corresponds to the natural rate of interest. Equations (6)-(8), however, leave scope for considering the effect of monetary policy. The above formulation and interest rate parity formula in Equation (5.3) provide the hypotheses to describe the effect of the policies and events at the time of the Great Depression on nominal interest rates. Equation (5.3) is presented again below:

$$i_t = \tilde{i}_t + E_t \log s_{t+1} - \log s_t \tag{5.3}$$

I categorize the policies and events at the time of the Great Depression into five different components. First, as Equation (5.3) shows, rises in yen depreciation forecasts and in foreign interest rates lead to rises in nominal interest rates in Japan. This means that forecasts of yen depreciation caused by events related to Japan abandoning the gold standard before it actually did, led to rises in $E_t \log s_{t+1}$ in Equation (5.3) and thus in nominal interest rates. Moreover, higher foreign interest rates also led, via $\tilde{i}_t$, to higher Japanese interest rates.

Japan's withdrawal from the gold standard, at the same time, induced specie outflow, which can be interpreted as a result of the fact that there was specie shipment for both foreign exchange intervention and the payment of transactions made but not settled before the abandonment.[12] Second, events related to fiscal expansion caused forecasts of the emergence of positive demand shock, caused rises in natural interest rates via g_t in Equation (5.6), and caused rises in short-term interest rates (in particular around two or three years).[13] Third, monetary policy statements and events related to the JGB underwriting by the BoJ gave rise to expectations of inflation accompanying an increase in money supply and can be seen as causing higher nominal interest rates via $E_t\pi_{t+1}$ in Formula (5.7). Fourth, increases or decreases in interest rates set by the BoJ link both short-term and long-term interest rates through the right-hand side of Equation (5.7).[14][15] Fifth, events related to international relations and war are incorporated as uncertain shocks (demand or supply shocks) and can be considered to be leading to higher nominal interest rates.

5.4.2 Event Regression

This study adopts an event study approach to test the hypotheses presented in the previous subsection. This approach regresses short-run changes (typically daily) in stock prices or interest rates on explanatory variables based on events such as economic news. Cook and Hahn (1989), pioneers of this approach, estimate an equation that regresses the scale of the

[12]This method of temporally classifying specie outflow is based on comments received from Professor Masato Shizume.

[13]Umeda (2006) focuses on the fact that there were indications of the BoJ underwriting deficit JGBs in the fiscal policy speech of June 1932. However, because, as in Table 5.2, there had already been unofficial indications in March, it was included here among fiscal policy events.

[14]As indicated by Romer (2011), in the formulation using the time structure of interest rates, a term premium is included in long-term spot rates and forward rates. However, because we cannot say that consensus has been obtained with regard to these changes, here term premium has been not included among the factors changing interest rates.

[15]However, Gurkaynak et al. (2005) employ a positive analysis using US Treasury forward rates to show that long-term forward rates in periods of change in the strategic interest rate moved in the opposite direction to the strategic rate, and the impact on long-term interest rates is thus not clear.

change in market interest rates on that in the policy rate, while Kuttner (2001) measures the impact of monetary policy surprises (the fraction of the change in the policy rate not predicted by the market) on interest rates.[16] This study follows this approach by conducting regression analysis with dummy variables.

The regression model is described below. First, by using indicative price data in the Tokyo Stock Exchange JGB market daily report, the yields on the Ko-Go Five Percent Loan Bond and on the Five Percent Exchequer Note are calculated for all business days from July 1, 1931, to December 28, 1932, following the method described in Section 5.2. Then, from the spot rates calculated by using the Nelson-Siegel model, yields for two, three, five, ten, and thirty years are calculated. For each period, the difference from the previous day's yield is taken and expressed as $\Delta R_i (i = 2, 3, 5, 10, 30)$. At the same time, the one-year forward rate is calculated for one, two, three, five, nine, fourteen, and nineteen years ahead. In the same way, the difference from the previous day is taken and expressed as $\Delta F_i (i = 2, 3, 5, 9, 14, 19)$.[17] Using these interest rates, the following regression equations are estimated with the least-squares method:

$$\Delta R_i = \alpha_0 + \sum_{k=1}^{19} \alpha_k X_k + U \tag{5.9}$$

$$\Delta F_i = \alpha'_0 + \sum_{k=1}^{19} \alpha'_k X_k + U' \tag{5.10}$$

The number of observations in each case is 443.

