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Saving by Shopping? The Limits of Substitution in Household Production

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household production, time allocation, price, elasticity of substitution

JEL Classification

D13, E32, E52, J22

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Saving by Shopping?

The Limits of Substitution in Household Production*

Miyu Iwasaki† Kozo Ueda‡

January 28, 2026

Abstract

To what extent can households buffer cost-of-living shocks by shopping more efficiently? Using novel retailer scanner data linked to individual shoppers, we isolate the savings generated by the intensive margin of shopping. We develop a structural model of endogenous shopping frequency and estimate the elasticity of substitution between time and market goods to be approximately 0.3, which is significantly lower than the values exceeding unity typically assumed in macroeconomics. This implies that households are rigid in their ability to smooth consumption. Welfare analysis shows that increases in fixed time costs lead to sizable welfare losses.

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1 Introduction

Shopping constitutes a fundamental yet frequently overlooked input in household production. By allocating time to search and timing purchases, households effectively lower the prices they pay; however, the magnitude of this trade-off depends critically on the elasticity of substitution between time and market goods. Accurately estimating this parameter is of central importance in macroeconomics, as it serves as a key mechanism to resolving puzzles regarding labor supply and consumption dynamics. The relevance of this margin is further amplified by structural shifts, including population aging, supermarket closures, and unequal access to digital markets, which threaten to raise shopping costs. These frictions may generate considerable welfare losses, particularly among disadvantaged groups. A rigorous assessment of these effects requires measuring both the returns to shopping and utilizing a structural framework to interpret their welfare implications.

The primary objective of this study is to rigorously evaluate the costs and benefits of shopping and to structurally estimate the elasticity of substitution between time and market goods. Our approach departs from the existing literature in two key dimensions. First, we utilize novel retailer scanner data that tracks individual transaction histories within a single supermarket. Unlike household scanner panels that conflate store switching (the extensive margin) with shopping effort, our data allow us to isolate the returns to pure shopping timing—the intensive margin of household production. Second, rather than relying on noisy self-reported time-use surveys, we construct a structural model where shopping frequency is endogenously determined by the frequency and magnitude of temporary sales. This allows us to estimate the elasticity of substitution directly from observed transaction behavior.

A distinct contribution of this paper is the quantitative assessment of shopping disadvantaged households who face high time costs or limited mobility. While standard models suggest households can mitigate shopping frictions by reallocating time, we explicitly analyze how increases in shopping costs (e.g., due to aging or the digital divide) affect welfare when time and goods are not easily substitutable. We simulate various scenarios involving changes in the intercept (wasted time) and slope (marginal cost) of the shopping cost function to identify which frictions drive inequality. This analysis provides new insights into how structural changes in the retail landscape disproportionately impact vulnerable groups who cannot easily substitute time for money.

Our most striking result concerns the elasticity of substitution between time and market goods. We estimate this parameter to be approximately 0.3, a value substantially lower than unity. This finding stands in sharp contrast to the consensus estimates of 1.5 to 2.0 reported in prominent studies such as Aguiar and Hurst (2007) and Nevo and Wong (2019). Our significantly lower estimate suggests that households possess far less flexibility to buffer economic shocks through shopping effort than previously thought, implying that household production offers a more limited safety net against income fluctuations.

Beyond the elasticity estimate, we document several key findings. First, empirically, we confirm a significant positive association between shopping frequency and savings, even after controlling for fixed effects: doubling shopping frequency from once to twice a week yields savings of approximately 0.66%. Second, our structural estimation reveals that shopping costs are convex. Third, our welfare analysis shows that wasted time (fixed shopping costs) generates large welfare losses that are almost one-to-one with the reduction in available time, whereas changes in the marginal cost of shopping have more limited welfare effects. Finally, we find that endogenizing shopping frequency dampens the real effects of monetary policy, as effective prices become more flexible than posted prices.

This study contributes to the literature on household production following Becker (1965). Shopping is a central component of household production: by allocating time to search and visiting supermarkets more frequently, households can purchase goods at lower effective prices. A key parameter in this literature is the elasticity of substitution between time and market goods, which governs households' intratemporal trade-off between time inputs and purchased goods. This elasticity plays a crucial role in explaining a range of macroeconomic phenomena, including the too small fluctuations of output and labor and co-movement between consumption and labor supply (Benhabib et al. (1991); Greenwood and Hercowitz (1991)).

The studies closest to ours are Aguiar and Hurst (2007) and Nevo and Wong (2019), both of which estimate the elasticity of substitution between time and market goods and report values around 1.5. Our study departs from their approach in three key dimensions. First, the data differ. We use retailer-level scanner data, whereas Aguiar and Hurst (2007) and Nevo and Wong (2019) combine household scanner data with time-use surveys. Second, the empirical strategy differs. Instead of relying on self-reported time-use data, we derive a structural relationship for shopping frequency that depends on the frequency and magnitude of temporary sales and nominal spending, without relying on time-use data. The coefficients in this specification are directly linked to the elasticity of substitution and the convexity of shopping costs. Third, the results differ. We estimate an elasticity of substitution below one, whereas Aguiar and Hurst (2007) and Nevo and Wong (2019) as well as Aguiar et al. (2013) find values exceeding one. Fang and Zhu (2017) and Chapela (2011) estimate even higher values, approximately 2. This difference suggests that households in our setting exhibit more limited substitutability between time and market goods.

Beyond household production, our study also contributes to the literature on household heterogeneity and inequality (Griffith et al. (2009); Kaplan (2017); Coibion et al. (2021)). Differences in shopping behavior and access to sales can generate heterogeneity in effective prices paid across households, which may amplify consumption inequality even in the absence of differences in nominal prices or incomes.

Finally, our analysis is related to the literature examining the interaction between shopping behavior, price dynamics, and monetary policy (Guimaraes and Sheedy (2011); Coibion et al. (2015); Sudo et al. (2018); Chevalier and Kashyap (2019)).

When shopping effort is endogenous, the effective prices households pay become more flexible than posted prices, potentially dampening the real effects of monetary policy. By providing micro-level evidence on shopping frequency and its determinants, our study offers new insights into how consumer behavior shapes price adjustment and the transmission of monetary policy.

The remainder of the paper is organized as follows. Section 2 describes the data and presents key facts on shopping behavior and savings. Section 3 introduces the model, derives its main predictions, and develops the equation for shopping frequency. Section 4 combines the model and the data to estimate the parameters governing shopping costs and the elasticity of substitution between time and market goods. Section 5 presents simulation results under changes in shopping costs. Section 6 concludes.

2 Shopping Frequency and Saving

2.1 Data

This study uses retailer scanner data provided by Magee, a commercial data provider in Japan. The data contain transaction-level records from a single supermarket located in Tokyo over the period 2011–2019. Each transaction includes detailed information on the purchase date, item identification code, price, and quantity. Transactions are further classified by whether the purchase was made by a loyalty card holder. For loyalty card holders, the data provide a unique member identifier, which allows purchases to be tracked over time at the individual level. In addition, limited demographic information is available for members, including birth year and gender.

The data cover processed food and household nondurable goods. Unlike the consumer price index (CPI), they do not include fresh food, durable goods such as televisions and mobile phones, or services, including rent, dining out, and utilities. According to the Family Income and Expenditure Survey, items covered by the scanner data account for approximately 17% of total household expenditure. Each product is identified by a Japanese Article Number (JAN) code. In addition, Magee provides a three-digit category classification code, which we use to classify products into categories such as yogurt, beer, tobacco, and toothbrushes.

Compared with household scanner data and widely used retailer scanner data, our data have both advantages and limitations. A key advantage is that we can measure savings or returns from frequent shopping more cleanly, defined as purchasing a given product at a lower sale price within the same supermarket. When household scanner data are used, observed savings may partly reflect differences in store choice across households rather than shopping intensity per se. Even after controlling for region and product, shoppers living near supermarkets with systematically lower prices may appear to achieve higher savings. For example, if lower-income or non-employed households disproportionately reside near discount supermarkets, this may mechanically generate a positive relationship between shopping frequency and savings.

Another advantage relative to standard retailer scanner data is the granularity of our data. Our dataset records transactions at the transaction level rather than at a daily or weekly frequency, whereas retailer scanner data are often aggregated weekly. This high-frequency information is particularly important in the Japanese context, where supermarkets frequently run temporary sales that last only a few days. Capturing such short-lived price changes is therefore crucial for accurately measuring savings from shopping (see Abe and Tonogi (2010) and Sudo et al. (2014) for micro price dynamics in Japan). Furthermore, the transaction-level nature of the data allows us to measure the exact purchase price paid by each member.

A limitation of our data is that they do not allow us to observe shoppers' search behavior across different supermarkets. As a result, our analysis captures savings from within-store shopping behavior but not from store switching. This limitation likely leads us to underestimate the total savings generated by frequent shopping.

Table 1: Descriptive Statistics: Supermarket Sales

Member dummy	N	Spending (billion yen)	Share
0.00	–	0.61	0.40
1.00	7,563	0.93	0.60

Note: As of 2012. N denotes the number of members who shopped at the retailer in 2012. The exchange rate was approximately 80 yen per US dollar, so one billion yen corresponded to about 12.5 million US dollars.

2.2 Descriptive Statistics

Table 1 presents descriptive statistics for the supermarket in 2012. The number of loyalty card holders who made at least one purchase during the year is 7,563. These members account for sales of 0.93 billion yen (approximately 11.6 million U.S. dollars), representing about 60% of total supermarket sales.

Table 2 reports descriptive statistics on the shopping behavior of loyalty card holders. The majority of members are female (77%), and the mean age is 52 years. The recorded minimum and maximum ages are 3 and 112, respectively, indicating that some demographic records may be inaccurate. Average annual spending per member is 122 thousand yen (approximately 1.53 thousand U.S. dollars). The final row reports daily shopping frequency. The mean shopping frequency is 0.22, implying that members shop approximately once every 4.5 days.[1] It should be noted that this measure likely overstates shopping frequency for the general customer population, as it is calculated only for loyalty card holders.

Figure 1 presents boxplots of shopping frequency by age and nominal spending as of January 2012. The left panel shows that shopping frequency exhibits no clear pattern across age groups, in stark contrast to Aguiar and Hurst (2007), who document an increase in shopping frequency with age. This lack of association persists even after

[1] Japanese households are often described as shopping more frequently throughout the week. They typically walk to nearby supermarkets, purchase small quantities of goods, and carry them home on foot. In contrast, U.S. households tend to concentrate their shopping on weekends and rely primarily on cars. According to the Survey of Consumer Behavior conducted by the Japanese Meat Information Service Center, the average shopping frequency in the 2000s was three to four times per week.

