Working Less and Bargain Hunting More:

Macro Implications of Sales during Japan's Lost Decades

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Abstract

Standard New Keynesian models have often neglected temporary sales. In this study, we ask whether this treatment is appropriate. In the empirical part of the study, we use Japanese point of sale scanner data covering the last two decades and find a negative correlation between the frequency of sales and hours worked. We then construct a dynamic stochastic general equilibrium model that takes households' decisions regarding their allocation of time for work, leisure, and bargain hunting into account. Using this model, we show that the decline in hours worked during Japan's lost decades explains the rise in the frequency of sales we observe in the data. We also find that the real effect of monetary policy shocks weakens by around 40% due to the presence of temporary sales, but monetary policy still matters.

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1 Introduction

Standard New Keynesian models, such as those in Woodford (2003) and Gali (2008), often neglect temporary sales, although the frequency of sales is far higher than that of regular price changes,[1] hence it is not necessarily guaranteed that the assumption of sticky prices holds. Researchers can justifiably ignore this fact if retailers' decision to hold sales is independent of macroeconomic conditions. If this is the case, temporary sales do not eliminate the real effect of monetary policy. In fact, Guimaraes and Sheedy (2011, hereafter GS) develop a dynamic stochastic general equilibrium (DSGE) model incorporating sales and show that the real effect of monetary policy remains largely unchanged. Empirical studies such as Eichenbaum, Jaimovich, and Rebelo (2011), Anderson et al. (2012), and Berardi, Gautier, and Le Bihan (2014) argue that retailers' decision to hold a sale is actually orthogonal to changes in macroeconomic conditions.

However, in Japan, there is a negative secular link between the frequency of temporary sales and working hours. Since the start of the 1990s, the Japanese economy experienced what has come to be called "lost decades," a period of sluggish GDP growth and very low inflation or deflation. During the lost decades, the frequency of sales increased gradually but monotonically, allowing households to purchase a greater number of goods at sale prices rather than at regular prices. At the same time, hours worked per worker followed a secular decline Thus, there appears to be a negative correlation between the frequency of sales and working hours.

This study has two aims. First, we examine empirically whether there is a link between the frequency of temporary sales and changes in macroeconomic conditions, particularly working hours, making extensive use of Japanese supermarket scanner data. Second, we investigate whether temporary sales mitigate the real effect of monetary policy, employing a model that considers households' decisions about allocations of time for work, leisure, and bargain hunting. To this end, we extend the GS model so that bargain hunting is endogenously determined. The more bargain hunting, the more the household can substitute away from relatively expensive items. However, the search for lower prices reduces the time available for work and leisure, imposing a cost on the household. These two opposing effects constitute a household's optimal bargain hunting intensity.

Our analysis provides new empirical and theoretical findings. Our empirical analysis using Japanese supermarket scanner data spanning two decades reveals a secular correlation between labor market conditions and the frequency of temporary sales. The frequency increased when

[1] See, for example, Bils and Klenow (2004) and Nakamura and Steinsson (2008) for the United States and Sudo, Ueda, and Watanabe (2014) for Japan.

employment fell. Further, during these lost decades, households spent more time shopping. Our analysis also shows a significant correlation between labor market conditions and the frequency of sales over in terms of business cycles.

Our model calibrated to Japan illustrates that the secular decline in hours worked explains the secular increase in the frequency of temporary sales during the lost decades. It also implies that bargain hunting intensity has grown in and that households have become increasingly price sensitive. In addition, the effect of a monetary policy shock on real economic activity is weaker when the model includes both temporary sales and endogenous bargain hunting, although monetary policy shocks still have real effects. For example, an expansionary monetary policy shock increases hours worked, which in turn decreases bargain hunting intensity. Observing this, firms lower the frequency of sales. Because the quantity of goods sold is typically higher at sales prices than at regular prices, these changes in households' and firms' behavior lead to downward pressure on aggregate demand for goods. The real effect of monetary policy thus diminishes.[2] According to our simulation, the real effect of monetary policy weakens by about 40% due to endogenous bargain hunting.

Consistent with our empirical results, an increasing number of recent studies such as Klenow and Willis (2007) and Kryvtsov and Vincent (2015) show that business cycles in the United States and the United Kingdom influence sales decisions. Coibion, Gorodnichenko, and Hong (2015) find evidence of consumer switching from high- to low-end stores during recessions. Regarding the interaction between hours worked and bargain hunting, Nevo and Wong (2015) document the increase in shopping intensity and the decline in households' opportunity cost of time during the Great Recession. Aguiar and Hurst (2007) find that older households shop the most frequently and pay the lowest prices. Lach (2007) finds that immigrants from the former Soviet Union to Israel have a higher price elasticity and lower search costs than the native population.[3]

The second strand of research relates to the models of temporary sales. While there are several reasons why retailers hold temporary sales, including the desire to liquidate excess stock and implicit contracts between retailers and manufacturers, we focus here on retailers' use of sales to maximize profits by exploiting consumer heterogeneity. Specifically, our approach is

[2] An additional mechanism contributing to this effect is intensified strategic substitutability of sales. Suppose that all firms except for firm A raise the frequency of sales. As in GS, firm A does not have an incentive to follow others and raise the frequency of sales because this decreases the marginal revenue from sales. In our model, an additional channel emerges. When all firms except for firm A hold more frequent sales, the aggregate price level falls. This increases aggregate demand for goods, and in turn, aggregate demand for labor. Households supply more labor and lose time for bargain hunting. The proportion of loyal customers increases and that of bargain hunters decreases. Observing this, firm A holds less frequent sales. This intensified strategic substitutability of sales mitigates the real effect of monetary policy.

[3] See also Pashigian and Bowen (1991), Sorensen (2000), Brown and Goolsbee (2002), McKenzie and Schargrodsky (2004), and Pashigian, Peltzman, and Sun (2003).

most closely related to approaches adopted by Salop and Stiglitz (1977), Varian (1980), and Guimaraes and Sheedy (2011). Guimaraes and Sheedy (2011) assume that each household is a bargain hunter for a fixed proportion of goods and loyal to the other goods. Our study is closely related to Guimaraes and Sheedy (2011), but differs from it in that in our model bargain hunting intensity is endogenously determined. Kryvtsov and Vincent (2015) construct a similar DSGE model incorporating endogenous bargain hunting by introducing heterogeneous households with respect to fixed cost of shop searching.[4]

The structure of this paper is as follows. Using micro price data for Japan, Section 2 provides evidence that bargain hunting and the frequency of temporary sales are related to macroeconomic conditions and hence are endogenously determined. In Section 3, we develop the DSGE model of temporary sales to examine the implications of endogenous bargain hunting. Section 4 applies our model to Japan to explain the increase in the frequency of temporary sales during the lost decades and Section 5 considers the implications for the macroeconomy by presenting impulse responses to a monetary policy shock. Section 6 concludes.

2 Evidence for Endogenous Bargain Hunting

This section presents the evidence related to endogenous bargain hunting. Using household surveys for Japan, we first show that working time moves in the opposite direction of shopping time. Second, using point-of-sales (POS) scanner data, we show that temporary sales had an increasingly important role in retailers' business during Japan's lost decades. The frequency of sales is significantly correlated with macroeconomic indicators, especially labor market indicators. We find that when hours worked are long, the frequency of sales tends to be low.

2.1 Survey on Time Use

We begin by looking at the *Survey on Time Use and Leisure Activities for Japan*. The Statistics Bureau of Japan conducts the survey every five years. The survey asks around 200,000 members in 83,000 households about their daily patterns of time allocation, including questions about time used for working and shopping. These questions help us to examine the relationship between the time spent working and the time spent shopping, which is important for our model.

[4]These studies are related to the literature on consumer search regarding how consumers search across shops and products influences how retailers set prices. Although they do not explicitly model temporary sales, studies incorporating consumer search and price setting include those by Benabou (1988), Watanabe (2008), and Coibion, Gorodnichenko, and Hong (2015). Our study is also related to that by Kehoe and Midrigan (2015), which has a similar research interest to ours (i.e., examining the stickiness of the aggregate price level and the real effect of monetary policy), although they do not construct their model based on consumer heterogeneity.