[16] Studies using the same method include those by Fukuda and Kei (2002), Bernanke and Kuttner (2005), Grkaynak et al. (2005), Honda and Kuroki (2006), and Kontonikas et al. (2013).

[17] Regression analysis was also carried out regarding $\Delta F_i (i = 4, 24, 29)$ but the Durbin-Watson ratio was not close to 2, and it has been excluded from the results because of concern about error term first-stage serial correlation.

Table 5.2: Details of the explanatory variables in the regression model

Variable	Event	No. of times	Day of occurrence or report
X_1	Britain abandons the gold standard	1	September 21, 1931
X_2	Japan abandons the gold standard	1	December 13, 1931
X_3	Gold standard political statement	4	October to November 1931
X_4	Outflow of specie (before leaving gold standard)	21	October to December 1931
X_5	Outflow of specie (after leaving gold standard)	8	December 1931to June 1932
X_6	JGBs, Treasury bills issued	52	July 1931 to December 1932
X_7	Deposit Section financing	13	August 1931 to December 1932
X_8	Fiscal expansion decision/statement	4	December 1931 to August 1932
X_9	March announcement of the BoJ JGB underwriting	1	March 9, 1932
X_{10}	October news report on the BoJ JGB underwriting	1	October 26, 1932
X_{11}	November implementation of the BoJ JGB underwriting	1	November 25, 1932
X_{12}	Monetary policy/system statements	4	April to May 1932
X_{13}	Interest rate reduction	3	March 11, June 7, August 17, 1932
X_{14}	Interest rate hike	2	October 5, November 4, 1931
X_{15}	Armed conflict	32	July 1931 to December 1932
X_{16}	Manchurian Incident	1	September 18, 1931
X_{17}	Lytton Commission report	1	October 2, 1932
X_{18}	British rate hike	3	July 23, July 30, September 20, 1931
X_{19}	US rate hike	2	October 8, October 15, 1931

X_k is the dummy variable for the policies and events considered to be factors that explain changes in interest rates (see Table 5.2). Among these factors, $X_1 - X_5$ are proxy variables expressing the gold standard and foreign exchange, $X_6 - X_8$ fiscal expansion, $X_9 - X_{11}$ JGB underwriting by the BoJ, $X_{12} - X_{14}$ monetary policy, $X_{15} - X_{17}$ international relations and war, and $X_{18} - X_{19}$ changes in foreign interest rates. In principle, X_k was set as 1 on the business day after the event and as 0 on other days. As an exception, announcements of laws related to policies and $X_9 - X_{11}$ were set as 1 on the day of the event (or the next business day when the event occurred on a weekend or holiday) and 0 on other days.[18] The aforementioned hypotheses imply that $X_1 - X_4$, $X_6 - X_{12}$, and $X_{14} - X_{19}$ have a positive coefficient value and X_{13} a negative coefficient value, with no clear implication with regard to X_5.[19][20]

As explained above, these regression models are employed to explain the change in interest rates from the previous day by the introduction of new policies and the occurrence of events. This event study approach has been used in a number of existing studies including Cook and Hahn (1989). However, they measured the impact of the event in question on market interest rates by including in their sample a limited number of days (the day that the event occurred and the few months before and after).[21] In contrast, this study takes an analysis period of 18 months for the same approach. Because the analysis period includes days on which no events occur, there is ordinary volatility in the dependent variables during that

[18] Announcement of laws is via the official parliamentary gazette and reaction is often on the same day. Hence, the BoJ JGB underwriting reports tended to be in the morning newspapers and attract a great deal of attention, making it appropriate to assume that the market reacted on the same day as the report was published.

[19] Regarding X_5, if emphasis is on the element attributable to the payment of unsettled transactions, a positive value would be expected; on the contrary, if emphasis is on the element attributable to the forex intervention, a negative value would be expected.

[20] Before and after Japan's withdrawal from the gold standard, some variables possibly have the opposite effect on interest rates. To address this issue, I split X_6, X_7, and X_{15} before and after the withdrawal from the gold standard and employ the event regression. The results obtained are very similar to the baseline results.