Table 2: Descriptive Statistics: Loyalty Card Holders' Shopping

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Female dummy	7,199	0.771	0.420	0	1	1	1	1
Age	7,563	52.289	18.742	3	38	51	65	112
Spending (thou yen)	7,563	122.494	171.687	0.000	12.142	55.324	160.683	1,937.379
Shop frequency	7,563	0.222	0.229	0.032	0.061	0.135	0.306	2.029

Note: As of 2012. Shop frequency denotes the daily shopping frequency (e.g., a value of 0.5 indicates that a member shops once every two days, and a value greater than 1 indicates that a member shops more than once per day).

controlling for nominal spending. In contrast, the right panel displays a clear positive relationship between shopping frequency and nominal spending, where nominal spending on the horizontal axis is grouped into five bins based on 20-percentile intervals. This relationship suggests that greater shopping needs lead to more frequent shopping.

2.3 Returns to Shopping: Savings

2.3.1 Definition of Savings

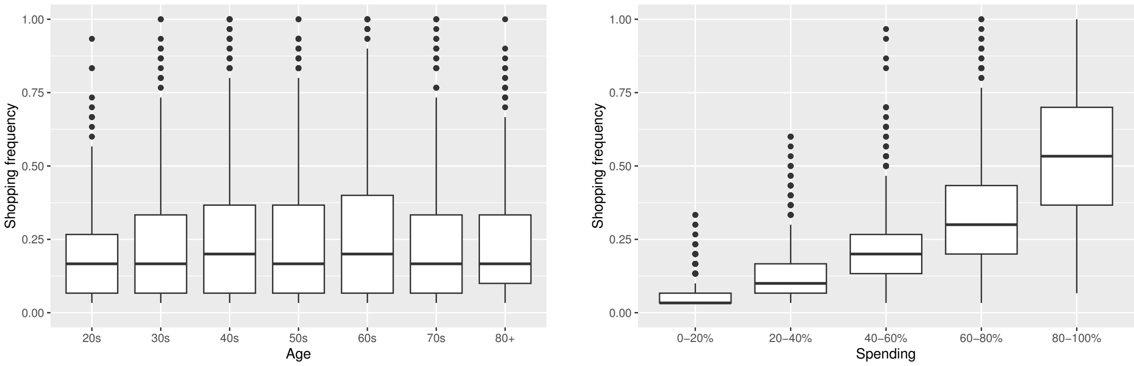
To investigate how frequent shopping reduces spending, we define savings following Aguiar and Hurst (2007) and Nevo and Wong (2019). Specifically, savings for member i in month t are defined as

$$\text{Saving}_{it} = \frac{\text{Hypothetical spending}_{it} - \text{Actual spending}_{it}}{\text{Actual spending}_{it}}. \tag{1}$$

Actual spending is given by

$$\text{Actual spending}_{it} = \sum_{f \in \Omega} p_{ift} q_{ift},$$

Figure 1: Shopping Frequency by Ages and Nominal Spending



Note: As of January 2012. The boxplot displays the distribution of the variable across observations. The central line in each box indicates the median. The lower and upper edges of the box correspond to the first and third quartiles (the interquartile range, IQR). The whiskers extend to the most extreme values within 1.5 times the IQR from the quartiles. Observations beyond this range are plotted individually as outliers.

where p_{ift} and q_{ift} denote the price and quantity of product f purchased by member i in month t, and Ω is the set of products purchased. The hypothetical (average) price of product is defined as

$$\text{Hypothetical (average) price } \hat{p}_{ft} = \sum_i p_{ift} q_{ift} / \sum_i q_{ift},$$

which corresponds to the quantity-weighted average price across all members. Hypothetical spending is then calculated as

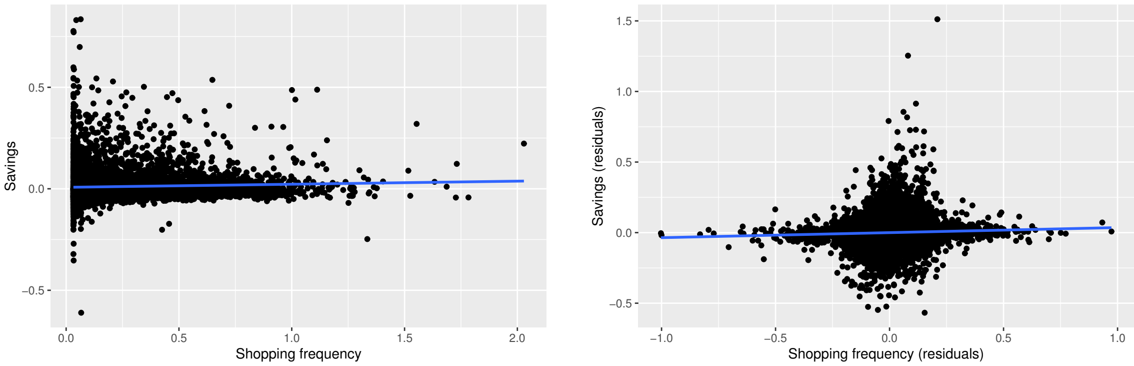
$$\text{Hypothetical spending}_{it} = \sum_{f \in \Omega} \hat{p}_{ft} q_{ift}.$$

This measure captures the extent to which a member saves by purchasing products at prices lower than the average price paid by all shoppers in the same month.

2.3.2 Shopping Frequency and Savings

Figure 2 presents a scatter plot of shopping frequency and savings. In the left panel, each dot represents a member, where shopping frequency and savings are computed

Figure 2: Shopping Frequency and Savings



Note: As of 2012. The figures show scatter plots in which each dot represents a member who made at least one purchase during the year. For the right panel, shopping frequency and savings are each estimated using regressions with member and time fixed effects and nominal spending as controls, and the plotted values are the corresponding residuals for each member and month in 2012.

as the averages of their monthly values from January to December 2012. Despite substantial dispersion, the figure reveals a positive association between shopping frequency and savings, suggesting that members who shop more frequently tend to achieve larger savings.

To examine this relationship more formally, we estimate the following regression:

$$savings_{it} = \alpha_i + \alpha_t + \beta \cdot shopping_{it} + \gamma \log(spending_{it}) + \varepsilon_{it}. \tag{2}$$

We control for nominal spending and account for individual time-invariant heterogeneity and aggregate factors by including individual and time fixed effects (α_i and α_t). The data form an unbalanced panel consisting of observations with positive spending from January 2011 to December 2019. Standard errors are clustered at the individual level.

Table 3 reports the estimation results. Columns (1) and (2) show that the coefficient on shopping frequency is significantly positive, regardless of whether fixed effects are included. In column (2), the size of the coefficient on shopping frequency, 0.046, indicates that an increase in shopping frequency from $f = 1/7$ to $f = 2/7$ (i.e., from once to twice per week) implies an increase in savings of $0.046 \times 1/7 = 0.00657$,

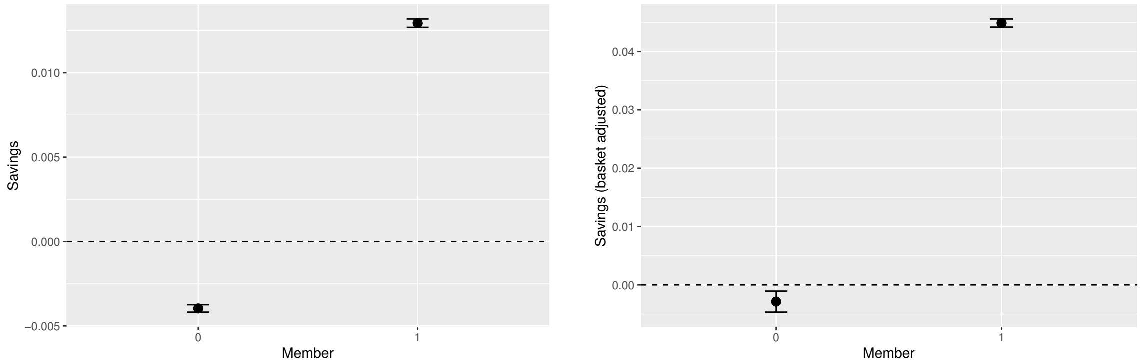
Table 3: Estimation of Returns to Shopping

	Dependent variable:			
	Savings		Savings (basket adj)	
	(1)	(2)	(3)	(4)
Shop freq	0.105***	0.046***	0.359***	0.372***
	(0.005)	(0.002)	(0.008)	(0.007)
log(spending)	−0.026***	−0.009***	−0.104***	−0.111***
	(0.001)	(0.0005)	(0.002)	(0.001)
Constant	0.218***		0.893***	
	(0.007)		(0.013)	
Observations	631,048	631,048	631,048	631,048
FE	No	i, t	No	i, t
Adjusted R^2	0.054	0.511	0.110	0.373
Note:				*p<0.1; **p<0.05; ***p<0.01

corresponding to approximately 0.66%. The corresponding scatter plot for column (2) is shown in the right panel of Figure 2, where shopping frequency and savings are each residualized with respect to nominal spending and two-way fixed effects using data from January to December 2012, and the resulting residuals are plotted. This again indicates a positive association between shopping frequency and savings. The coefficient on log spending is significantly negative, indicating that savings decline as spending increases.

These estimation results suggest that frequent shoppers save money by purchasing products when prices are low. An alternative interpretation, however, is that frequent shoppers receive greater discounts through coupons or loyalty rewards. To assess the relevance of this alternative explanation, we decompose price variation into interday and intraday components. If different shoppers pay different prices for the same product on the same day, intraday price variation should account for a large share of total price variation. By contrast, if temporary sales, rather than shopper-

Figure 3: Savings of Members and Non-members



Note: Averages are calculated over the period 2011–2019. Loyalty card holders (members) are assigned a value of one, and non-members are assigned a value of zero.

specific discounts, are the primary source of price variation, interday price variation should dominate. In Appendix B, we show that interday price variation is dominant, suggesting that temporary sales, rather than shopper-specific discounts, are the main driver of the observed savings.

Shoppers can save money by purchasing cheaper products within the same product category. In Appendix A, we introduce a basket-adjusted measure of savings that captures such product substitution. Using this measure, we re-estimate the same regression as above. Columns (3) and (4) of Table 3 show that the coefficients on shopping frequency remain significantly positive. Moreover, the estimated coefficients are substantially larger, indicating that frequent shoppers benefit not only from purchasing the same products at lower prices but also from substituting toward lower-priced products within the same category.