Table 1 shows the time household members spent on shopping and working (including commuting time to work or school). The sample consists of those aged 15 and over. The table reports the weekly average minutes per day. Two trends are worth highlighting. First, those not working tend to spend more time shopping than those who work. Moreover, women tend to spend more time shopping than men and spend less time working. Second, time spent shopping steadily increased from 1986 to 2011. At the same time, hours worked continued to decline, although they increased slightly between 2001 and 2006. These findings support our assumption that bargain hunting negatively depends on hours worked.

Because this result may be caused by other structural changes, in particular, demographic aging, we collect micro data for 2006 survey respondents and examine the relationship between shopping and working, controlling for sex, age, and area of residence. We choose household members who are either a household chief or spouse. We classify ages into 16 bins in five-year increments; the variable *female* is a dummy for female and *non-city* takes a value of one unless households live in three major cities of Japan. We regress the time spent shopping with the time spent working. Table 2 summarizes the results. The coefficient on time spent working is -0.06 and significant, regardless of whether we use the entire sample, only the persons who report that they mainly spend their time working, or only men who report that they mainly spend their time working. This suggests that a one minute increase in time spent working is associated with 0.06 minute decrease in time spent shopping, although this does not show causality.[5]

2.2 POS Data

Next, we look at temporary sales using POS scanner data.[6] Nikkei Digital Media collects these POS data from retail shops around Japan. The data consist of daily data covering March 1, 1988 to October 31, 2013. There are 6 billion records, where each record contains the number of units sold and the sales amount in yen for product i at shop s on date t. The data contain 1.8 million products (cumulative) during the sample period. The data include processed food and domestic articles, but unlike the official consumer price index (CPI) released from the Ministry of Internal Affairs and Communications, do not include fresh food, recreational durable goods (such as television sets or personal computers), or services (rent and utilities). Overall, the POS data cover 170 out of the 588 items in the CPI, which, according to data from the *Family Income and Expenditure Survey*, make up 17% of households' expenditure. We identify each product i with its Japanese Article Number (JAN) code.

[5] See Online Appendix A.1 for detail about the data and the estimation results.

[6] See Abe and Tonogi (2010) and Sudo, Ueda, and Watanabe (2014) for earlier studies using these data.

Figure 1 compares the yearly inflation rates based on the CPI and POS-CPI. The CPI consists of processed food and domestic articles to match the POS' coverage. We calculate the POS-CPI inflation rate as the Törnqvist index. This graph confirms that the POS data are not considerably different from the CPI.

Our POS data have three noteworthy advantages. First, the data include quantity information as well as price information. Second, the data are at a daily frequency. This contrasts with the U.S. weekly scanner data used in existing studies. Third, the POS data span a long observation period, starting from 1988 and continuing to the present, thus covering the lost decades.

To calculate the aggregated variables of interest, such as the frequency and magnitude of sales, we aggregate the POS data using in four steps. First, at the lowest (i.e., most detailed) JAN code level, we collect data for the variable of interest, such as price for product i at shop s on date t. Second, we aggregate these data across shops using revenue as the weight to derive the weighted mean. Third, we aggregate these values at the 3-digit code product level,[7] again using revenue as the weight to derive the weighted mean. Finally, we aggregate the values obtained in the previous step across 3-digit codes, again using revenue as the weight to derive the weighted mean. We base the weights on the monthly revenue. That is, if date t is January 1, 2012, for instance, we use the revenue for January 2012 as the weight.

2.2.1 Temporary Sales

We measure the price of a particular product at a particular retailer on a particular date from the POS records by dividing the revenue for product i at shop s on date t by the number of units sold of that product at that shop on that date. Recorded revenue excludes consumption tax, which was introduced in April 1989 and raised in April 1997.

The POS data do not include information about whether a price is the regular price or a temporary sales price. Therefore, to isolate temporary sales prices, we use two kinds of sales filters. First, following Eichenbaum, Jaimovich, and Rebelo (2011), and more precisely, Kehoe and Midrigan (2015), we define the most common (mode) price during a certain window length of period t as the regular price of a product at period t. We identify temporary sales when the posted price differs from the regular price. The benchmark window is 42 days before and after the date (85 days, in total). Our choice of the window is similar to Eichenbaum, Jaimovich, and Rebelo (2011) and Kehoe and Midrigan's (2015) settings, which use 1.5 and 2.5 months, respectively. For robustness, we also use a 7-day window since the glossary of the Japanese official CPI states that prices are not counted as regular prices if they last less than 7 days.

[7] Nikkei Digital Media classifies products using 3-digit codes, where each code represents a product category such as yogurt, beer, tobacco, toothbrushes, etc.

The second type of sales filter is Nakamura and Steinsson's (2008) V-shaped filter. When we find a V-shaped pattern, we identify its price dip as a sales price. More specifically, we follow the procedure explained in Nakamura and Steinsson (2010) using a window of $L = K = 42$ or 7 days.

Table 3 provides summary statistics for posted, regular, and temporary sales prices. The first row shows that the frequency of posted price changes is 0.202 daily, suggesting that firms revise their prices every five days. The second row shows that the frequency of regular price changes ranges from 0.002 to 0.029 daily, depending on sales filters. Multiplied by 365/12, it amounts to a monthly frequency of 0.061 to 0.392.

The third to eighth rows in the table show basic statistics for temporary sales. We focus in particular on four variables: (i) the frequency of sales, (ii) the magnitude of sales discounts, (iii) the ratio of quantities sold at the sale price to those at the regular price, and (iv) the ratio of revenue at the sale price to total revenue in a month.[8] The quantity ratio (iii) shows the amount of products sold at sale prices relative to the amount sold at regular prices on a certain date. The table also provides the amounts at sales and regular prices, computed by e to the power of the weighted average of the logarithm amount. The revenue ratio (iv) shows the contribution of temporary sales to a retailer's total revenue in a certain month, meaning that this variable depends on the frequency of sales.

The average frequency of temporary sales lies between 0.13 and 0.24 depending on the sales filter. The magnitude of the sales discounts is about 0.1, implying 10% discounts from regular prices. The quantity ratio is about two. The table shows the decomposition of total quantities sold into the quantity at sales and regular prices. On average, retailers sell 12 units at sales prices and six units at regular prices. The revenue ratio is about 0.2, which suggests that sales account for 20% of revenue in a typical month.

Compared with other advanced economies, Japan has an extremely high frequency of posted price changes, while that of regular price changes and temporary sales are not so different. For example, Nakamura and Steinsson (2008) report that for the United States the mean monthly frequency of posted price changes is 0.265, the mean monthly frequency of regular price changes is 0.211, and the frequency of temporary sales is 0.15 for processed food. There are two reasons for this phenomenon. First, Japan has shorter sales durations. Even with very similar frequencies of sales, Japanese retailers do more frequent switches between regular and sales prices than U.S. retailers, which generates a higher frequency of posted price changes. The second reason is that Japan's POS data are collected at a daily frequency. Weekly or monthly data miss high frequencies, such as 0.202 daily.

[8] We denote these variables by s, $1 - \mu$, χ, and $s\chi\mu/(1 - s + s\chi\mu)$, respectively, in the model described below.

Figure 2 shows time-series changes in sales-associated variables, suggesting that, regardless of the choice of sales filter, sales have become increasingly important for retailers during the lost decades. The frequency of sales rose steadily by about 10% points. Parallel to the increase in frequency, the magnitude of sales discounts steadily declined. Despite these two developments, the ratio of quantities sold at sales prices to those at regular prices has been relatively stable at around 2. Consequently, revenue from temporary sales reached 30% of total revenue during the 2000s compared to 20% in the 1990s.[9]

2.3 The Link between the Frequency of Sales and Macroeconomic Conditions

2.3.1 Labor Market Indicators

To examine the link between the frequency of sales and macroeconomic conditions, we start by looking at labor market indicators. Figure 3 plots the frequency of sales against the unemployment rate in the upper panel and hours worked in the lower panel. We measure the frequency of sales based on the mode filter with a 42-day window. The figure shows that during the two decades, the unemployment rate increased, while hours worked decreased. These developments reflect the deterioration in the labor market following the burst of the asset price bubble. In addition, the decline in hours worked also reflects the reduction in the statutory workweek length resulting from a revision of the Labor Standards Law.[10]

These secular developments in the unemployment rate and hours worked seem to have implications for the secular increase in the frequency of sales.