[21] Among the studies mentioned here, that by Gurkaynak et al. (2005) is an exception, as it includes a long period (from 1990 to 2002) to measure the impact of various news items on US Treasury yields.

period. In addition, even if calculation errors exist due to applying the Nelson-Siegel model, as long as the dependent variable does not change to a degree that substantially exceeds this volatility, the coefficient on explanatory variables will not be statistically significant. Of course, interest rates also move because of factors not included in the regression models, so that it is not possible to categorically say that the coefficient of determination is at a "good" level. However, a notable feature of this study compared to other studies using the event study approach is the higher importance of whether the coefficient on explanatory variables is statistically significant.

5.4.3 Estimation Results

Tables 5.3 and 5.4 present the results of the regression analysis. These tables show that among the 19 explanatory variables, 12 had a significant impact on at least one kind of interest rates. In addition, for all interest rates, the null hypothesis of coefficients on all explanatory variables being 0 was rejected at the 1 percent level.

Only the major findings will be discussed below. First, I discuss the results for $X_1 - X_3$, the variables related to the abandonment of the gold standard. The withdrawal of Britain from the gold standard in September 1931 was found to have significantly raised the 30-year spot rate and forward rates from nine years ahead, which is consistent with the hypothesis in Section 5.4.1. This means that there was an expectation that Japan would follow Britain's decision, leading to yen depreciation in the long run. Next, political statements on the gold standard in October and November 1931 significantly raised the two-year to ten-year spot rates and the two-year and three-year forward rates, a result supporting the hypothesis. However, the forward rate from nine years ahead fell significantly. These results can be attributable to the impact of forecasts that, given the repeated statements in October and November related to staying in or leaving the gold standard, Japan would leave the gold standard relatively early and the yen would depreciate in the short term, but that the long-

Table 5.3: Results of the spot rate regression analysis

	ΔR_2	ΔR_3	ΔR_5	ΔR_{10}	ΔR_{30}
X_1	-0.08%	-0.07%	-0.05%	0.03%	0.161%***
X_2	0.04%	0.04%	0.04%	-0.01%	-0.060%**
X_3	0.147%***	0.154%***	0.123%***	0.035%***	-0.074%***
X_4	-0.035%**	-0.033%***	-0.025%***	-0.011%**	0.00%
X_5	-0.051%**	-0.043%**	-0.030%**	0.00%	0.01%
X_6	0.01%	0.00%	0.00%	0.00%	0.00%
X_7	-0.01%	0.00%	0.00%	0.00%	-0.01%
X_8	0.00%	0.00%	0.00%	0.02%	-0.02%
X_9	0.01%	0.01%	0.01%	-0.01%	-0.060%**
X_{10}	0.00%	0.00%	0.00%	0.00%	0.00%
X_{11}	0.00%	0.00%	0.01%	0.00%	-0.02%
X_{12}	0.01%	0.01%	0.01%	0.01%	0.00%
X_{13}	0.00%	0.01%	0.00%	0.00%	-0.01%
X_{14}	-0.01%	-0.01%	-0.01%	0.02%	0.077%***
X_{15}	0.031%***	0.030%***	0.023%***	0.011%**	-0.01%
X_{16}	-0.03%	-0.04%	-0.02%	0.03%	0.090%***
X_{17}	0.00%	0.00%	0.00%	0.01%	0.01%
X_{18}	0.04%	0.02%	0.02%	0.032%*	0.043%**
X_{19}	0.324%***	0.331%***	0.291%***	0.174%***	0.048%***
R^2	0.21	0.327	0.426	0.272	0.288
DW	2.021	2.111	2.126	2.006	1.965

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.4: Results of the forward rate regression analysis