The returns to shopping can also be examined by comparing savings between members and non-members. The left panel of Figure 3 shows that savings for members are significantly positive, at around 0.015, whereas savings for non-members are significantly negative, at approximately −0.005. This implies that non-members pay prices that are, on average, about 0.5% higher than the average price for the same product. The resulting difference in savings between the two groups amounts

Table 4: Heterogeneity in Returns to Shopping

	Dependent variable:			
	Savings			
	(1)	(2)	(3)	(4)
Shop freq	0.046***	0.440***	0.066***	0.051***
	(0.002)	(0.019)	(0.005)	(0.006)
log(spending)	−0.009***	−0.010***	−0.009***	−0.009***
	(0.0005)	(0.0005)	(0.0005)	(0.001)
shop:log(spending)		−0.037***		
		(0.002)		
shop:age			−0.0004***	
			(0.0001)	
shop:female dummy				−0.003
				(0.003)
Observations	631,048	631,048	613,607	600,119
Adjusted R^2	0.511	0.513	0.509	0.509
Note:				*p<0.1; **p<0.05; ***p<0.01

to roughly 2 percentage points. The right panel presents basket-adjusted savings, for which the difference is even larger.

2.3.3 Heterogeneity

Table 4 examines heterogeneity in returns to shopping by augmenting column (2) of Table 3 with interaction terms between shopping frequency and individual characteristics. Specifically, we interact shopping frequency with the logarithm of nominal spending, age, and a female dummy. The results show that the interaction terms with nominal spending and age are significantly negative, indicating that returns to shopping decline with higher spending levels and older age. By contrast, gender does not have a statistically significant effect on returns to shopping.

3 Model

To provide a theoretical framework for the empirical results, this section introduces a partial-equilibrium model of consumer behavior. Consumers choose how to allocate their time among labor, shopping, and leisure. By devoting more time to shopping, consumers can search for and purchase lower-priced goods, thereby reducing expenditure, but at the cost of foregone labor income and leisure. The model highlights the trade-off underlying shopping frequency and savings. The model delivers key parameters, such as shopping costs and the elasticity of substitution between time and market goods, which are later used for counterfactual analysis.

3.1 Setup

Consumer utility is defined as

$$u(C, Q, L), \tag{3}$$

subject to the budget constraint:

$$PC + Q = A + wl, \tag{4}$$

where C, Q, L, and A denote consumption of the non-numeraire good, consumption of the numeraire good (whose price is normalized to one), leisure, and initial wealth, respectively. Labor income wl is the product of the wage rate w and labor supply l. Preferences satisfy standard conditions: $u_C, u_Q, u_L > 0$ and $u_{CC}, u_{QQ}, u_{LL} < 0$.

The price of the consumption good occasionally features temporary sales and is given by

$$P = \begin{cases} P_H & with 1 - s \\ P_L & with\ s, \end{cases} \tag{5}$$

where $P_H > P_L$ and s represents the exogenous probability of sales.

Each period, the consumer shops with frequency f. If the price is low, she purchases the good; if the price is high, she postpones the purchase until the end of the period. Consequently, the probability that a consumer with shopping frequency f ends up purchasing at the high price P_H is $(1-s)^f$. For simplicity, we assume $sf \ll 1$, so that this probability can be approximated by $1 - sf$.

The consumer is endowed with one unit of time, which is allocated according to

$$1 = g(f) + l + L, \tag{6}$$

where $g(f)$ represents the time cost of shopping. This function satisfies $g(f) > 0$, $g'(f) > 0$, and $g''(f) > 0$, implying increasing and convex time costs of shopping.

Within each period, decisions unfold as follows. First, the consumer allocates time among f, l, and L. Second, the purchase price P is realized conditional on f. Third, the consumer chooses C and Q. Because the consumer chooses f prior to making purchase decisions, she cannot subsequently reduce f (i.e., stop visiting the supermarket) even if she purchases the good at the lower price earlier in the period. This assumption captures the constraints of multi-product shopping, where securing a discount on a single item does not eliminate the need to search for other goods in the consumption basket.

3.2 Equilibrium

We solve the model by backward induction. First, conditional on the realized price and the time allocation, the consumer chooses C and Q. Specifically, the consumer maximizes utility in equation (3) subject to equation (4). The first-order condition is $u_C = Pu_Q$. Let $v(P; l, L)$ denote the resulting indirect utility function.

Second, we consider the optimal time allocation. Expected utility is given by $(1-sf)v(P_H; l, L) + sfv(P_L; l, L)$, which the consumer maximizes by choosing f and l, taking into account the time constraint. The first-order condition with respect to

f is

$$s\left\{v(P_L;l,L)-v(P_H;l,L)\right\}=g'(f)\left\{(1-sf)v_L(P_H;l,L)+sfv_L(P_L;l,L)\right\}, \qquad (7)$$

where we use $\partial L/\partial f = -g'(f)$. This condition equates the marginal benefit of increasing shopping frequency—namely, a higher probability of purchasing at the low price—to the marginal cost in terms of reduced leisure.

The first-order condition with respect to l is

$$(1-sf)v_l(P_H;l,L)+sfv_l(P_L;l,L)=(1-sf)v_L(P_H;l,L)+sfv_L(P_L;l,L), \qquad (8)$$

where we use $\partial L/\partial l = -1$. This condition states that the marginal benefit of supplying labor, through increased labor income, equals the marginal cost of foregone leisure.

3.3 Equilibrium Properties in a Special Case

As a special case, we assume the following utility function:

$$u(C,Q,L)=(X^{\frac{\rho-1}{\rho}}+\phi L^{\frac{\rho-1}{\rho}})^{\frac{\rho}{\rho-1}}, \qquad (9)$$

where $X \equiv (\alpha C^{\frac{\eta-1}{\eta}}+(1-\alpha)Q^{\frac{\eta-1}{\eta}})^{\frac{\eta}{\eta-1}}$. This specification is motivated by the theoretical frameworks developed by Benhabib et al. (1991) and Greenwood and Hercowitz (1991) and has been widely used in empirical studies, including Aguiar and Hurst (2007) and Nevo and Wong (2019). The parameter $\rho > 0$ governs the elasticity of substitution between time (leisure L) and market goods (X), while $\eta > 0$ determines the elasticity of substitution between the non-numeraire good C and the numeraire good Q. The parameter ϕ denotes a weight on leisure.

As we explain in Appendix C, we can obtain the following indirect utility function:

$$v(P;l,L) = \left(\{\Omega(P)(A+wl)\}^{\frac{\rho-1}{\rho}} + \phi L^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}},$$

where we define

$$\Omega(P) \equiv \left\{ \alpha \left(\frac{P^{-\eta}\left((1-\alpha)/\alpha\right)^{-\eta}}{1+P^{1-\eta}\left((1-\alpha)/\alpha\right)^{-\eta}} \right)^{\frac{\eta-1}{\eta}} + (1-\alpha) \left(\frac{1}{1+P^{1-\eta}\left((1-\alpha)/\alpha\right)^{-\eta}} \right)^{\frac{\eta-1}{\eta}} \right\}^{\frac{\eta}{\eta-1}}. \tag{10}$$

It can be shown that $\Omega(P)$ is strictly decreasing in P. Consequently, the indirect utility $v(P;l,L)$ is also decreasing in P, reflecting the welfare cost of higher prices.

3.3.1 Equilibrium

The first-order conditions with respect to f and l yield

$$s\left\{v(P_L;l,L) - v(P_H;l,L)\right\} = g'(f)\phi L^{\frac{-1}{\rho}} \left\{(1-sf)v(P_H;l,L)^{\frac{1}{\rho}} + sfv(P_L;l,L)^{\frac{1}{\rho}}\right\}, \tag{11}$$

and

$$\begin{aligned} & w(A+wl)^{\frac{-1}{\rho}} \left\{(1-sf)\Omega(P_H)^{\frac{\rho-1}{\rho}} v(P_H;l,L)^{\frac{1}{\rho}} + sf\Omega(P_L)^{\frac{\rho-1}{\rho}} v(P_L;l,L)^{\frac{1}{\rho}}\right\} \\ & = \phi L^{\frac{-1}{\rho}} \left\{(1-sf)v(P_H;l,L)^{\frac{1}{\rho}} + sfv(P_L;l,L)^{\frac{1}{\rho}}\right\}, \end{aligned} \tag{12}$$

respectively.

Equation (11) indicates that the benefit from shopping more frequently (left-hand side) equals the cost of lost leisure time (right-hand side). As the price gap between P_H and P_L widens, the left-hand side increases. Thus, the benefit from shopping increases, leading to a higher shopping frequency f and lower leisure L. Similarly, as the frequency of sales s increases, f increases. When spending $A+wl$ increases, the left-hand side increases because the indirect utility v increases with spending. Thus, the benefit from shopping increases, inducing an increase in f. As leisure L increases, f increases because $g''(f) > 0$.

Equation (12) shows that the marginal benefit from supplying labor through increased labor income (left-hand side) equals the marginal cost of lost leisure time (right-hand side). An increase in wage w encourages labor supply (reducing L) through the substitution effect, but when $A + wl$ is sufficiently large, the income effect may dominate, discouraging labor. Moreover, a higher shopping frequency f lowers the average purchase price, reducing the marginal benefit of labor and thereby increasing leisure L.

In summary, the model yields the following claims.

Claim 1. Shopping frequency increases with total expenditure.

Claim 2. Shopping frequency increases with leisure.

Claim 3. Shopping frequency increases with both the frequency and the magnitude of sales.

3.3.2 Purchase Price, Cost-of-Living Index

A marginal change in the expected purchase price resulting from a change in shopping frequency f is given by

$$\begin{aligned} \frac{d(P/P_H)}{df} &= \frac{d}{df}\left(\frac{(1-sf)P_H + sfP_L}{P_H}\right) \\ &= -s(1 - P_L/P_H). \end{aligned} \tag{13}$$

Suppose $s = 0.16$, $P_H = 1$, and $P_L = 0.8$. The marginal effect then equals -0.032, which is close in magnitude to the empirical estimate reported in Table 3, namely 0.046 in column (2).

The cost-of-living index is defined as the minimum expenditure required to attain a given level of utility. When exogenous prices P (namely P_H, P_L, and s) change, consumers optimally adjust shopping frequency f to partially offset the resulting price shocks. Consequently, changes in expenditure are less volatile than those implied by an index that holds f fixed.

The Consumer Price Index (CPI) typically tracks only regular prices P_H, thereby excluding temporary sales P_L and the frequency of sales s. As a result, the CPI may both overstate and understate changes in the true cost of living. On the one hand, it overlooks fluctuations arising from variations in sales activity. On the other hand, it may overstate the impact of changes in regular prices, since consumers can mitigate these effects by adjusting their shopping frequency f.

Claim 4. Higher shopping frequency is associated with lower purchase prices. Specifically, the marginal effect of shopping frequency on the purchase price is $-s(1 - P_L/P_H)$.