2.3.2 Correlation between Sales and Macroeconomic Conditions

The relationship described in the previous subsection covers a relatively long time horizon (two decades). Next, we examine the link between the frequency of sales and macroeconomic conditions for a shorter time horizon, the business cycle. We isolate the cyclical component of the time series of temporary sales and macroeconomic conditions between 1.5 to 8 years using the Baxter-King band pass filter and compute the contemporaneous correlation. The indicators of macroeconomic conditions we look at are the unemployment rate, total hours worked, and the monthly growth rate of CPI. To account for the possibility that the Baxter-King band pass filter may yield spurious correlations, we calculate the 90% and 95% confidence intervals using Monte Carlo simulation. That is, we first generate two i.i.d. time-series variables drawn from

[9] Online Appendix A.2 decomposes goods into processed food and domestic articles.

[10] The revision stipulated a gradual shortening of the workweek length from 48 to 40 hours. See Kawaguchi, Naito, and Yokoyama (2008) for an analysis of the impact of the revision on hours worked, as well as Kuroda (2010), who argues that hours worked remained essentially unchanged after controlling for demographic changes.

the standard normal distribution. Then, we extract their business-cycle components using the Baxter-King band pass filter and calculate their correlations. The 90% and 95% confidence intervals become 0.3316 and 0.3879, respectively.

Table 4 shows that the frequency of sales is significantly correlated with labor market indicators, especially, hours worked. Regardless of the choice of sales filter, the correlation is negative for the aggregated product category. That is, when hours worked are high, the frequency of sales tends to be low. The correlation with the unemployment rate is positive but insignificant using a 42-day window. However, it is positive and significant using a 7-day window. That is, the frequency of sales tends to be high when the unemployment rate is high.[11] These results suggest that retailers raise the frequency of sales when households are less busy working, which is plausible if such households increase time spent bargain hunting.

This cyclicality may depend on the product category. In the United States, Kryvtsov and Vincent (2015) point out that the acyclicality in Coibion, Gorodnichenko, and Hong (2015) arises because food products dominate their sample and these show an upward trend in the frequency of sales, unlike other types of products. To examine this, we divide the sample into processed food and domestic articles. In contrast to the U.S. case, the table shows that counter-cyclicality arises mainly from processed food in Japan, which dominates our POS data.[12]

There is no clear correlation between the frequency of sales and the CPI inflation rate. Moreover, the bottom panel of the table shows that, except for domestic articles, there is no significant correlation between the magnitude of sales discounts and macroeconomic factors. Therefore, we focus on the frequency of sales in particular in the next section rather than the magnitude of sales to construct a DSGE model.[13]

2.3.3 Panel regression

Next, as in Coibion, Gorodnichenko, and Hong (2015), we extend our data to the cross-section dimension and conduct a panel regression. To this end, we collect the monthly time series of hours worked for respondents working at establishments with more than 30 employees by prefecture based on the Monthly Labor Survey released from the Ministry of Health, Labour and Welfare. Because there were several revisions to the survey in terms of industry categorizations and the scope of the sampled establishments, easily accessible and consistent panel data are available only until December 2004. We apply seasonal adjustments using the X12 ARIMA

[11] As for the differing results between hours worked and the unemployment rate, Braun et al. (2006) show that in Japan, labor input adjustment occurs mostly through changes in hours per worker rather than changes in number of workers, while in the United States, the adjustment occurs through changes in number of workers.

[12] As Online Appendix A.2 shows, both processed food and domestic articles show an upward trend in the frequency of sales in Japan. This trend does not influence our results per se, because the Baxter-King band pass filter filters this out in our analysis.

[13] Online Appendix A.2 provides the correlations between sales and a number of macroeconomic variables.

to the series of hours worked in each prefecture and classify 47 prefectures in Japan into nine regions: (i) Hokkaido, (ii) Tohoku, (iii) Minami-Kanto, (iv) Kita-Kanto and Koshin, (v) Hokuriku, (vi) Tokai, (vii) Kinki, (viii) Chugoku and Shikoku, and (ix) Kyusyu and Okinawa, following the classification of the Ministry of Internal Affairs and Communication, and construct the time series of hours worked for each region. We then regress the frequency of sales on time and region dummies as well as hours worked in the region.

Table 5 shows that the coefficient on hours worked is significantly negative at the 5% level using the mode filter to identify the frequency of sales. Even at a cross-section level, the frequency of sales has a negative relationship with hours worked.

2.4 Differences from the United States

This section so far has provided various pieces of evidence about the frequency of sales and its relationship to the macroeconomic environment. The key finding is that the frequency of temporary sales moves in the opposite direction of hours worked, not only in the long run but also in the time horizon of business cycles. This is likely because when hours worked are lower, households have more time for bargain hunting and are therefore more price sensitive. Thus, retailers hold more frequent temporary sales.

However, many studies show contradictory results for the United States. Eichenbaum, Jaimovich, and Rebelo (2011), Anderson et al. (2012), and Coibion, Gorodnichenko, and Hong (2015) argue that retailers' decision to hold sales is orthogonal to macroeconomic circumstances, although Klenow and Willis (2007) and Kryvtsov and Vincent (2015) argue that business cycles influence sales decisions. The relationship between the frequency of sales and the macroeconomic environment in the United States is not so strong as that in Japan.

There are at least two possible explanations for this difference. First, pricing strategies in Japan and the United States differ. Unlike in Japan, many retailers in the United States use an every-day-low-price strategy. According to Coibion, Gorodnichenko, and Hong (2015), it is mainly lower-priced stores such as Wal-Mart that adopt an every-day-low-price strategy, while higher-priced stores hold temporary sales. Given this situation, if we assume a rise in unemployment, customers are likely to switch from higher- to lower-priced stores to reduce their expenditure. Higher-priced stores give up on such price-sensitive customers and concentrate on loyal customers. They thus reduce the frequency of temporary sales. In Japan, by contrast, even lower-priced stores conduct very frequent temporary sales. As Sudo, Ueda, and Watanabe (2014) point out, prices in Japan are revised ten times more frequently than those in the United States, due to frequent temporary sales.[14] Although these differences yield different results in

[14]Japanese households are said to go shopping more frequently from Monday to Sunday; they walk to super-

Coibion, Gorodnichenko, and Hong's (2015) study of the link between unemployment and the frequency of sales, the effect of unemployment on the average prices consumers pay (effective prices) is in the same direction in both cases. That is, average prices decrease when the unemployment rate rises.

The second possible explanation is that our POS data cover a very long period, from 1988 to 2013. This is considerably longer than the typical duration of business cycles, which helps illustrate both secular and cyclical developments in sale pricing. By contrast, Coibion, Gorodnichenko, and Hong (2015) use U.S. price data for a relatively short period, from 2001 to 2011. The popular Dominicks supermarket dataset covers from 1989 to 1997. Unless the observation period is sufficiently long relative to the duration of business cycles, it is difficult to accurately estimate the link between the frequency of sales and macroeconomic conditions. If the second reason explains most of the difference, our findings for Japan may hold more generally; that is, the frequency of sales decreases when hours worked rise.

3 Model

In this section, we present the DSGE model of temporary sales by extending the GS model to incorporate endogenous bargain hunting. To this end, we introduce two innovations, each of which corresponds to the cost and benefit of bargain hunting. On the one hand, bargain hunting decreases the time for leisure and hence utility. On the other hand, bargain hunting enables a household to optimize brand choices in each product type.[15]

3.1 Setup

The Household A representative household consists of a household chief and an infinite number of shoppers responsible for purchasing the goods of brand $b \in B$ of product type $\tau \in T$. GS gives the example of beer and dessert as product types, and Corona beer and Ben & Jerry's ice cream as brands falling into those product categories, respectively. These shoppers are populated over the interval $[0, 1]$. The fraction, $1 - L_t$ ($L_t \in (0, 1]$), of shoppers have sufficient time for bargain hunting and can purchase goods optimally. The fraction, L_t, of shoppers do not have enough time for shopping and observe only the price of one brand for all product types. Whether a shopper belongs to the former or latter type and which brand the latter type purchases are randomly chosen in each period and exogenous to the chief of

markets nearby, purchase a small amount of products, and bring them back on foot. In contrast, U.S. households shop mainly on weekends and by car. According to the *Survey of Consumer Behavior* by the Japanese Meat Information Service Center, the average shopping frequency in the 2000s was three to four times a week. These country-specific characteristics may explain these differences in retailers' pricing strategies.