	ΔF_2	ΔF_3	ΔF_5	ΔF_9	ΔF_{14}	ΔF_{19}
X_1	-0.06%	-0.04%	0.04%	0.172%***	0.222%***	0.232%***
X_2	0.06%	0.06%	-0.01%	-0.091%**	-0.103%***	-0.090%**
X_3	0.168%***	0.107%***	0.00%	-0.096%***	-0.127%***	-0.133%***
X_4	-0.029%***	-0.017%**	0.00%	0.01%	0.01%	0.01%
X_5	-0.028%*	-0.02%	0.01%	0.032%**	0.028%**	0.01%
X_6	0.00%	0.00%	-0.01%	-0.01%	0.00%	0.00%
X_7	0.01%	0.01%	0.00%	0.00%	-0.01%	-0.01%
X_8	-0.01%	-0.01%	0.028%*	0.035%*	0.00%	-0.038%**
X_9	0.01%	0.00%	-0.01%	-0.03%	-0.057%*	-0.086%**
X_{10}	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
X_{11}	0.01%	0.02%	0.00%	-0.02%	-0.03%	-0.03%
X_{12}	0.02%	0.02%	0.01%	-0.01%	-0.02%	-0.02%
X_{13}	0.01%	0.01%	-0.01%	-0.01%	-0.01%	-0.01%
X_{14}	-0.03%	-0.02%	0.02%	0.077%***	0.102%***	0.108%***
X_{15}	0.026%***	0.016%***	0.00%	0.00%	-0.01%	-0.011%*
X_{16}	-0.05%	-0.02%	0.051%*	0.108%***	0.120%***	0.120%***
X_{17}	0.00%	0.00%	0.01%	0.01%	0.01%	0.01%
X_{18}	-0.02%	0.01%	0.037%*	0.049%*	0.050%**	0.049%*
X_{19}	0.344%***	0.273%***	0.122%***	0.01%	-0.02%	-0.02%
R^2	0.383	0.364	0.124	0.18	0.301	0.293
DW	2.006	2.04	1.965	2.133	1.987	2.157

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

term impact would be smaller than so far anticipated.

In addition, Japan's withdrawal from the gold standard in December 1931 significantly depressed the 30-year spot rate and the forward rate from nine years ahead, which is not consistent with the hypothesis. The background to this can be seen as the JGB market trading floor being shut until December 16 after the decision to leave the gold standard on December 13, and futures transactions ahead of delivery on December 18 causing a certain level of demand in the JGB spot market.[22][23] The abandonment of the gold standard represented a dramatic change for a nation's trade and finance, making any interpretation of the results up to this point in the context of Equation (5.7) challenging. In addition, no comprehensive mechanism for analyzing them is presented in this study. However, given that these forecasts of yen depreciation were connected to the forecasts of the future increase in prices of imported goods, the results support Umeda (2006), who shows a link among commodity prices in Japan, the United States, and Britain at the time.[24]

Next, we discuss the coefficients on $X_9 - X_{11}$ related to the JGB underwriting by the BoJ. Among these events, the only event with statistically significant effect on interest rates was the March notice of the intended JGB underwriting by the BoJ, which caused a significant decline in the 30-year spot rate and in the forward rate from 14 years ahead. This result is not consistent with the hypothesis. Based on Equation (5.7), it is difficult to consider a logical reason for why this policy announcement reduced nominal interest rates, so that it would be appropriate to attribute this to demand factors in the JGB market. As suggested

[22] The evening edition of the Tokyo Asahi Shimbun on December 18, 1931 carried the following comment regarding the state of the market at the time, in an article entitled Kokusai made ga honzen hantou (Even JGBs see a sudden jump): " ...sellers ⋯ immediately ahead of delivery on December 18, took advantage of low indicative prices while the market was shut and for the time being took the stance of buying back. "

[23] Incidentally, on December 11, the day after the Minseito Party administration left office, the forward rate from nine years ahead rose sharply. and it is possible that forecasts of Japan leaving the gold standard strengthened even more at that time. However, Japan followed Britain in leaving the gold standard and, over that period, there were many statements and news reports about secession. Therefore, analyzing the timescale over which Japan's secession from the gold standard was reflected in market interest rates is challenging.