3.3.3 Demand Elasticity and Monetary Policy Effect

Demand elasticity measures the marginal response of demand to an exogenous change in prices. When shopping frequency is endogenous, the calculation of demand elasticity becomes more involved, because the effective purchase price is no longer exogenous. Consider an exogenous change in the regular price P_H. The corresponding demand elasticity can be written as

$$\frac{d\log C}{d\log P_H} = \frac{\partial \log C}{\partial \log P^H} + \frac{\partial \log C}{\partial \log f}\frac{\partial \log f}{\partial \log P_H}. \tag{14}$$

The elasticity on the left-hand side and the first term on the right-hand side are negative, while $\partial C/\partial f$ is positive. If $\partial f/\partial P_H > 0$, which is plausible when higher regular prices induce more frequent shopping to take advantage of sales, the absolute value of demand elasticity satisfies $|d\log C/d\log P_H| < |\partial \log C/\partial \log P_H|$.

This framework can be extended to a New Keynesian setting along the lines of Coibion et al. (2015). Rather than introducing a numeraire good, one can consider a continuum of differentiated goods indexed by $j \in [0,1]$. Endogenizing optimal pricing with temporary sales, however, as in Guimaraes and Sheedy (2011), substantially complicates firms' pricing problems (see also Sudo et al. (2018)).

We conjecture that the real effects of monetary policy would be attenuated in such a model, because endogenously determined shopping frequency effectively increases price flexibility.

Claim 5. Allowing for endogenous shopping frequency reduces the absolute value of demand elasticity with respect to regular prices.

Claim 6. The real effects of monetary policy are weaker when shopping frequency is endogenous.

3.3.4 Consumption Gap

Consumption of the bundled goods C and Q is given by

$$(\alpha C^{\frac{\eta-1}{\eta}} + (1-\alpha)Q^{\frac{\eta-1}{\eta}})^{\frac{\eta}{\eta-1}} = (A + wl)\left(P^{1-\eta}\alpha^{\eta} + (1-\alpha)^{\eta}\right)^{\frac{1}{\eta-1}}.$$

Thus, total consumption increases with total expenditure by the factor $(P^{1-\eta}\alpha^{\eta} + (1-\alpha)^{\eta})^{\frac{1}{\eta-1}}$, thereby narrowing the consumption gap by the same magnitude. On average, this factor can be expressed as

$$\left(P^{1-\eta}\alpha^{\eta} + (1-\alpha)^{\eta}\right)^{\frac{1}{\eta-1}} \simeq \left\{\left((1-sf)P_H^{1-\eta} + sfP_L^{1-\eta}\right)\alpha^{\eta} + (1-\alpha)^{\eta}\right\}^{\frac{1}{\eta-1}},$$

which increases as P_L decreases or f increases. Suppose $\alpha = 0.17$, $s = 0.16$, $P_H = 1$, $P_L = 0.8$, and $\eta = 2$. Under these parameter values, the factor equals 0.7180 when $f = 1/7$, which increases by 0.22% relative to the case with no shopping $f = 0$. This calculation suggests that the quantitative effect of endogenous shopping on consumption is small.

Claim 7. The consumption gap decreases by the factor $(P^{1-\eta}\alpha^{\eta} + (1-\alpha)^{\eta})^{\frac{1}{\eta-1}}$.

4 Shopping Costs and the Elasticity of Substitution between Time and Market Goods

In this section, we propose a method to estimate two key parameters governing household production: shopping costs and the elasticity of substitution between time and market goods. By approximating the equilibrium conditions, we derive a tractable equation that allows the two parameters to be estimated jointly.

4.1 Method

We assume that P_L is close to P_H and that shopping costs follow $g'(f) = \exp(\beta + \gamma f)$, where the parameter γ governs the convexity of shopping costs. Under these assumptions, the first-order conditions given in equations (11) and (12) can be approximated as follows:

$$f_{it} = c + \frac{1}{\gamma} \underbrace{\left\{ \log(s_{it}) + \log\left(\frac{\Omega(P_L) - \Omega(P_H)}{\Omega(P_H)}\right)_{it} - \log(w_{it}) \right\}}_{S_{it}} + \frac{1}{\rho\gamma} \log\left(\widehat{A + wl}\right)_{it} + \varepsilon_{it}, \tag{15}$$

where i and t index individuals and months, respectively, and

$$c \equiv \log\left[v(P_H; l, L)^{\frac{\rho-1}{\rho}} \frac{\{\Omega(P_H)(A+wl)\}^{\frac{\rho-1}{\rho}}}{\{\Omega(P_H)(A+wl)\}^{\frac{\rho-1}{\rho}} + \phi L^{\frac{\rho-1}{\rho}}} \frac{1}{\Omega(P_H)^{\frac{\rho-1}{\rho}}} \right] - \frac{1}{\rho\gamma} \log\left\{ \frac{P_H^{1-\eta}\left((1-\alpha)/\alpha\right)^{-\eta}}{1 + P_H^{1-\eta}\left((1-\alpha)/\alpha\right)^{-\eta}} \right\},$$

$$\log\left(\widehat{A + wl}\right)_{it} \simeq \log(PC)_{it} - \left[(1 - sf)_{it} \log\left\{ \frac{\left((1-\alpha)/\alpha\right)^{-\eta}}{1 + \left((1-\alpha)/\alpha\right)^{-\eta}} \right\} + (sf)_{it} \log\left\{ \frac{P_L^{1-\eta}\left((1-\alpha)/\alpha\right)^{-\eta}}{1 + P_L^{1-\eta}\left((1-\alpha)/\alpha\right)^{-\eta}} \right\}_{it} \right]. \tag{16}$$

See Appendix for the derivation. The variable $(PC)_{it}$ in equation (16) denotes nominal spending for individual i in month t, as recorded in the scanner data. Because total nominal expenditure $A + wl$, which includes spending on the remaining $1 - \alpha$

numeraire good, is not directly observable, we approximate it using equation (16).

Equation (15) allows us to estimate the convexity of shopping costs γ and the elasticity of substitution between time and market goods ρ simultaneously. The expression inside the curly brackets in the second term S_{it} captures the marginal benefit of shopping relative to working. This marginal benefit increases with the frequency of sales s and the magnitude of sales $\Omega(P_L) - \Omega(P_H)$ and decreases with wages w. An increase in this term therefore raises shopping frequency. The coefficient $1/\gamma$ governs the sensitivity of shopping frequency to this margin and declines as shopping costs become more convex (i.e., as adjustment costs increase). The third term implies that shopping frequency rises with total expenditure. Its sensitivity is given by $1/(\rho\gamma)$, indicating that shopping frequency responds less to changes in expenditure when the elasticity of substitution between time and market goods ρ is high.[2]

To estimate equation (15), we construct an unbalanced panel at the individual–month level over the period 2011–2019, including observations for which purchase records are positive (i.e., $f_{it} > 0$, $(PC)_{it} > 0$). For each i and t, we also construct measures of temporary sales s_{it} and $(P_L/P_H)_{it}$ and wage w_{it}, as described below.

4.1.1 Temporary Sales

We identify temporary sales at the product–month level using price distributions observed in the scanner data. For each product and month, we compute the first and second modal prices. A product is classified as being subject to a temporary sale if the second modal price differs from the first modal price by at least two yen. In such cases, the higher modal price is defined as the regular price, while the lower modal price is defined as the sale price.

[2]The assumption that the shopping cost function satisfies $g'(f) = \exp(\beta + \gamma f)$ implies that $\log(g'(f)) = \beta + \gamma f$ is linear in f. More generally, for sufficiently small fluctuations of f around steady state, a wide class of shopping cost functions can be well approximated by a linear function in f, which leads to equation (15).

Table 5: Frequency and Magnitude of Temporary Sales

Frequency (w)	Magnitude (w)	Frequency (un)	Magnitude (un)
0.16	0.20	0.15	0.24

Note: As of 2012. "w" and "un" denote weighted and unweighted averages, respectively.

We measure the frequency of temporary sales as the fraction of purchase days on which the sale price is observed. Specifically, we first count the number of days in a given product–month with positive recorded transactions (i.e., days with positive prices and quantities). We then count the number of those days on which the sale price is observed. The frequency of temporary sales is defined as the ratio of sale-price days to total transaction days. In other words, all transaction days other than those classified as sale days are treated as days with regular prices.

To construct aggregate measures of temporary sales, we aggregate the frequency and magnitude of sales across products within a month either using sales-weighted averages or unweighted averages. Table 5 reports these aggregate measures as of 2012. The sales-weighted average frequency of sales s is 0.16, while the sales-weighted average magnitude of sales, which corresponds to $1 - P_L/P_H$, is 0.20.

Furthermore, we construct individual–month level measures of sales, denoted by s_{it} and $(P_L/P_H)_{it}$ to account for heterogeneity in individuals' consumption baskets. To mitigate endogeneity concerns arising from item-level purchase choices, which may become largely endogenous in the estimation of equation (15), we rely on variation at the product-category level rather than the item level. Specifically, we first compute aggregate measures of temporary sales at the product-category–month level. We then aggregate these measures to the individual–month level using weights based on each individual's purchase shares across product categories.

4.1.2 Labor Market Variables

Because the scanner data do not report individual wages w_{it}, we construct this variable using official statistics. The aggregate wage series w_t is obtained from the Monthly Labour Survey and is defined as total earnings (seasonally adjusted, establishments with five or more employees). From the Basic Survey on Wage Structure as of 2012, which is conducted every five years, we obtain cross-sectional wage information w_i of female by age group, defined in five-year bins. Combining this time-series information with the cross-sectional wage profiles and individual age data from the scanner records, we construct individual–month wages w_{it}. In addition, we collect the aggregate jobs-to-applicants ratio $(v/u)_t$ from the Report on Employment Services.

4.1.3 Instrument Variables

The explanatory variables S_{it} and $\left(\widehat{A+wl}\right)_{it}$ in equation (15) are potentially endogenous. For example, unobserved individual spending needs could simultaneously drive both expenditure and shopping frequency, resulting in biased estimates. To address this concern, we use aggregate-level variables as instruments. Specifically, we instrument S_{it} and $\left(\widehat{A+wl}\right)_{it}$ with wage w_t, jobs-to-applicants ratio $(v/u)_t$, and spending $(PC)_t$. The identifying assumption is that these aggregate labor market and demand conditions influence individual shopping behavior only through the specified explanatory variables—an assumption we consider plausible in this context. In addition, we include sales-related variables, frequency s_t and magnitude $(P_L/P_H)_t$, as robustness checks.

To complete the dataset for estimation, we set the parameter values as follows. The elasticity of substitution between the non-numeraire and numeraire goods η is 2; we also consider values of 5 or 1.1 as robustness checks. The expenditure share of non-numeraire goods α is set to 0.17, reflecting that approximately 17 percent of total household expenditure is devoted to goods sold in supermarkets. The regular price P_H is normalized to one.