[15]See Online Appendix B for the model's details.

the household. We refer to the former and latter types of shoppers as bargain hunters and loyal customers, respectively, and call L_t and $1 - L_t$ loyalty and bargain hunting intensity, respectively. This L_t is a choice variable for the chief of the household.[16]

Specifically, the household has the following lifetime utility function:

$$U_t = \sum_{j=0}^{\infty} \beta^j \mathrm{E}_t \left[v(C_{t+j}) - Z_{t+j}^h v \left(H_{t+j} + \phi_L H \frac{(1 - L_{t+j})^{\theta_L}}{(1 - \lambda)^{\theta_L}} \right) \right], \tag{3.1}$$

where C_t is an aggregate composite of differentiated consumption goods defined below and H_t is hours worked. Parameter $\beta \in (0, 1)$ is the subjective discount factor, ϕ_L represents the utility weight for bargain hunting, and $\theta_L > 0$ represents the elasticity of loyalty with respect to changes in hours worked. Z_t^h represents a stochastic shock to the utility weight of labor supply with unit mean, and we denote the logarithm deviation of the stochastic shock by ε_t^h. A positive shock decreases labor supply and increase loyalty. The function $v(C_t)$ is strictly increasing and strictly concave in C_t, and $v(X_t)$ is strictly increasing and convex in X_t. H and λ represent the initial steady-state levels of H_t and L_t, respectively.

The household's budget constraint is

$$P_t C_t^* + E_t[\Theta_{t+1|t} A_{t+1}] \leq W_t H_t + D_t + A_t, \tag{3.2}$$

where P_t and C_t^* represent the average aggregate price level and aggregate consumption spending, respectively. That is, they satisfy

$$P_t C_t^* \equiv \int_{\tau \in T} \int_{b \in B} p_t(\tau, b) c_t(\tau, b) db d\tau, \tag{3.3}$$

where $p_t(\tau, b)$ and $c_t(\tau, b)$ represent the price and consumption of brand b of product type τ, respectively, and C_t^* is different from C_t, as we discuss below. W_t is the wage, D_t is dividends received from firms minus the lump-sum tax, Θ_t is the asset pricing kernel, and A_t is the household's portfolio of Arrow-Debreu securities.

The first innovation in our model is the inclusion of the last term, L_{t+j}, in equation (3.1). This suggests that the utility of the representative household increases as bargain hunting intensity falls. Bargain hunting, like supplying labor, decreases the time for leisure and hence utility. Because of the convexity of $v(\cdot)$, more hours worked raise the marginal disutility of bargain hunting.

[16]Even if L_t is constant, this assumption gives a slightly different interpretation to the model from that of GS. In the GS model, each household is a bargain hunter for a fixed proportion of goods and loyal for other goods. In our model, a household consists of bargain hunters and loyal customers for each good.

The overall aggregator of consumption is

$$C_t \equiv \left[\int_{\tau \in T} \left(\int_{b \in B} c_t(\tau, b)^{\frac{\eta-1}{\eta}} db \right)^{\frac{\eta(\epsilon-1)}{\epsilon(\eta-1)}} d\tau \right]^{\frac{\epsilon}{\epsilon-1}} . \tag{3.4}$$

Following GS, we assume that $\eta > \epsilon$, so household shoppers are more willing to substitute different brands of a specific product type than different product types.

The household chief solves the expenditure minimization problem subject to equation (3.4). Suppose, for the moment, that there are no loyal customers among shoppers; cost minimization then leads to the following demand function for goods:

$$c_t(\tau, b) = \left(\frac{p_t(\tau, b)}{p_{B,t}(\tau)} \right)^{-\eta} \left(\frac{p_{B,t}(\tau)}{P_t} \right)^{-\epsilon} C_t^*, \tag{3.5}$$

where the price index associated with a product type τ, $p_{B,t}(\tau)$, is

$$p_{B,t}(\tau) = \left(\int_{b \in B} p_t(\tau, b)^{1-\eta} db \right)^{\frac{1}{1-\eta}} . \tag{3.6}$$

The second innovation is the informational friction confronting loyal customers, who do not have enough time to collect price information for other brands, say $p_t(\tau, \tilde{b})$, and observe only the price of brand b, $p_t(\tau, b)$, exclusively. They thus cannot construct the price index for product type $p_{B,t}(\tau)$, which appears in the demand function for bargain hunters (3.5). The shopper's best guess is to assume $p_{B,t}(\tau) = p_t(\tau, b)$ and decide how much to spend on the goods under this premise. Hence, the demand function is collapsed to[17]

$$c_t(\tau, b) = \left(\frac{p_t(\tau, b)}{P_t} \right)^{-\epsilon} C_t^*. \tag{3.7}$$

For the representative household as a whole, the demand function is the combination of equations (3.5) and (3.7). For each brand b for product τ, a $1 - L_t$ portion of shoppers purchase the goods following equation (3.5) and an L_t portion of shoppers purchase the goods following equation (3.7) within a period. The former type of shoppers can optimize shopping. By shopping around, they can observe the price index of a product type $p_{B,t}(\tau)$ and spend less

[17] The demand function of a bargain hunter (3.5) and that of a loyal customer (3.7) can be simultaneously derived by the household's chief optimization problem, which maximizes the utility expressed in equation (3.4) under a budget constraint that incorporates a wedge. The wedge, which we denote with $\gamma_t(\tau, b)$, captures the informational friction associated with having loyal customers among the shoppers. The budget constraint is given by $\int_{\tau \in T} \int_{b \in B} \gamma_t(\tau, b) p_t(\tau, b) c_t(\tau, b) db d\tau$. The wedge takes unity if a shopper is a bargain hunter, leading to the demand function in (3.5). The wedge equals $\gamma_t(\tau, b) = (p_{B,t}(\tau)/p_t(\tau, b))^{(\eta-\epsilon)/\eta}$ if a shopper is a loyal costumer, leading to the demand function in (3.7).

on brand b if the price of the good from brand $p(\tau, b)$ is high relative to the price index $p_{B,t}(\tau)$. The latter type of shoppers cannot observe the price index $p_{B,t}(\tau)$ and determine the amount to purchase without referring to $p_{B,t}(\tau)$. For a firm that produces goods $c_t(\tau, b)$, the demand functions have exactly the same form as that in GS, which drastically simplifies our analysis below.[18]

In choosing the optimal L_t, the household chief faces a trade-off. On the one hand, an increase in L_t raises the household's utility. As equation (3.1) shows, the household increases leisure time by decreasing the time spent on bargain hunting. On the other hand, the increase in L_t decreases the benefit of bargain hunting. The household decreases its utility by selecting the sub-optimal amount of demand because it is forced to purchase products according to the demand function (3.7). We illustrate this second effect by the relationship between utility-related consumption C_t and spending-related consumption C_t^* : C_t depends not only on C_t^* but also on the following consumption wedge $\digamma_t$:

$$C_t = \digamma_t \cdot \left(\frac{P_{B,t}}{P_t}\right)^{-\epsilon} C_t^*, \tag{3.8}$$

where

$$\digamma_t \leq 1 \text{ and } d\digamma_t / dL_t < 0. \tag{3.9}$$

$P_{B,t} = p_B(\tau)$ is the common value of the bargain hunters' price index in equilibrium.[19] As the household engages in more bargain hunting, L_t decreases and $\digamma_t$ increases. The household enjoys higher utility from the same amount of consumption spending C_t^*. If the household engages in bargain hunting for all product types, that is, $L_t = 0$, then $\digamma_t$ is its highest value, $\digamma_t = 1$.

Additionally, following GS, we introduce Calvo-type wage stickiness into the model. That is, the household supplies differentiated labor input to firms, and wages can be adjusted at a probability of $1 - \phi_w$.

Firms An advantage of our model is that it describes firms' behavior in exactly the same way as in GS. Firms' demand function, given by equations (3.5) and (3.7), is the same as that in GS.