[24] Eichengreen and Sachs (1985) argued that currency depreciation benefited the initiating countries. This study, focusing on Japan's experience, provides supporting evidence for their argument, in that it shows that forecasts on the withdrawal from gold standard raised inflation expectations.

by Christiano (1991), not only does unexpected monetary easing have the effect of increasing inflation expectations, it also has a liquidity effect that pushes down nominal interest rates.[25] The article in Chuugai shougyou shinpou (Chugai business update) in Table 5.2 that reported the JGB underwriting by the BoJ also mentioned the possibility of a public debt purchase operation by the Bank. As a result, it is not unreasonable to think that demand increased for ultra long-term bonds, for which the amount issued was remarkably large.

Strictly speaking, the reduction in nominal rates found by this study did not occur at the time of liquidity supply itself but when its notice was given. The fact that market interest rates can be changed by such monetary easing announcements was theoretically demonstrated by Guthrie and Wright (2000). In their model, first, there is an announcement of the interest rate level desired by the central bank. If market rates differ from this level, arbitrage in the market realizes the interest rate desired by the central bank, as long as there is confidence in the commitment of the central bank for correcting the level via operations. When we consider the situation in Japan in March 1932, the statement by Minister of Finance Takahashi was reported in many newspapers and can be considered to have raised expectations about monetary easing by the BoJ. Under such circumstances, it is possible to consider that the market had confidence in the government's commitment, and the results found in this study, namely that market interest rates responded to the notice of liquidity supply, can be considered to be consistent with the model of Guthrie and Wright (2000).

In addition, looking at the coefficients on X_{18} and X_{19}, related to hikes in foreign interest rates, the rate hike by the Bank of England caused a significant rise in 10-year to 30-year spot rates and in the forward rate from five years ahead, and the rate hike by the Federal Reserve Bank of New York caused a significant rise in two-year to 30-year spot rates and the forward rates for two-five years ahead. These results indicate that changes in monetary policy in foreign countries had a strong effect on the Japanese market, supporting Shizume's

[25]The initial studies of this liquidity effect such as those by Lucas (1990), Christiano and Eichenbaum (1992), and Walsh (2010) published a relevant commentary.

(2009) suggestion that Japan at the time was a "small open economy."

Among $X_6 - X_8$, related to fiscal expansion, the statement about extra fiscal spending alone caused a rise in five-year to nine-year forward rates at a significance level of 10 percent; however, this result is somewhat puzzling. If the budget decision is seen simply as a temporary demand shock, the effect would last only for a few years and does not explain a medium-term (from five- to nine-year) effect. However, if we assume that the fiscal expansion was pump-priming and that this caused forecasts of the continual expansion of private-sector investment (i.e., $x_t < x_{t+1}$), medium-term nominal interest rates may have risen. On the other hand, the 19-year forward rate was significantly depressed, and the long-term implications of these fiscal policies are still not clear.[26]

5.4.4 Comparison with Prior Studies and Discussion

The results in the previous subsection show that while Britain's withdrawal from the gold standard and the debates on Japan's withdrawal had a significant positive effect on forward rates, the notice of the JGB underwriting by the BoJ had a significant negative effect. The former is consistent with the findings of Iida and Okada (2004) and Shizume (2009); the latter is, however, consistent with Shizume (2009), but contradicts Iida and Okada (2004). Below, I discuss the latter result.

Figure 5.6 shows the trends in the yield of the Ko-Go Five Percent Loan Bond (maturing 1963)[27] and JGBs (maturing in June 1932 in September 1932) in March 1932. While we should keep in mind that on each day the time remaining until maturity differs, each yield

[26]The robustness of the results so far was checked by using various methods, Specifically, for example, dummy variables based on the newspaper report date and high-level serial correlation were used, but the results did not change greatly. Further, regarding before and after Britain's abandonment of the gold standard and the official notice of JGB underwriting by the BoJ, changes in forward rates were calculated based not on the values estimated in the Nelson-Siegel model, but on actual calculated interest rates. In this case, the results again changed very little. (Details available as supporting documentation upon request.)

[27]For information on the Ko-Go Five Per Cent. Loan Bond, see Ministry of Finance (1936). For information on the historical circumstances leading to the issue of public debt, see Noda (1980).