Table 6: Estimation Results of Shopping Frequency

	Dependent variable:						
	Shop freq f						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
S_{it}	0.003***	0.005***					
	(0.001)	(0.001)					
log(spend)	0.112***	0.111***					
	(0.001)	(0.001)					
S_{it}			0.051***	0.001	0.050***	0.016*	0.064***
			(0.012)	(0.004)	(0.012)	(0.009)	(0.012)
log(spend)			0.161***	0.157***	0.160***	0.160***	0.161***
			(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Estimation	OLS	OLS	IV	IV	IV	IV	IV
		Two-way FE	Baseline	More IVs	PC	η 5	η 1.1
1st-stage F			48.96	32.29	48.74	48.96	48.96
Observations	498,333	498,333	498,333	498,333	498,333	498,333	498,333
Adjusted R^2	0.844	0.846	0.822	0.828	0.824	0.825	0.820

Note: *p<0.1; **p<0.05; ***p<0.01

4.2 Estimation Results

We estimate equation (15). In the baseline specification, we include individual fixed effects, while time fixed effects are excluded in order to exploit aggregate variables as instruments. The individual fixed effects capture unobserved heterogeneity, such as health conditions or preferences that influence time allocation. However, we maintain the assumption that the parameters ρ and γ are common across all individuals. Standard errors are clustered at the individual level.

Table 6 reports the estimation results and shows significant positive coefficients on S_{it} and $\left(\widehat{A+wl}\right)_{it}$. These estimates imply that both ρ and γ are positive. Columns (1) and (2) present OLS estimates with individual fixed effects only and with both individual and time fixed effects, respectively. Column (3) reports our preferred baseline specification. In this specification, the estimated coefficients on S_{it} and

$\left(\widehat{A+wl}\right)_{it}$ are 0.051 and 0.161, respectively, implying $\gamma = 19.6$ and $\rho = 0.316$. In column (4), we augment the instrument set with sales-related variables; under this specification, the coefficient on S_{it} becomes insignificant. Column (5) replaces adjusted total expenditure $\left(\widehat{A+wl}\right)_{it}$ with observed supermarket spending $(PC)_{it}$. Columns (6) and (7) report results obtained using alternative values for the elasticity of substitution between the non-numeraire and numeraire goods η. Overall, the results consistently indicate positive and significant coefficients across specifications. That is, shopping costs satisfy convexity (i.e., $g''(f) > 0$), and the elasticity of substitution between time and market goods is positive.

The estimated elasticity of substitution between time and market goods ρ is 0.316 in column (3). This value is well below one and substantially smaller than estimates reported in earlier studies. For example, Aguiar and Hurst (2007) and Nevo and Wong (2019), report values of 1.8 and 1.7, respectively. The estimated value of ρ is even smaller—0.04—under the OLS specification in column (2). These results may be concerning, given that many macroeconomic models, such as Benhabib et al. (1991) and Greenwood and Hercowitz (1991) rely on considerably higher elasticities to account for a wide range of macroeconomic phenomena.

Our study departs from Aguiar and Hurst (2007) and Nevo and Wong (2019) in two key dimensions. First, the data differ. We use retailer-level scanner data with shopper information, whereas Aguiar and Hurst (2007) and Nevo and Wong (2019) combine household scanner data with time-use surveys. In their approach, savings from shopping are measured by comparing the prices paid by households to the average price of the same product within a region and month. As a result, differences in observed prices may reflect heterogeneity in store choice—since different supermarkets may follow distinct pricing and promotion strategies—rather than differences in shopping intensity per se. Our data allow us to address this concern by focusing on households purchasing at the same supermarket, thereby holding store-level pricing policies fixed. However, a key limitation of our data is that we cannot directly match retailer transactions to individual time-use information. In addition, our analysis is based on data from Japan, whereas the related studies use U.S. data.

Second, the empirical strategy differs. Instead of relying on self-reported time-use data, we derive a structural relationship for shopping frequency that depends on the frequency and magnitude of temporary sales and nominal spending, without relying on time-use data. The coefficients in this specification are directly linked to the elasticity of substitution and the convexity of shopping costs. This structural approach allows us to infer the elasticity from observed transaction behavior alone, bypassing the measurement error often associated with time-use surveys.[3]

These differences in data and strategy likely explain our lower estimate for the elasticity of substitution. While Aguiar and Hurst (2007) and Nevo and Wong (2019) capture the broad returns to shopping, including the extensive margin of store switching, our analysis isolates the returns to shopping intensity and timing within a single retailer. If the primary way households substitute time for market goods is by visiting multiple stores rather than increasing the frequency of visits to the same store, then the elasticity estimated from within-store data should naturally be lower. Furthermore, the decision to avoid self-reported time-use data in favor of a structural approach ensures that our estimated parameters are internally consistent with the observed price-discovery process. Consequently, our results suggest that the flexibility of household production may be more constrained than previously recognized in studies using more aggregated data.

In Appendix, we provide reduced-form estimation results on shopping frequency. The results show virtually the same results as here from a slightly different angle. Specifically, shopping frequency tends to increase when wages decline, total expen-

[3]In Aguiar and Hurst (2007), the purchase price is assumed to be log-linear in shopping frequency, an assumption that is central to their identification strategy. By contrast, our model implies that expected purchase prices are linear, rather than log-linear, in shopping frequency. Moreover, unlike in Aguiar and Hurst (2007) and Nevo and Wong (2019), the implied coefficient is not constant but varies with both the frequency and magnitude of sales (s and $P_H - P_L$). We exploit individual- and time-level variation in sales frequency and magnitude to incorporate these effects into the estimation.

diture rises, and the magnitude of sales increases. These findings are all consistent with the model's predictions.

5 Implications on Shopping Cost Increases

Despite innovations associated with e-commerce, shopping costs do not necessarily decline uniformly across individuals. In particular, some households may be disadvantaged rather than benefit from these innovations, as they are unable to effectively utilize online platforms and as brick-and-mortar supermarkets increasingly close, especially in less populated areas. Older individuals may also face higher shopping costs due to the physical burden of traveling to and shopping in stores.

Using the model calibrated to the Japanese economy, this section quantitatively evaluates the implications of increases in shopping costs.

5.1 Method

We assume that shopping costs are given by

$$g(f) = g_0 + \frac{\exp(g_1 + g_2 f)}{g_2}, \tag{17}$$

where $g_2 = \gamma$ as defined in the previous section. We use the notation g_0, g_1, and g_2 to reflect the zeroth-, first-, and second-derivative components of the shopping cost function, respectively.

We consider increases in each of these parameters separately as alternative forms of higher shopping costs. First, an increase in g_0 corresponds to an increase in fixed or wasted time. It should be noted that g_0 does not necessarily involve time spent shopping directly; rather, it reduces time available for all activities, including leisure and labor. Second, an increase in g_1 raises the marginal shopping cost $g'(f)$. Third, an increase in g_2 increases the convexity of shopping costs, as measured by $g''(f)/g'(f)$.

We solve for the equilibrium allocation of time f, l and L that satisfies the first-order conditions in equations (11) and (12), together with the time constraint $g(f)+l+L=1$. The calibrated parameters largely follow those used in the previous section: $\eta = 2$, $\alpha = 0.17$, $s = 0.16$, $P_L/P_H = 0.80$ based on the scanner data; $\rho = 0.316$, $\gamma = g_2 = 1/0.051$, taken from the estimate of column (3) in Table 6. In addition, we calibrate four parameters: two shopping cost parameters g_0 and g_1, utility weight on leisure ϕ, and initial wealth A, as well as one initial variable of wage w_0. The calibration targets five variables: average monthly nominal spending based on the scanner data $\alpha(A + w_0 l_0) = 122.494$ thousand yen; average monthly labor income from official statistics $w_0 l_0 = 233.1$ thousand yen; the share of time spent working, approximated as $l_0 = (8hours \times 5days)/(24 \cdot 7)$; shopping frequency, approximated as $f_0 = 1/7$ (once a week); and time spent shopping per trip, assumed to be one hour, implying $g(f_0) = 1/24 \cdot f_0$.

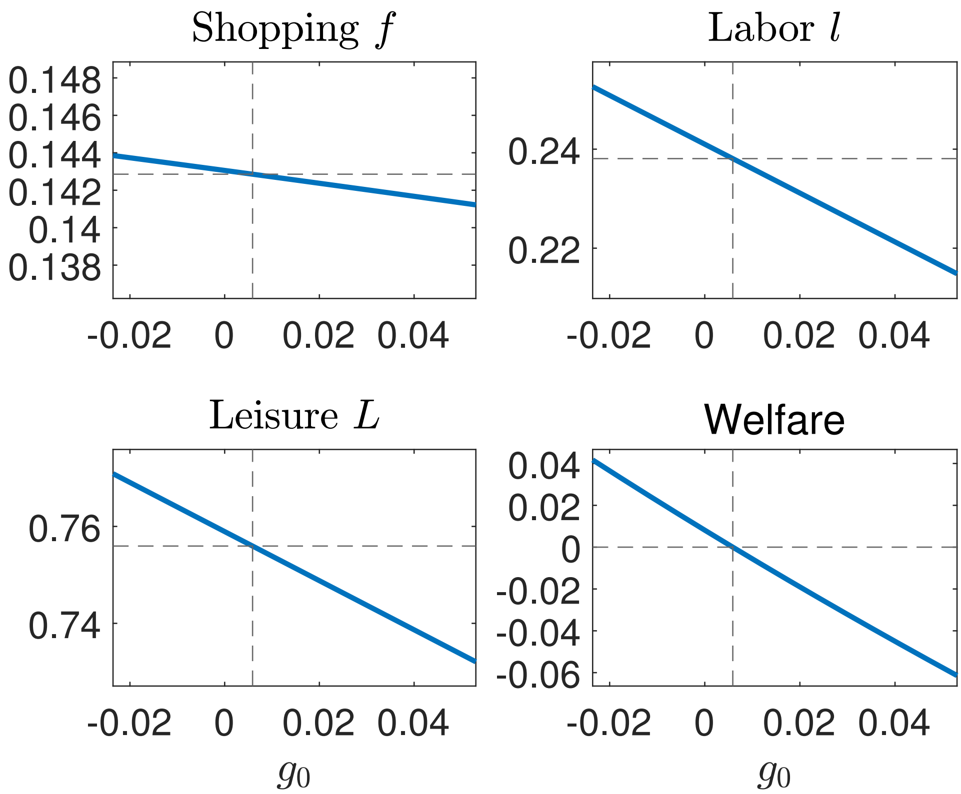
5.2 Simulation Results

We simulate equilibrium by changing each of shopping-cost parameters. In addition to time allocation, we also compute welfare changes in the unit of consumption given fixed leisure L.