[18] This formulation is economically analogous to that in Kryvtsov and Vincent (2015) and Coibion, Gorodnichenko and Hong (2015). They introduce a fixed cost of shop searching, which enables a household to substitute from a relatively expensive brand b' to a less expensive brand b'' elastically. The advantage of our model is that we need not assume discrete two-price equilibria, as in Kryvtsov and Vincent (2015), but we can derive this as firms' optimal choices due to the following demand function (3.5). Similarly, Nevo and Wong (2015) simply assume a reduced-form price function that is decreasing with shopping intensity.

[19] Similar to GS, we assume that a firm takes the downward-sloping demand curve as given. In addition, we assume that each firm's decision takes loyalty L_t as given. The rationale for the latter assumption is that L_t is the function of macroeconomic variables and not the function of a specific price $p_t(\tau, b)$ that a specific firm sets.

Although loyalty L_t changes depending on returns on bargain hunting, each firm is sufficiently small that it cannot influence $P_{B,t}$ in equation (3.8), and in turn, L_t. It is thus optimal for firms to randomize their prices across shopping moments from a distribution with two prices given L_t . Firms set a normal high price, $P_{N,t}$, with a frequency of $1 - s_t$ and a low sale price, $P_{S,t}$, with a frequency of s_t. Following GS, we refer to the higher price as the normal price instead the regular price. While important, the only difference from GS is that firms optimize their pricing decisions by observing changes in loyalty L_t.

As GS argues, the strategic substitutability of sales plays a crucial role in firms' pricing. The more other firms hold sales, the less an individual firm will want to have a sale. Suppose that other firms always have a sale. If an individual firm stops holding a sale and sells its good at the normal price, its profit increases, since price-insensitive loyal customers tend to buy the good even at the normal price. As the opposite case, suppose that other firms do not hold sales. Because sales attract price-sensitive bargain hunters, an individual firm can increase its profit by having sales. Such strategic substitutability leads firms to randomize their prices between the high normal price and the low sale price.

We characterize firms' adjustments to normal prices by Calvo-type price stickiness. That is, in each period, firms can reset their normal prices with a probability of $1 - \phi_p$. Firms can adjust sale prices freely.

Wholesalers produce goods using labor input:

$$Q_t = Z_t^a H_t^\alpha, \tag{3.10}$$

where α represents the elasticity of output with respect to labor input and Z_t^a represents a stochastic shock to productivity, which has a mean of one, and where ε_t^a denotes the logarithm deviation.

Monetary Authority The monetary authority sets the nominal interest rate i_t based on the following monetary policy rule:

$$i_t = \rho i_{t-1} + (1 - \rho)\phi_\pi \pi_t^N + \varepsilon_t^i, \tag{3.11}$$

where π_t^N represents the change in the normal price. The official CPI excludes sales, so we assume that the monetary authority refers to the inflation rate based on the normal price. Policy parameters ρ and ϕ_π represent interest rate inertia and the size of the response to the inflation rate, respectively. ε_t^i represents a shock to monetary policy with zero mean.

Resource Constraint The resource constraint for goods is given by

$$Y_t = C_t^* + Z_t^d, \tag{3.12}$$

where Z_t^d represents a stochastic shock to external demand. Its mean is zero and we denote the logarithm deviation from the steady-state Y by ε_t^d.

3.2 Log-Linearized Equations

We explain some key log-linearized equations to help explain the important mechanism in our model. We denote log deviations of variables from the initial steady state with small letters.

Sale Pricing It is optimal for a firm j to adjust its sale price, $p_{S,j,t}$, one-for-one in line with any change in its nominal marginal cost, $x_t + p_t$, that is,

$$p_{S,j,t} = x_t + p_t, \tag{3.13}$$

where x_t denotes the real marginal cost.

The frequency of sales is

$$ss_t = -\frac{1-\theta_B}{\varphi_B}\frac{1}{1-\psi}x_t - \left(\frac{1-\theta_B}{\varphi_B}\frac{A}{1-\psi} + \frac{1}{(\eta-\epsilon)(1-\lambda)\varphi_B}\right) l_t. \tag{3.14}$$

The second term on the right-hand side, which is not in the original GS model, indicates that as loyalty l_t increases, firms decrease the frequency of sales s_t. In other words, when households reduce bargain hunting, the benefits of holding sales decreases, and firms thus decrease the frequency of sales. Like in the GS model, an increase in the real marginal cost x_t decreases the frequency of sales. Because the sale price responds one-for-one to changes in marginal costs, the sale price increases more than the normal price. This decreases the relative demand for goods when they are on sale, thereby decreasing the frequency of sales.

Loyalty Loyalty l_t is given by

$$\begin{aligned}
0 = &\left(\theta_c^{-1} + \frac{1}{1+\gamma\delta}\frac{\theta_h^{-1}}{\alpha} - 1\right) y_t - \frac{\delta}{1+\gamma\delta}\frac{\theta_h^{-1}}{\alpha} w_t - \frac{\theta_h^{-1}}{\alpha}\varepsilon_t^a + \varepsilon_t^h - (\theta_c^{-1} - 1)\varepsilon_t^d \\
&- \left(\frac{1}{1+\gamma\delta}\frac{\theta_h^{-1}}{\alpha}B + (\theta_L - 1)\frac{\lambda}{1-\lambda} + \theta_h^{-1}\phi_L\frac{\lambda}{1-\lambda}\right) l_t \\
&+ \frac{\Xi}{1-\Xi}\xi_t + \frac{\eta-1}{\eta}f_t, + (\theta_c^{-1} - 1)\left\{f_t - \epsilon\left(x_t + \frac{1}{(\eta-\epsilon)(1-\lambda)}l_t\right)\right\}
\end{aligned} \tag{3.15}$$

where θ_c and θ_h are the elasticity of consumption and the inverse of the elasticity of labor supply, respectively.

Two things are worth noting. First, loyalty l_t increases with aggregate demand, y_t, and consequently, hours worked, h_t. As hours worked increase, the disutility from bargain hunting increases, and hence loyalty increases.

Second, loyalty l_t increases with the consumption wedge, f_t. A larger consumption wedge means greater utility from a given amount of consumption spending. As the wedge grows, the benefit from bargain hunting diminishes, thus increasing loyalty. We can also show that the consumption wedge increases with the ratio of the sale price to the normal price, $\mu_t = P_{S,t}/P_{N,t}$, and decreases with the sale frequency, s_t. In other words, as the sale price converges to the normal price or sales become less frequent, prices for different brands become more homogeneous and the consumption wedge grows.

Phillips Curve with Sales The New Keynesian Phillips curve with sales is given by

$$\pi_t = \beta E_t \pi_{t+1} + \frac{1}{1-\psi} \left\{ \kappa x_t + \psi(\Delta x_t - \beta E_t \Delta x_{t+1}) + \kappa A l_t + A(\Delta l_t - \beta E_t \Delta l_{t+1}) \right\}. \tag{3.16}$$

Compared with the standard New Keynesian Phillips curve, this equation has two additional terms. First, as in GS, changes in the real marginal cost, Δx_t, influence the inflation rate, π_t. This is because the overall price depends on the sales price, which is itself proportional to the real marginal cost, as shown in equation (3.13). Second, unlike in GS, loyalty l_t influences the inflation rate. As loyalty increases, the household substitutes less from relatively expensive brands to cheaper brands. Observing this, firms lower the frequency of sales, and hence the overall price index increases.

4 Why Did the Frequency of Sales Rise During Japan's Lost Decades?

As we saw in Figure 2, the frequency of sales, s_t, rose during Japan's lost decades. In this section, we examine why the frequency of sales rose using our model and argue that the decline in hours worked explains this phenomenon. Moreover, we calibrate the elasticity of loyalty with respect to changes in hours worked, θ_L, which plays an important role in determining the real effect of monetary policy.