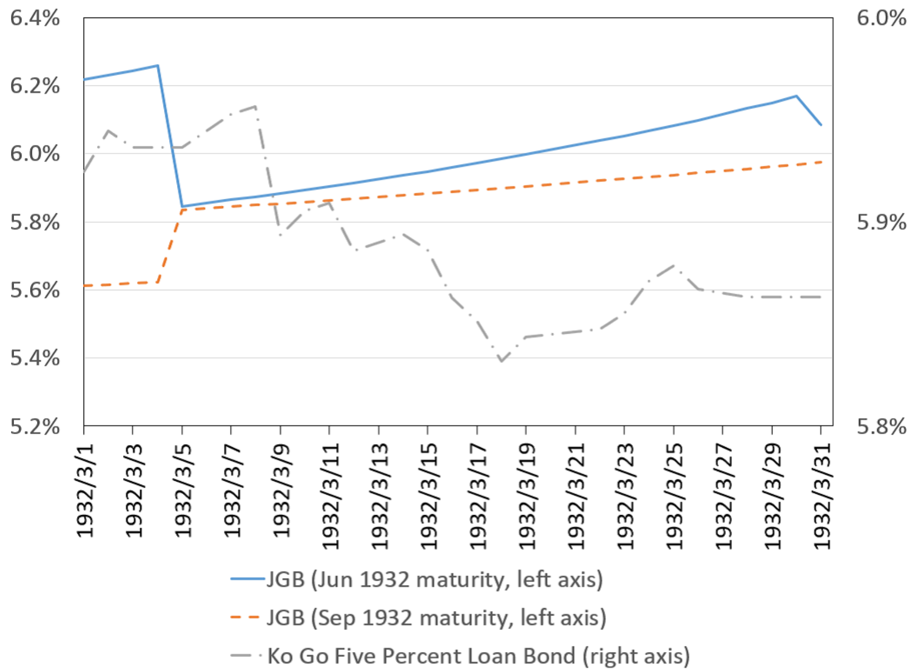

Figure 5.6: Yield trends in March 1932

roughly corresponds to long-term, three-month, and six-month interest rates, respectively. This figure shows that, except for a decline in the long-term rate in the wake of the announcement of the JGB underwriting, hardly any change in interest rates was observed on March 9, 1932.[28] That said, in the steady state, nominal interest rates are the sum of real interest rates and the expected rate of inflation, so that a lack of change in nominal interest rates does not necessarily indicate a lack of change in each of these components.

However, the daily data used in this study allow us to proceed with the following discussion. As emphasized by Iida and Okada (2004), this study assumes that JGB underwriting by the BoJ caused a rise in the expected inflation rate at a time (March 9, 1932) when the JGB underwriting became widely known; hence, it should surely be reflected in JGB yields. However, as already mentioned, no significant change in JGB yields can be observed on that day. Therefore, if it is correct to emphasize the fact that the expected inflation rate rose,

[28]Other rates also reacted little, apart from a decline in rates on products with more than 15 years until maturity.

logically, there must have been a separate piece of news that depressed real interest rates on the same day as the announcement of the JGB underwriting by the BoJ. It is also implied that the scale of that downward pressure was the same as the scale of the rise in the expected inflation rate. However, surely the likelihood of such a shock occurring on that specific day is low. In addition, no events consistent with this hypothesis are visible in the *Asahi Shimbun* or other major newspapers. Of course, we cannot totally exclude the possibility that a shock placing downward pressure on real interest rates did happen on March 9 and that the media at the time overlooked it. However, rather than following that train of thought, it is more reasonable to think that neither a rise in the expected inflation rate nor a decline in real interest rates occurred on March 9 and, as a result, nominal interest rates did not move.

5.5 Conclusion

This study examined the impact of policies adopted during the Great Depression on expectations about inflation and future nominal interest rates by using event studies and yield curve and forward rate curve analysis. These analyses are based on monthly and daily JGB yields estimated by the Nelson-Siegel model. Remarkable changes in the monthly curve were observed around the time that Britain, and then Japan, abandoned the gold standard, and a change in the curve was also observed upon the notice of the intended JGB underwriting by the BoJ. However, it became clear that in order to gauge the policy effect, a more detailed investigation would be required.