Figure 4 illustrates changes in time allocation and welfare when the zeroth-derivative component of the shopping cost function, g_0, varies by approximately -2 to 5 percent. Changes in g_0 affect the total time available for all activities. As g_0 increases, time devoted to shopping f, labor l, and leisure L all decrease, leading to a deterioration in welfare. Quantitatively, the welfare effect is substantial: a 5 percent increase in g_0 reduces welfare measured in consumption units by nearly the same magnitude. By contrast, the decline in shopping frequency is small, on the order of 0.001, indicating that the large welfare loss associated with higher g_0 primarily reflects reductions in labor and leisure rather than changes in shopping behavior.

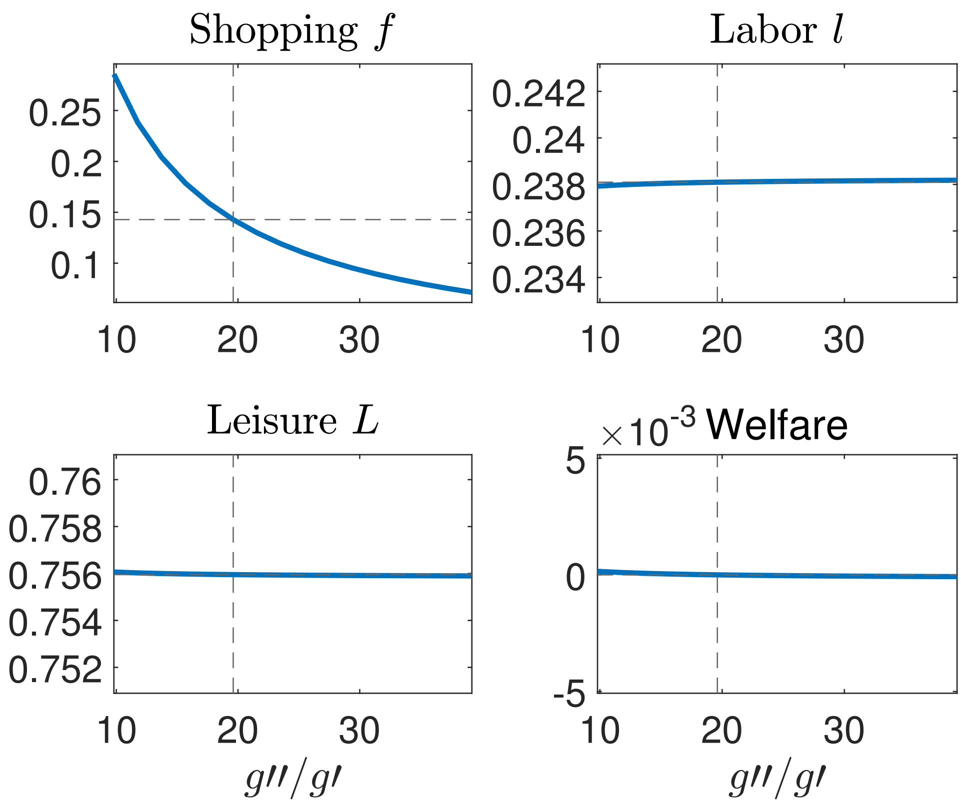
Next, Figure 5 illustrates changes in time allocation and welfare when the second-

Figure 4: Effects of Shopping Cost Changes in $g(f)$



Note: This figure illustrates changes in shopping frequency f, labor l, leisure L, and welfare (measured in consumption units) as the zeroth-derivative component of the shopping cost function, g_0, varies along the horizontal axis. The vertical and horizontal dashed lines indicate the baseline values.

Figure 5: Effects of Shopping Cost Changes in $g''(f)/g'(f)$



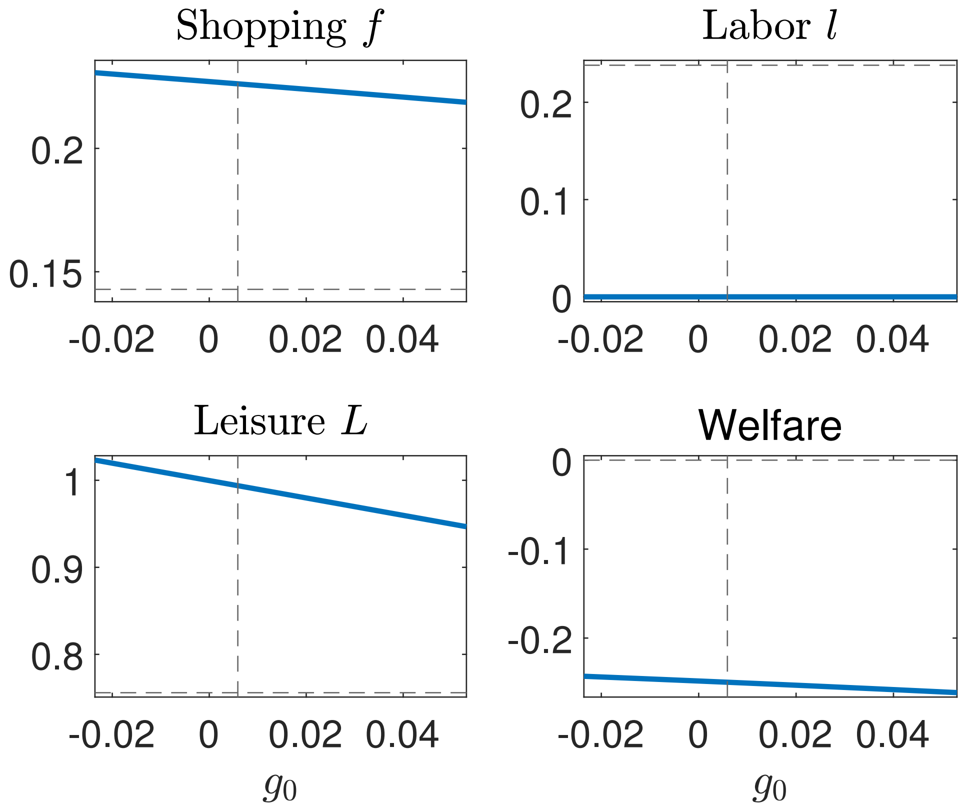
Note: This figure illustrates changes in shopping frequency f, labor l, leisure L, and welfare (measured in consumption units) as the second-derivative component of the shopping cost function, $g_2 = g''(f)/g'(f)$, varies along the horizontal axis. The vertical and horizontal dashed lines indicate the baseline values.

derivative component of the shopping cost function, $g_2 = g''(f)/g'(f)$, varies. The magnitude of the change in g_2 is chosen so that shopping frequency f changes by approximately a factor of two. As convexity g_2 increases, shopping frequency and leisure decline, while labor supply rises. These patterns differ qualitatively from those observed when varying g_0. Despite the substantial change in shopping frequency, time allocated to labor and leisure as well as welfare are only weakly affected by changes in g_2. In the Appendix, we present simulation results for variations in the first-derivative component of the shopping cost function, g_1; the results are both qualitatively and quantitatively similar to those obtained when varying g_2. Overall, these findings indicate that changes in shopping-specific costs have limited effects on other activities and on welfare.

Furthermore, to account for the possibility that disadvantaged individuals may be more severely affected by increases in shopping costs, we examine the effects of shopping cost changes for the non-employed (e.g., retired or full-time homemaker). Specifically, we compute the equilibrium under the restriction that labor supply is fixed at $l = 0$, rendering the first-order condition with respect to labor, equation (12), slack. Figure 6 presents the simulation results and yields two notable findings. First, relative to the baseline indicated by the dashed lines, shopping frequency f and leisure L increase substantially, while labor supply falls to zero for a given value of g_0. Although increased shopping and leisure partially mitigate the adverse effects, welfare declines markedly by more than 0.2 in log consumption units. Second, with respect to changes in g_0, the direction of the responses mirrors those in the baseline case: increases in g_0 reduce both f and L, thereby lowering welfare. Quantitatively, however, the welfare loss is somewhat smaller. The welfare change across the range of g_0 is approximately 0.05, compared with about 0.1 in the baseline. This attenuation reflects the greater ability of non-employed individuals to adjust time allocated to shopping and leisure in response to the shock.[4]

[4]In the Appendix, we consider an alternative value for the estimated elasticity of substitution between time and market goods, ρ, by setting $\rho = 1.5$. The simulation results are virtually unchanged.

Figure 6: Effects of Shopping Cost Changes in $g(f)$ for the Retired with $l = 0$



Note: This figure illustrates changes in shopping frequency f, labor l, leisure L, and welfare (measured in consumption units) as the zeroth-derivative component of the shopping cost function, g_0, varies along the horizontal axis. The vertical and horizontal dashed lines indicate the baseline values.

6 Concluding Remarks

This paper studies endogenous shopping behavior within a household production framework using scanner data, jointly estimating shopping costs and the elasticity of substitution between time and market goods. We show that households adjust shopping frequency in response to sales, thereby attenuating price shocks. While the welfare effects of shopping-specific costs are modest on average, time costs that affect all economic activities play an important role in determining welfare.

An important avenue for future research concerns endogenous price setting. In this study, firms' pricing decisions are treated as exogenous, although they are likely to depend on household behavior. A second direction for future work is to examine more directly the role of e-commerce and its implications for shopping behavior. Third, shopping may differ in important ways from other forms of home production, such as residential investment, warranting separate analysis.

References

Abe, Naohito and Akiyuki Tonogi, "Micro and macro price dynamics in daily data," *Journal of Monetary Economics*, September 2010, *57* (6), 716–728.

Aguiar, Mark and Erik Hurst, "Life-Cycle Prices and Production," *American Economic Review*, December 2007, *97* (5), 1533–1559.

_ , _ , and Loukas Karabarbounis, "Time Use during the Great Recession," *American Economic Review*, August 2013, *103* (5), 1664–1696.

Becker, Gary S., "A Theory of the Allocation of Time," *The Economic Journal*, 1965, *75* (299), 493–517.

Benhabib, Jess, Richard Rogerson, and Randall Wright, "Homework in Macroeconomics: Household Production and Aggregate Fluctuations," *Journal of Political Economy*, 1991, *99* (6), 1166–87.

Chapela, Jorge Gonzalez, "Recreation, home production, and intertemporal substitution of female labor supply: evidence on the intensive margin," *Review of Economic Dynamics*, July 2011, *14* (3), 532–548.

Chevalier, Judith A. and Anil K. Kashyap, "Best Prices: Price Discrimination and Consumer Substitution," *American Economic Journal: Economic Policy*, February 2019, *11* (1), 126–159.

Coibion, Olivier, Yuriy Gorodnichenko, and Dmitri Koustas, "Consumption Inequality and the Frequency of Purchases," *American Economic Journal: Macroeconomics*, October 2021, *13* (4), 449–482.