4.1 Calibration

We base most of the calibration of our model parameters on GS (see Table 6). The exceptions are the parameters associated with sales, which we choose in order to maintain consistency with the POS data for Japan shown in Table 3. Based on the mode filter with a 42-day window, the average frequency of sales, s, is 0.211; the average ratio of quantities sold at the sale and normal prices, χ, is 2.055; and the average magnitude of sales discounts is 15.5%, which means $\mu = 0.845$. Then, we obtain the elasticity between product types $\epsilon = 2.677$, the elasticity between brands $\eta = 13.640$, and the mean of loyalty $\lambda = 0.878$. See Table 7. We choose the value of θ_L =1.7 to match the historical change in the frequency of sales, as we show below. We calculate the theoretical elasticity of loyalty with respect to the real wage as $\theta_h^{-1}(\theta_L - 1)^{-1} = 2.0$. Although not strictly comparable, this value is similar to the estimate by Nevo and Wong's (2015) point estimate of 1.7 for the elasticity of substitution between time and market goods in home production.

4.2 Simulation Method

In conducting the simulation, we assume that the steady state in each year changes due to exogenous changes in the size of external demand Z_t^d. External demand changes annually and the economy converges to a steady state consistent with the change in external demand. With this assumption, we draw the time-series path of Z_t^d to account for the actual movements in hours worked in Japan. We choose Z_t^d exclusively because the GDP series the model generates with Z_t^d replicates the actual GDP movements better than that with other factors, as we discuss below. Moreover, prior empirical studies support this assumption.[20]

Using the value for Z_t^d we obtain from the method above, we simulate the time-series paths of variables associated with temporary sales. We use two models for comparison: the GS model and our model with endogenous changes in loyalty. We use hours worked multiplied by one minus the unemployment rate to account for total labor input. The sample period is from 1981 to 2013.

[20] For Japan, Sugo and Ueda (2008) estimate a sticky-price DSGE model similar to Smets and Wouters (2003), and find that one of the main driving forces of business cycles was investment adjustment cost shocks. Bayoumi (2001) and Caballero, Hoshi, and Kashyap (2008) argue that financial shocks caused Japan's lost decade(s). Although investment adjustment cost and financial shocks do not necessarily represent demand shocks, these studies suggest that Japan's business cycles do not only result from technology shocks. For the United States, Nevo and Wong (2015) argue that the changes in household shopping behavior during the Great Recession were driven not by non-market shocks such as shocks to labor supply in our model, but rather unanticipated income and wealth shocks.

4.3 Simulation Results

Figure 6 shows the simulated paths of variables associated with temporary sales; namely, the frequency of sales (s_t), the magnitude of sales discounts ($1 - \mu_t$), the quantity ratio (χ_t), and the revenue ratio along with the macroeconomic variables of hours worked and real GDP growth rates. The top-middle panel illustrates that our model explains the secular increase in the frequency of sales, s_t, both qualitatively and quantitatively. By contrast, the GS model predicts no change in the frequency of sales. However, as for the magnitude of sales discounts and the quantity ratio, the simulated paths show no fluctuations. In summary, these simulation results suggest that our model improves on the GS model in explaining the extensive margin of sales (the frequency of sales) but not the intensive margin (sales discounts). As for the revenue ratio, our model performs well in accounting for its movement.

Our model also shows changes in loyalty and household price elasticity, which are unobservable. The middle-right panel indicates that loyalty remained almost constant in the 1980s, but shows a downward trend during the lost decades of the 1990s and 2000s. Put differently, bargain hunting intensity increased. Obviously, in the GS model, loyalty remains constant. In the bottom-left panel, we report a path of household price elasticity, which we calculate by a weighted average of the elasticity of bargain hunters and that of loyal customers. The household price elasticity showed a secular increase. Finally, the bottom-middle panel shows that the model-based real GDP changes move very closely to the actual changes. The former explains the latter with an R-squared measure of 0.35 for the full sample period. The R-squared increases to 0.60 when we compute the number based on the subsample period of the lost decades from 1992 to 2013.

When we assume technology (Z_t^a) or labor supply (Z_t^h) factors instead of external demand as a driver of the actual hours worked, the model performs poorly.[21] Most notably, changes in Z_t^h yield a decrease in the frequency of sales together with the decrease in hours worked, which is contrary to what we observed in the data. An increase in Z_t^h increases the disutility of the labor supply, decreasing both hours worked and bargain hunting. Thus, a positive correlation is generated between hours worked and the frequency of sales. This result is in line with Nevo and Wong (2015), who investigate the Great Recession in the United States and find that the elasticity between expenditures on market goods and time spent on home production did not change in the wake of the Great Recession. In that regard, they argue that the recession was not driven by shocks to the non-market sector, that is, labor supply shocks. Moreover, in our model, when we assume technology Z_t^a, the frequency of sales increases, which is consistent with the data. However, it fails to explain the actual changes in the GDP. Our simulation

[21] See Online Appendix C.

implies, similar to Nevo and Wong (2015), that the secular decline in hours worked and the secular increase in the frequency of sales in Japan were driven by stagnant demand rather than supply factors.

5 Impulse Response Functions

To study the implications for the macroeconomy, we simulate impulse response functions (IRFs) of economic variables to an accommodative monetary policy shock, ε_t^i.[22] Different from GS, we assume that the central bank follows an interest rate monetary policy rule, with $\rho = 0.8$ and $\phi_\pi = 1.5$, while in GS the central bank follows a money growth rate rule. We set two alternative values for θ_L: 1.7 and 100. A lower θ_L implies a higher elasticity of loyalty with respect to changes in hours worked.

5.1 The Effects of Endogenous Bargain Hunting

We examine the IRFs of our model and compare them with those of the GS model. Figure 6 shows the IRFs of eight economic variables, with the blue solid lines representing the IRFs of the GS model. The thick solid lines and the lines with asterisks represent the IRFs of our model with endogenous changes in loyalty for the two different elasticity parameter values θ_L =1.7 and 100, respectively. The horizontal axis shows the time up to 12 quarters after a shock.

The figure indicates that temporary sales dampen the monetary policy effect on aggregate demand by around 40%. The mechanism runs as follows. In response to the monetary policy shock resulting from a lower nominal interest rate, aggregate demand increases. This increases hours worked. Since the household spends more time working, its disutility from bargain hunting increases. With endogenous bargain hunting, loyalty (bargain hunting) increases (decreases). Observing this, firms lower the frequency of sales. Since firms sell a higher quantity of goods when goods are on sale, the decrease in the frequency of sales dampens the increase in aggregate demand. The effect of monetary policy on demand decrease as θ_L decreases.

The increased strategic substitutability of sales also explains the attenuated real effect of monetary policy. Suppose that all firms except for firm A raise the frequency of sales. As in GS, this reduces the incentive for firm A to increase the frequency of sales, since doing so would decrease the marginal revenue from sales. In our model, an additional channel emerges. When all firms except for firm A raise the frequency of sales, the aggregate price level falls. This increases aggregate demand for goods and, in turn, aggregate demand for labor. The

[22] The IRFs to an external demand shock, which we used in the previous section, are qualitatively similar to those to a monetary policy shock. To conserve space, we report the IRFs to the other three types of shocks, that is, wholesalers' production technology, external demand, and labor supply, in Online Appendix D.

household supplies more labor and reduces time for bargain hunting. Observing this, firm A lowers the frequency of sales. This intensified strategic substitutability of sales mitigates the real effect of monetary policy.

The inflation rate excluding sales (i.e., changes in normal prices) also fluctuates less in this model than in the GS model. As we explained in the previous section, an increase in loyalty decreases the real wage and the real marginal cost. Although the accommodative monetary policy shock increases hours worked and puts upward pressure on the real marginal cost, the effect of the increase in loyalty dominates when θ_L is low. On the other hand, the model yields greater increases in the inflation rate including sales than the GS model because the aggregate price level increases due to the rise in loyalty and the decline in the frequency of sales in response to the shock.

Finally, although our model shows that temporary sales dampen the real effect of monetary policy shocks, we should emphasize that monetary policy shocks still have real effects. Temporary sales do not fully eliminate the real effect of monetary policy shocks, despite the fact that aggregate price levels including sales look perfectly flexible.