Next, event studies based on the daily data revealed the following findings. First, all of the announcement, news, and implementation of the JGB underwriting by the BoJ failed to cause expectations of inflation. Indeed, at the time of the notice (March 1932), a decline in nominal interest rates was observed. These results can be considered to be consistent with the model of Guthrie and Wright (2000), who show that market interest rates can fluctuate as a result of monetary policy announcements. At the same time as the JGB underwriting, there were news reports of an operation by the BoJ to buy public debt, and it seems that no rise in inflation expectations could be detected. Therefore, the change in the curve observed in the monthly data analysis at that time should be seen as having a separate cause.

Second, the abandonment of the gold standard by Britain in September 1931 prompted market expectations of the same action by Japan and the subsequent depreciation of the yen, which led to significant expectations of higher interest rates. Incidentally, in Section 5.3.1, the possibility of a lack of expectations of the yen depreciation at the time was mentioned based on the monthly data. However, more detailed event studies using daily data, confirmed that expectations of a weakening of the yen did indeed have a large impact because political statements on the abandonment of the gold standard placed significant upward pressure on nominal interest rate expectations. In addition, the relevant coefficients were estimated to be large. The fact that foreign interest rates had a significant impact also shows that the Japanese economy at the time had a close relationship with the monetary policies of foreign countries.

Third, at the time the decision was made to expand fiscal spending, a rise in interest rates was observed. However, the impact was small compared with that of the abandonment of the gold standard and this result somewhat lacks robustness. In addition, it was hardly detectable in the monthly data analysis.

In terms of the limitations of this study, the calculation errors in the Nelson-Siegel model should first be mentioned. The addition of appropriate data on interest rates allows us not only to analyze short-term rates (especially shorter than two years), but also to more accurately estimate long-term rates between 15 and 25 years. Second, the hypotheses in this study were proposed under a model in which inflation expectations, demand shock forecasts, and output forecasts are included within nominal interest rate expectations; to carry out a more detailed investigation of how the Japanese economy escaped from the deflation, it would be more desirable to estimate the rate of expected inflation itself.[29] A third limitation relates to the period when the expectations formed. Some of the event study results—such as the observation that interest rates declined after Japan had left the gold standard—were not consistent with the hypothesis. There is thus scope for a more careful study of the timing of the formation of expectations. I intend to research these issues in future work.

Appendix: Nelson-Siegel Model

This Appendix describes the Nelson-Siegel model in depth. As mentioned in Section 5.2, this study uses JGB yields. However, the maturity of JGBs is predetermined, and it is not appropriate to compare yields at different times, even using the same issue. Thus, the decision was made to calculate the yield curve based on interest rates estimated from data and, based on these estimated values, to compare interest rates for the same maturity intertemporally. This decision was based on the argument that for interest rates with short maturity, there are more cases of small error with calculations based on yields (interest rates) than with calculation based on bond prices (Svensson, 1995). In addition, we took account of the fact that the Nelson-Siegel model, which specifies the functional form, is simpler than 3D spline curve calculation.[30]

Following Shiratsuka and Fujiki (2001), it is possible to use the Nelson-Siegel model to express the instantaneous forward rate $r(m)$ for settlement time m, as in Formula (5.11):

$$r(m) = \beta_0 + \beta_1 \exp\left(-\frac{m}{\tau_1}\right) + \beta_2 \left(\frac{m}{\tau_1}\right) \exp\left(-\frac{m}{\tau_1}\right) \tag{5.11}$$

Here, β_0, β_1, β_2, and τ_1 the parameters calculated from the data, and β_0 and τ_1 can be expected to have positive values. The instantaneous forward rate shown in Formula (5.11)

[29] As mentioned in Section 5.4, the handling of the term premium is also an important point for discussion.

[30] Regarding the calculation of yield curves by using spline curve methods, see, for example, Kawasaki and Andou (2002) and Yoshiba and Ieda (2001).

comprises three components. The first is a constant term, β_0, to which the instantaneous forward rate converges in the long term. The second is an exponential function, $\beta_1 \exp\left(-\frac{m}{\tau_1}\right)$. The third is $\beta_2 \left(\frac{m}{\tau_1}\right) \exp\left(-\frac{m}{\tau_1}\right)$, representing an inverted U shape when β_2 is positive and a U shape when β_2 is negative. Furthermore, the parameter τ_1 shows the convergence speed of the exponential function.[31]