_ , _ , and Gee Hee Hong, "The Cyclicality of Sales, Regular and Effective Prices: Business Cycle and Policy Implications," *American Economic Review*, March 2015, *105* (3), 993–1029.

Fang, Lei and Guozhong Zhu, "Time allocation and home production technology," *Journal of Economic Dynamics and Control*, None 2017, *78* (C), 88–101.

Greenwood, Jeremy and Zvi Hercowitz, "The Allocation of Capital and Time over the Business Cycle," *Journal of Political Economy*, 1991, *99* (6), 1188–214.

Griffith, Rachel, Ephraim Leibtag, Andrew Leicester, and Aviv Nevo, "Consumer Shopping Behavior: How Much Do Consumers Save?," *Journal of Economic Perspectives*, Spring 2009, *23* (2), 99–120.

Guimaraes, Bernardo and Kevin D. Sheedy, "Sales and Monetary Policy," *American Economic Review*, April 2011, *101* (2), 844–876.

Kaplan, Greg, "Inequality, Heterogeneity, and Consumption in the Journal of Political Economy," *Journal of Political Economy*, None 2017, *125* (6), 1767–1774.

Nevo, Aviv and Arlene Wong, "The Elasticity Of Substitution Between Time And Market Goods: Evidence From The Great Recession," *International Economic Review*, February 2019, *60* (1), 25–51.

Sudo, Nao, Kozo Ueda, and Kota Watanabe, "Micro Price Dynamics during Japan's Lost Decades," *Asian Economic Policy Review*, 2014, *9* (1), 44–64.

_ , _ , _ , and Tsutomu Watanabe, "Working Less and Bargain Hunting More: Macroimplications of Sales during Japan's Lost Decades," *Journal of Money, Credit and Banking*, March 2018, *50* (2-3), 449–478.

A Alternative Definition of Savings

We also introduce an alternative measure of savings that adjusts for product substitution within the same product category. Specifically, savings for member i in month t are defined as

$$\text{Saving}_{it} = \frac{\text{Basket-adjusted spending}_{it} \text{ - Hypothetical spending}_{it}}{\text{Actual spending}_{it}},$$

where c indexes product categories. The category-level average price in month t is defined as

$$\text{Category price } \hat{p}_{ct} = \sum_{i,f \in \Omega_c} p_{ift} q_{ift} / \sum_{i,f \in \Omega_c} q_{ift},$$

where Ω_c denotes the set of products belonging to category c. Basket-adjusted spending is then calculated as

$$\text{Basket-adjusted spending}_{it} = \sum_{f \in \Omega} \hat{p}_{ct} q_{ift},$$

where each product f is evaluated at the average price of its corresponding category.

This measure captures savings arising from consumers' preferences and/or ability to substitute across products within the same category, abstracting from price differences across individual items.

Table 7: Price Variations

	σ(P)	Intraday	Interday
Unweighted	0.1253	0.0672	0.1242
Weighted	0.1554	0.0977	0.1454

B Price Variations

We calculate price variations for each product as follows:

$$\text{Price variation: } \sigma\left[\frac{P_{it}-P}{P}\right] \equiv \sqrt{\frac{1}{|\Omega_{it}|}\sum_{i,t\in\Omega_{it}}\left[\frac{P_{it}-P}{P}\right]^2},$$

$$\text{Intraday variation: } \sigma\left[\frac{P_{it}-P_t}{P}\right] \equiv \sqrt{\frac{1}{|\Omega_{it}|}\sum_{i,t\in\Omega_{it}}\left[\frac{P_{it}-P_t}{P}\right]^2},$$

$$\text{Interday variation: } \sigma\left[\frac{P_t-P}{P}\right] \equiv \sqrt{\frac{1}{|\Omega_t|}\sum_{t\in\Omega_t}\left[\frac{P_t-P}{P}\right]^2},$$

where P_{it}, P_t, and P represent the price paid by member i on date t, the mean price on date t, and the mean monthly price. The sets Ω_{it} and Ω_t consist of observations with non-zero sales at the individual–date and date levels, respectively, and $|\Omega|$ denotes the observation number in each set. When aggregating across products, we use either unweighted averages or weighted averages, where the weights are based on sales for each product.

The second line, intraday price variation, reflects customer-specific pricing or within-day temporary discounts. The third line represents interday price variation, which primarily reflects temporary sales across days. We apply this definition to data from January 2012 and report the results in Table 7. The table shows that interday (sales-related) price variation accounts for the dominant share of total price variation.

C Model Details

C.1 Derivations of the Equilibrium Conditions

In the special case, the first-order condition from utility maximization, $u_C = Pu_Q$, implies

$$C/Q = ((1-\alpha)/\alpha)^{-\eta} P^{-\eta}. \tag{18}$$

Combining this condition with the budget constraint yields closed-form solutions for C and Q:

$$C = \frac{P^{-\eta}((1-\alpha)/\alpha)^{-\eta}(A+wl)}{1+P^{1-\eta}((1-\alpha)/\alpha)^{-\eta}}, \tag{19}$$

$$Q = \frac{A+wl}{1+P^{1-\eta}((1-\alpha)/\alpha)^{-\eta}}. \tag{20}$$

Substituting these expressions into the aggregator for market goods yields

$$X(C,Q,L) = (\alpha C^{\frac{\eta-1}{\eta}} + (1-\alpha)Q^{\frac{\eta-1}{\eta}})^{\frac{\eta}{\eta-1}}$$

$$= \left\{\alpha\left(\frac{P^{-\eta}((1-\alpha)/\alpha)^{-\eta}(A+wl)}{1+P^{1-\eta}((1-\alpha)/\alpha)^{-\eta}}\right)^{\frac{\eta-1}{\eta}} + (1-\alpha)\left(\frac{A+wl}{1+P^{1-\eta}((1-\alpha)/\alpha)^{-\eta}}\right)^{\frac{\eta-1}{\eta}}\right\}^{\frac{\eta}{\eta-1}}.$$

The resulting indirect utility function is therefore

$$v(P;l,L) = \left(\{\Omega(P)(A+wl)\}^{\frac{\rho-1}{\rho}} + \phi L^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}}, \tag{21}$$

where

$$\Omega(P) \equiv \left\{\alpha\left(\frac{P^{-\eta}((1-\alpha)/\alpha)^{-\eta}}{1+P^{1-\eta}((1-\alpha)/\alpha)^{-\eta}}\right)^{\frac{\eta-1}{\eta}} + (1-\alpha)\left(\frac{1}{1+P^{1-\eta}((1-\alpha)/\alpha)^{-\eta}}\right)^{\frac{\eta-1}{\eta}}\right\}^{\frac{\eta}{\eta-1}}. \tag{22}$$

It can be shown that $\Omega(P)$ is strictly decreasing in P. Consequently, the indirect utility $v(P;l,L)$ is also decreasing in P, reflecting the welfare cost of higher prices.

The partial derivative of the indirect utility function is expressed as

$$\begin{aligned} v_l(P;l,L) &= \Omega(P)w\frac{\rho-1}{\rho}\left\{\Omega(P)(A+wl)\right\}^{\frac{\rho-1}{\rho}-1} \\ &\cdot \frac{\rho}{\rho-1}\left(\left\{\Omega(P)(A+wl)\right\}^{\frac{\rho-1}{\rho}}+\phi L^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}-1} \\ &= \Omega(P)w\left\{\Omega(P)(A+wl)\right\}^{\frac{-1}{\rho}}v(P;l,L)^{\frac{1}{\rho}} \\ v_L(P;l,L) &= \frac{\rho-1}{\rho}\phi L^{\frac{\rho-1}{\rho}-1}\cdot\frac{\rho}{\rho-1}\left(\left\{\Omega(P)(A+wl)\right\}^{\frac{\rho-1}{\rho}}+\phi L^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}-1} \\ &= \phi L^{\frac{-1}{\rho}}v(P;l,L)^{\frac{1}{\rho}}. \end{aligned}$$

The first-order conditions with respect to f and l yield

$$s\left\{v(P_L;l,L)-v(P_H;l,L)\right\} = g'(f)\left\{(1-sf)v_L(P_H;l,L)+sfv_L(P_L;l,L)\right\}$$

$$s\left\{v(P_L;l,L)-v(P_H;l,L)\right\} = g'(f)\phi L^{\frac{-1}{\rho}}\left\{(1-sf)v(P_H;l,L)^{\frac{1}{\rho}}+sfv(P_L;l,L)^{\frac{1}{\rho}}\right\}, \tag{23}$$

and

$$(1-sf)v_l(P_H;l,L)+sfv_l(P_L;l,L) = (1-sf)v_L(P_H;l,L)+sfv_L(P_L;l,L)$$

$$\begin{aligned} &w(A+wl)^{\frac{-1}{\rho}}\left\{(1-sf)\Omega(P_H)^{\frac{\rho-1}{\rho}}v(P_H;l,L)^{\frac{1}{\rho}}+sf\Omega(P_L)^{\frac{\rho-1}{\rho}}v(P_L;l,L)^{\frac{1}{\rho}}\right\} \\ &= \phi L^{\frac{-1}{\rho}}\left\{(1-sf)v(P_H;l,L)^{\frac{1}{\rho}}+sfv(P_L;l,L)^{\frac{1}{\rho}}\right\}, \end{aligned} \tag{24}$$

respectively.