6 Concluding Remarks

In this study, we first examined empirically whether there is a link between the frequency of sales and changes in macroeconomic conditions. Based on Japanese supermarket scanner data spanning two decades, we found a significant negative correlation between the frequency of sales and hours worked. Second, we constructed a DSGE model with temporary sales and endogenous bargain hunting to examine the cause of the increase in the frequency of sales in Japan, and to examine the implications of endogenous sales frequency for monetary policy transmission. The model showed that the decline in hours worked during Japan's lost decades accounts for the actual rises in the frequency of sales and implies that the fraction of price-sensitive bargain hunters has increased. Because firms in Japan frequently hold sales and endogenous bargain hunting increases the strategic substitutability of sales, the real effect of monetary policy shocks weakens by around 40%, although monetary policy still matters for the real economy.

There are several potential avenues for future research. The first would be to pursue further qualitative and quantitative evidence for endogenous bargain hunting. In particular, more empirical research using micro data on how individuals optimize time spent between bargain hunting and working is necessary. Second, studies could improve our model to account for both the extensive margin (the frequency of sales) and the intensive margin (the size of sales discounts).

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Table 1: Time Spent (minutes per day)

	Men			Women		
	(who work) Shopping	(who work) Working	(who do not work) Shopping	(who work) Shopping	(who work) Working	(who do not work) Shopping
1986	6	493	9	27	371	37
1991	9	481	12	30	358	38
1996	11	469	15	30	345	39
2001	13	456	18	31	324	39
2006	14	470	20	31	335	39
2011	15	466	22	32	326	40

Note: Working time includes commuting time. Source: Statistics Bureau, *Survey on Time Use and Leisure Activities*.

Table 2: Regression Results for Time Spent Shopping (minutes per day)

	All	Persons who spend their time mainly working	Men who spend their time mainly working
working time	-0.059***	-0.063***	-0.058***
	(0.002)	(0.003)	(0.003)
non-city	4.911***	2.996***	3.389***
	(0.619)	(0.388)	(0.460)
female	12.034***	11.646***	
	(1.295)	(1.200)	
age control	Y	Y	Y
Observations	180,240	91,188	62,878

Notes: Figures in parentheses represent robust standard errors. ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively.

Table 3: Basic Statistics for the POS Data

Filter	mode		V-shaped		mode		V-shaped	
Window	42d		42d		7d		7d	
Frequency of posted price changes	0.202	(0.061)	0.202	(0.061)	0.202	(0.061)	0.202	(0.061)
Frequency of regular price changes	0.002	(0.001)	0.005	(0.002)	0.011	(0.002)	0.029	(0.004)
Frequency of sales	0.211	(0.034)	0.244	(0.033)	0.142	(0.038)	0.129	(0.031)
Magnitude of sales discounts	0.155	(0.020)	0.167	(0.018)	0.117	(0.016)	0.144	(0.017)
Quantity ratio	2.055	(0.222)	2.155	(0.247)	1.812	(0.127)	1.871	(0.177)
Quantity at sales	12.524	(3.199)	12.253	(1.200)	12.132	(3.031)	12.756	(3.483)
Quantity at regular	6.043	(1.200)	5.630	(0.034)	6.679	(1.559)	6.767	(1.558)
Revenue ratio	0.247	(0.034)	0.269	(0.036)	0.192	(0.039)	0.192	(0.034)

Notes: Figures in parentheses represent standard deviations. The sample is from March 1, 1988 to October 31, 2013 (daily). The frequency of price changes is daily.

Table 4: Correlation between the Frequency/Magnitude of Sales and the Macroeconomy

	Frequency of sales							
Filter	mode	V-shaped	mode	V-shaped	mode	mode	V-shaped	V-shaped
Window	42d	42d	7d	7d	42d	42d	42d	42d
Goods	all	all	all	all	food	domestic	food	domestic
Macro variables								
Unemp	0.215	0.147	0.479**	0.505**	0.239	0.017	0.162	-0.048
Hours	-0.428**	-0.393**	-0.480**	-0.444**	-0.471**	-0.020	-0.385*	-0.096
CPI	-0.243	-0.205	-0.251	-0.261	-0.330	0.150	-0.284	0.261

	Magnitude of sales discounts							
Filter	mode	V-shaped	mode	V-shaped	mode	mode	V-shaped	V-shaped
Window	42d	42d	7d	7d	42d	42d	42d	42d
Goods	all	all	all	all	food	domestic	food	domestic
Macro variables								
Unemp	-0.122	-0.157	-0.007	-0.135	-0.13	-0.147	-0.161	-0.112
Hours	0.249	0.305	0.282	0.325	0.253	0.419**	0.290	0.421**
CPI	-0.066	-0.105	-0.166	-0.088	-0.04	-0.024	-0.038	-0.203

Note: ** and * represent significance at the 5 and 10 percent levels, respectively.

Table 5: Panel Regression Results for the Frequency of Sales

Filter	mode	V-shaped	mode	V-shaped
Window	42d	42d	7d	7d
Explanatory variables				
Hours worked	-0.006**	-0.005	-0.006***	-0.004
	(0.003)	(0.005)	(0.002)	(0.003)
Time dummy	Y	Y	Y	Y
Region dummy	Y	Y	Y	Y
Observations	1684	1684	1,696	1,696
Number of Regions	9	9	9	9
Sample: April 1988 to Dec 2004				

Note: Robust standard errors in parentheses. ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively.

Table 6: Model Parameters

Parameters		
β	Discount factor	0.9975
θ_c	Elasticity of consumption	0.333
θ_h	Inverse elasticity of labor supply	0.7
ς	Elasticity btw differentiated labor	20
α	Elasticity of output to hours	0.667
γ	Elasticity of marginal cost	0.5
ϕ_p	Calvo price stickiness	0.889
ϕ_w	Calvo wage stickiness	0.889
ρ	Monetary policy rule inertia	0.8
ϕ_π	Monetary policy response to inflation	1.5

Table 7: Parameters Related to Sales

Target variables		
s	Frequency of sales	0.211
μ	1-sales discounts	0.845
χ	Quantity ratio	2.055
Calibrated parameters		
ϵ	Elasticity btw product types	2.677
η	Elasticity btw brands	13.640
λ	Loyalty	0.878

Calibrated parameters			
ϕ_L	Utility weight on loyalty	$2.5\,10^{-4}$	$\theta_L = 100$
		0.0146	$\theta_L = 1.7$