The spot rate $R(m)$ is found by integrating $r(m)$ from zero to m and dividing the result by m. Hence, the functional form used in our estimation is

$$R(m) = \beta_0 + \beta_1 \left(\frac{\tau_1}{m}\right) \left\{1 - \exp\left(-\frac{m}{\tau_1}\right)\right\} + \beta_2 \left[\left(\frac{\tau_1}{m}\right) \left\{1 - \exp\left(-\frac{m}{\tau_1}\right)\right\} - \exp\left(-\frac{m}{\tau_1}\right)\right] \tag{5.12}$$

β_0, β_1, β_2, and τ_1 are determined in a way that minimizes the residual sum of squares between the interest rate calculated from the price data and estimated value $r(m)$ expressed by Formula (5.12). In the calculations, restrictions were imposed such that the estimated values matched the calculated yields of the Ko-Go Five Per Cent. Loan Bond deemed to have had the highest liquidity.[32]

Figure 5.7 shows the applicability of the estimation (horizontal axis is the time until maturity). It applies to periods in which the yield curve has an ordinary upward slope, and calculations come out comparatively well for periods of around three to 10 years until maturity, for which there are many data points. Meanwhile, in periods in which rises in short-term interest rates occurred, there are sections that are rather unclear. In particular. with regard to periods of around 15-25 years until maturity, in addition to a paucity of data points, the impact of the aforementioned restrictions relating to the Ko-Go Five Per Cent. Loan Bond is strong, and the estimation error is comparatively large. In addition, regarding

[31]Shiratsuka and Fujiki (2001) interpret changes in the formation of the instantaneous forward curve by using parameter changes.

[32]Shiratsuka and Fujiki (2001) impose the restriction of using the overnight call rate. However, as mentioned in Section 5.2, it is not appropriate to include in our calculations the call rate at that time, which cannot be seen as the market rate.

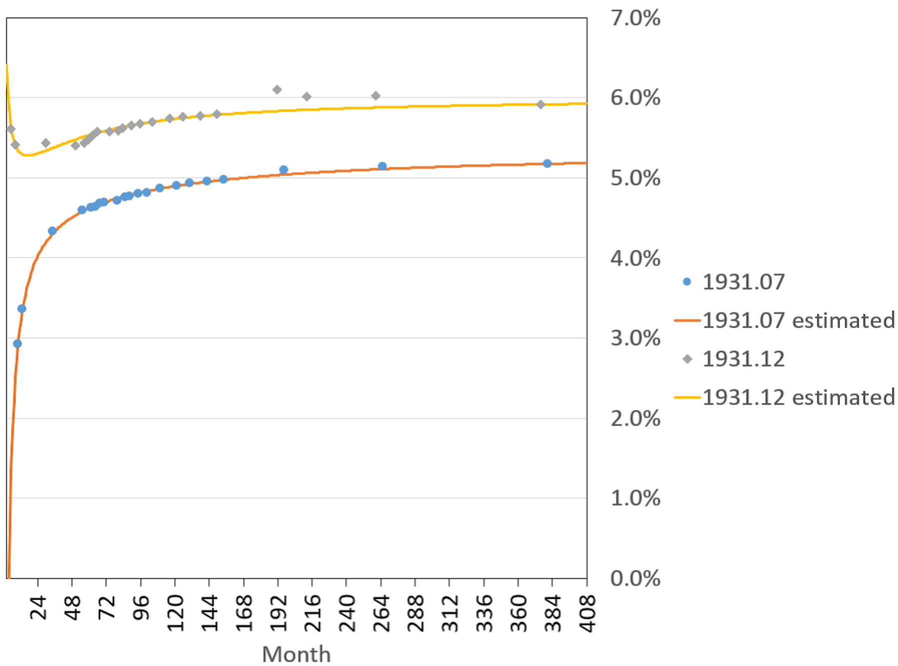

Figure 5.7: Applicability of the estimation

periods with less than two years until maturity, the minimum time remaining until maturity was set as two years in this study because it was not possible to secure data for the whole study period. However, when applicability was not good but the discrepancy was only around 0.2-0.3 percent, it was deemed that the impact on analysis would not be significant and such items were not excluded.

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