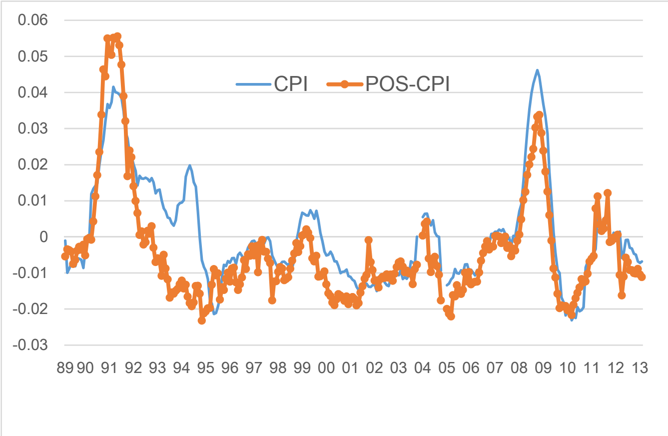

Figure 1: Inflation Rates Based on CPI and POS-CPI

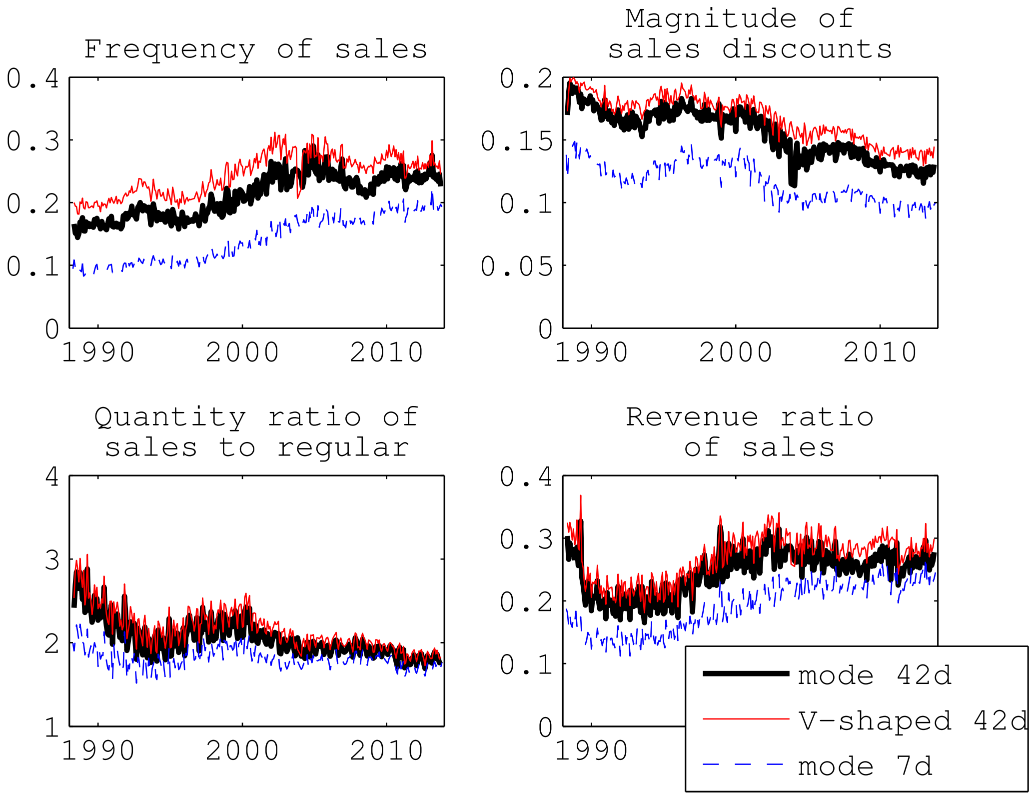

Figure 2: Variables Associated with Temporary Sales

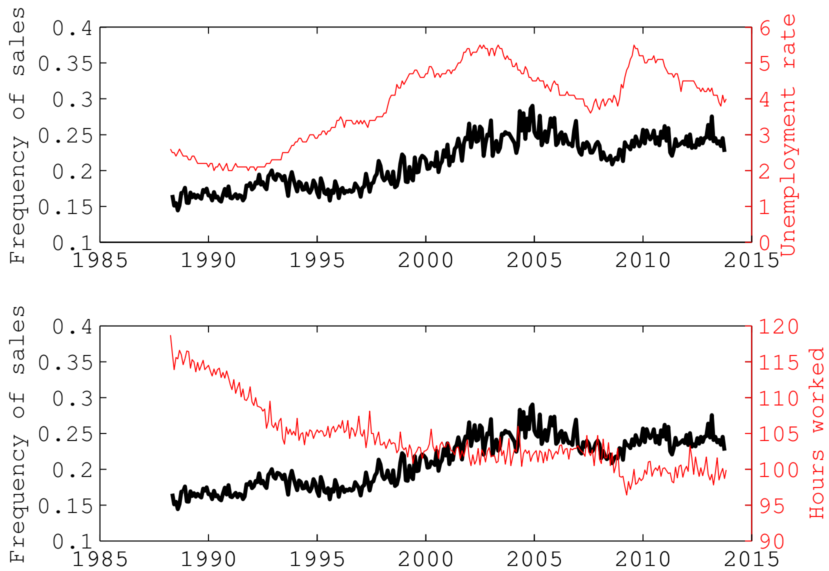

Figure 3: Frequency of Temporary Sales and Labor Market Indicators

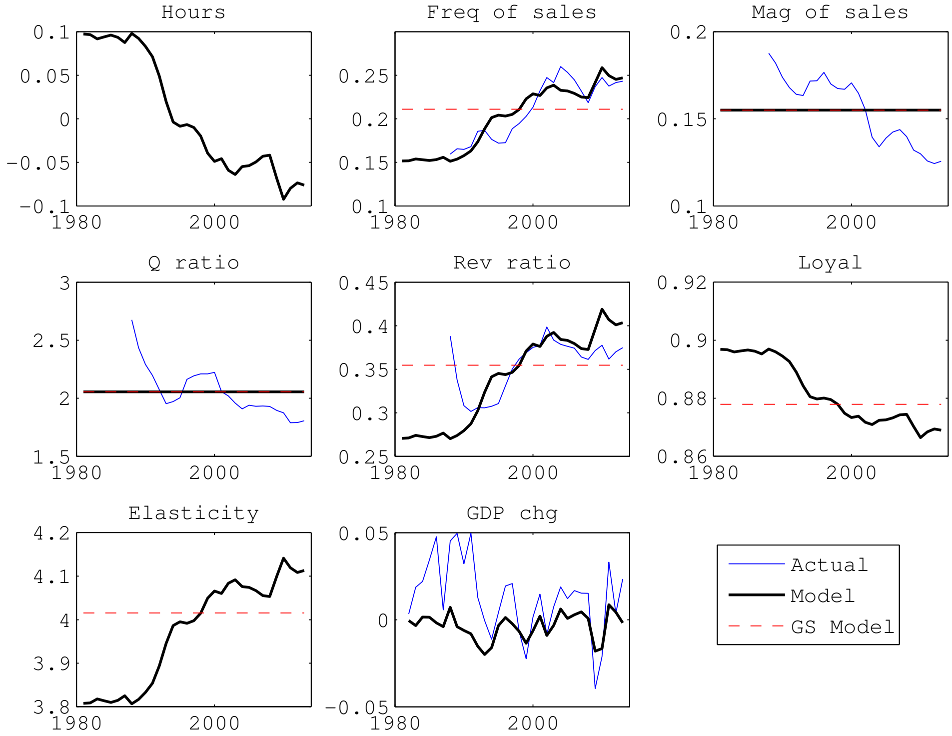

Figure 4: Model Simulation

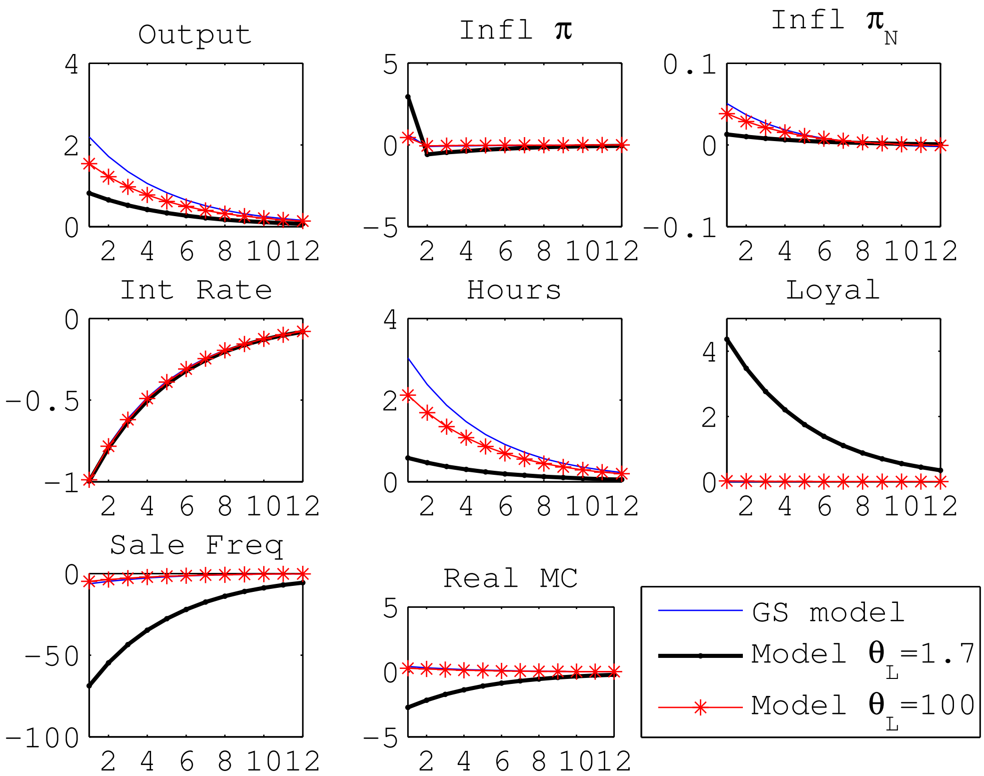

Figure 5: Impulse Responses to an Accommodative Monetary Policy Shock