C.2 Derivations of Shopping Frequency Equation

The first-order condition given by equations (11) and (12) can be combined to yield

$$
\begin{aligned}
& s\left\{v(P_L;l,L)-v(P_H;l,L)\right\} \\
& = wg'(f)(A+wl)^{\frac{-1}{\rho}}\left\{(1-sf)\Omega(P_H)^{\frac{\rho-1}{\rho}}v(P_H;l,L)^{\frac{1}{\rho}}+sf\Omega(P_L)^{\frac{\rho-1}{\rho}}v(P_L;l,L)^{\frac{1}{\rho}}\right\}.
\end{aligned}
$$

Here, we note

$$
\begin{aligned}
& v(P_L;l,L) \\
=& \left(\left\{\Omega(P_L)(A+wl)\right\}^{\frac{\rho-1}{\rho}}+\phi L^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}} \\
=& \left(\left\{\Omega(P_H)(A+wl)\right\}^{\frac{\rho-1}{\rho}}\left(1+\frac{\Omega(P_L)-\Omega(P_H)}{\Omega(P_H)}\right)^{\frac{\rho-1}{\rho}}+\phi L^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}} \\
\simeq& \left(\left\{\Omega(P_H)(A+wl)\right\}^{\frac{\rho-1}{\rho}}\left(1+\frac{\rho-1}{\rho}\frac{\Omega(P_L)-\Omega(P_H)}{\Omega(P_H)}\right)+\phi L^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}} \\
\simeq& \left(\left\{\Omega(P_H)(A+wl)\right\}^{\frac{\rho-1}{\rho}}+\phi L^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}}\left\{1+\frac{\frac{\rho}{\rho-1}\left\{\Omega(P_H)(A+wl)\right\}^{\frac{\rho-1}{\rho}}\frac{\rho-1}{\rho}\frac{\Omega(P_L)-\Omega(P_H)}{\Omega(P_H)}}{\left\{\Omega(P_H)(A+wl)\right\}^{\frac{\rho-1}{\rho}}+\phi L^{\frac{\rho-1}{\rho}}}\right\} \\
=& v(P_H;l,L)\left\{1+\frac{\left\{\Omega(P_H)(A+wl)\right\}^{\frac{\rho-1}{\rho}}}{\left\{\Omega(P_H)(A+wl)\right\}^{\frac{\rho-1}{\rho}}+\phi L^{\frac{\rho-1}{\rho}}}\frac{\Omega(P_L)-\Omega(P_H)}{\Omega(P_H)}\right\}
\end{aligned}
$$

Thus, we obtain

$$
\begin{aligned}
& s\left\{v(P_L;l,L)-v(P_H;l,L)\right\} \\
& = wg'(f)(A+wl)^{\frac{-1}{\rho}}\left\{(1-sf)\Omega(P_H)^{\frac{\rho-1}{\rho}}v(P_H;l,L)^{\frac{1}{\rho}}+sf\Omega(P_L)^{\frac{\rho-1}{\rho}}v(P_L;l,L)^{\frac{1}{\rho}}\right\}.
\end{aligned}
$$

This becomes

$$
\begin{aligned}
&sv(P_H; l, L)\frac{\{\Omega(P_H)(A+wl)\}^{\frac{\rho-1}{\rho}}}{\{\Omega(P_H)(A+wl)\}^{\frac{\rho-1}{\rho}}+\phi L^{\frac{\rho-1}{\rho}}}\frac{\Omega(P_L)-\Omega(P_H)}{\Omega(P_H)} \\
&= wg'(f)(A+wl)^{\frac{-1}{\rho}}\left\{(1-sf)\Omega(P_H)^{\frac{\rho-1}{\rho}}v(P_H; l, L)^{\frac{1}{\rho}}\right. \\
&\left. + sf\Omega(P_L)^{\frac{\rho-1}{\rho}}\left(v(P_H; l, L)\left\{1+\frac{\{\Omega(P_H)(A+wl)\}^{\frac{\rho-1}{\rho}}}{\{\Omega(P_H)(A+wl)\}^{\frac{\rho-1}{\rho}}+\phi L^{\frac{\rho-1}{\rho}}}\frac{\Omega(P_L)-\Omega(P_H)}{\Omega(P_H)}\right\}\right)^{1/\rho}\right\},
\end{aligned}
$$

$$
\begin{aligned}
&sv(P_H; l, L)\frac{\{\Omega(P_H)(A+wl)\}^{\frac{\rho-1}{\rho}}}{\{\Omega(P_H)(A+wl)\}^{\frac{\rho-1}{\rho}}+\phi L^{\frac{\rho-1}{\rho}}}\frac{\Omega(P_L)-\Omega(P_H)}{\Omega(P_H)} \\
&\simeq wg'(f)(A+wl)^{\frac{-1}{\rho}}v(P_H; l, L)^{\frac{1}{\rho}}\Omega(P_H)^{\frac{\rho-1}{\rho}}.
\end{aligned}
$$

Thus, we have

$$
sC\frac{\Omega(P_L)-\Omega(P_H)}{\Omega(P_H)} = wg'(f)(A+wl)^{\frac{-1}{\rho}},
$$

where

$$
c \equiv \log\left[v(P_H; l, L)^{\frac{\rho-1}{\rho}}\frac{\{\Omega(P_H)(A+wl)\}^{\frac{\rho-1}{\rho}}}{\{\Omega(P_H)(A+wl)\}^{\frac{\rho-1}{\rho}}+\phi L^{\frac{\rho-1}{\rho}}}\frac{1}{\Omega(P_H)^{\frac{\rho-1}{\rho}}}\right].
$$

$$
\log(s_{it})+\log\left(\frac{\Omega(P_L)-\Omega(P_H)}{\Omega(P_H)}\right)_{it}-\log(w_{it}) = -c+\log(g'(f_{it}))-\frac{1}{\rho}\log(A+wl)_{it}+\varepsilon_{it}
$$

Considering that f_{it} is endogenous and $g'(f)=\exp(\beta+\gamma f)$, we transform this to

$$
f_{it} = c+\frac{1}{\gamma}\left\{\log(s_{it})+\log\left(\frac{\Omega(P_L)-\Omega(P_H)}{\Omega(P_H)}\right)_{it}-\log(w_{it})\right\}+\frac{1}{\rho\gamma}\log(A+wl)_{it}+\varepsilon_{it} \tag{25}
$$

More precisely, what we observe is not total spending but spending in specific products, and thus

$$f_{it} = c + \frac{1}{\gamma}\left\{\log(s_{it}) + \log\left(\frac{\Omega(P_L)-\Omega(P_H)}{\Omega(P_H)}\right)_{it} - \log(w_{it})\right\}$$
$$+\frac{1}{\rho\gamma}\log\left\{\frac{P^{1-\eta}\left((1-\alpha)/\alpha\right)^{-\eta}(A+wl)_{it}}{1+P^{1-\eta}\left((1-\alpha)/\alpha\right)^{-\eta}}\right\} - \frac{1}{\rho\gamma}\log\left\{\frac{P^{1-\eta}\left((1-\alpha)/\alpha\right)^{-\eta}}{1+P^{1-\eta}\left((1-\alpha)/\alpha\right)^{-\eta}}\right\} + \varepsilon_{it}.$$

Thus, we have

$$f_{it} = c + \frac{1}{\gamma}\left\{\log(s_{it}) + \log\left(\frac{\Omega(P_L)-\Omega(P_H)}{\Omega(P_H)}\right)_{it} - \log(w_{it})\right\} + \frac{1}{\rho\gamma}\log\left(\widehat{A+wl}\right)_{it} + \varepsilon_{it}, \tag{26}$$

where

$$\log\left(\widehat{A+wl}\right)_{it} \simeq \log(PC)_{it} - \left[(1-sf)_{it}\log\left\{\frac{\left((1-\alpha)/\alpha\right)^{-\eta}}{1+\left((1-\alpha)/\alpha\right)^{-\eta}}\right\} + (sf)_{it}\log\left\{\frac{P_L^{1-\eta}\left((1-\alpha)/\alpha\right)^{-\eta}}{1+P_L^{1-\eta}\left((1-\alpha)/\alpha\right)^{-\eta}}\right\}_{it}\right. \tag{27}$$

D Reduced Form Estimation of Shopping Frequency

Table 8 reports the estimation results for shopping frequency. The wage w and the jobs-to-applicants ratio v/u are aggregate-level variables. Specifically, w is measured as total earnings (seasonally adjusted, establishments with five or more employees) from the Monthly Labour Survey, and v/u is taken from the Report on Employment Services, both published by the Ministry of Health, Labour and Welfare. We include individual fixed effects, and standard errors are clustered at the individual level.

The estimation results indicate that shopping frequency increases when wages decline, total expenditure rises, and the magnitude of sales increases. These findings are all consistent with the model's predictions.

Table 8: Reduced Form Estimation of Shopping Frequency

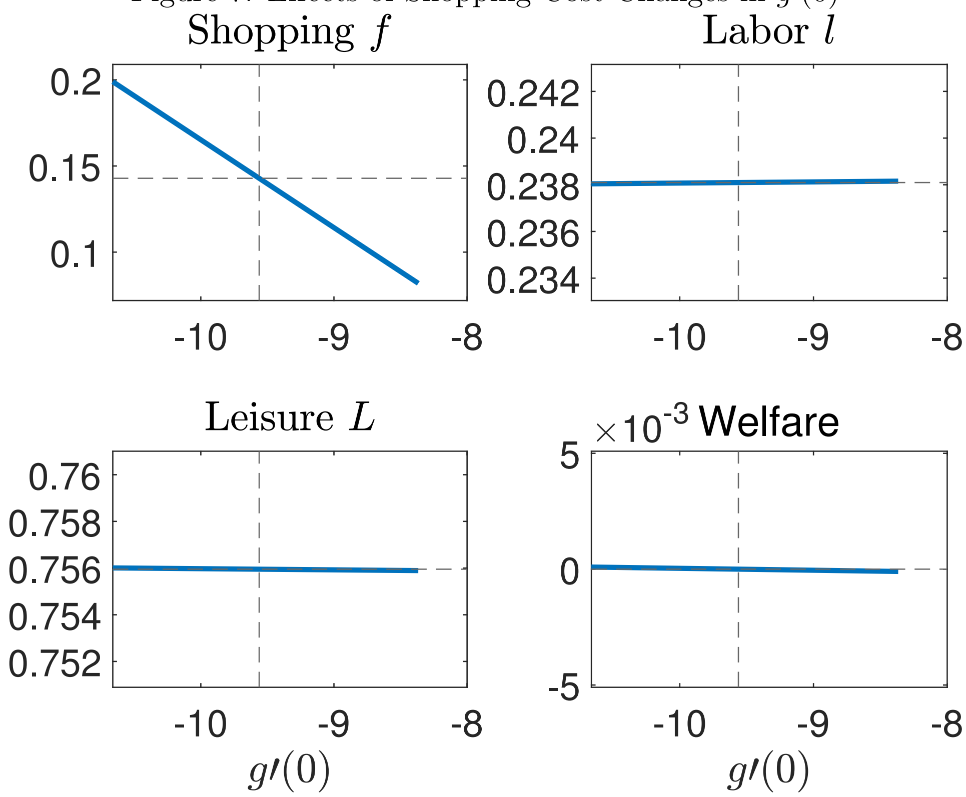
	Dependent variable:	
	Shopping freq	
	(1)	(2)
log(w)	-0.118^{***}	-0.068^{*}
	(0.036)	(0.035)
v/u	-0.029^{***}	-0.004
	(0.003)	(0.006)
log(spending)	0.112^{***}	0.112^{***}
	(0.001)	(0.001)
freq of sales	-0.018	-0.016
	(0.012)	(0.012)
size of sales	0.075^{***}	0.074^{***}
	(0.009)	(0.009)
trend		-0.0003^{***}
		(0.0001)
Observations	631,141	631,141
FE	i	i
Adjusted R^2	0.849	0.849
Note:	*p<0.1; **p<0.05; ***p<0.01	

E Simulation Results

E.1 When the First-Derivative Component of the Shopping Cost Function Changes

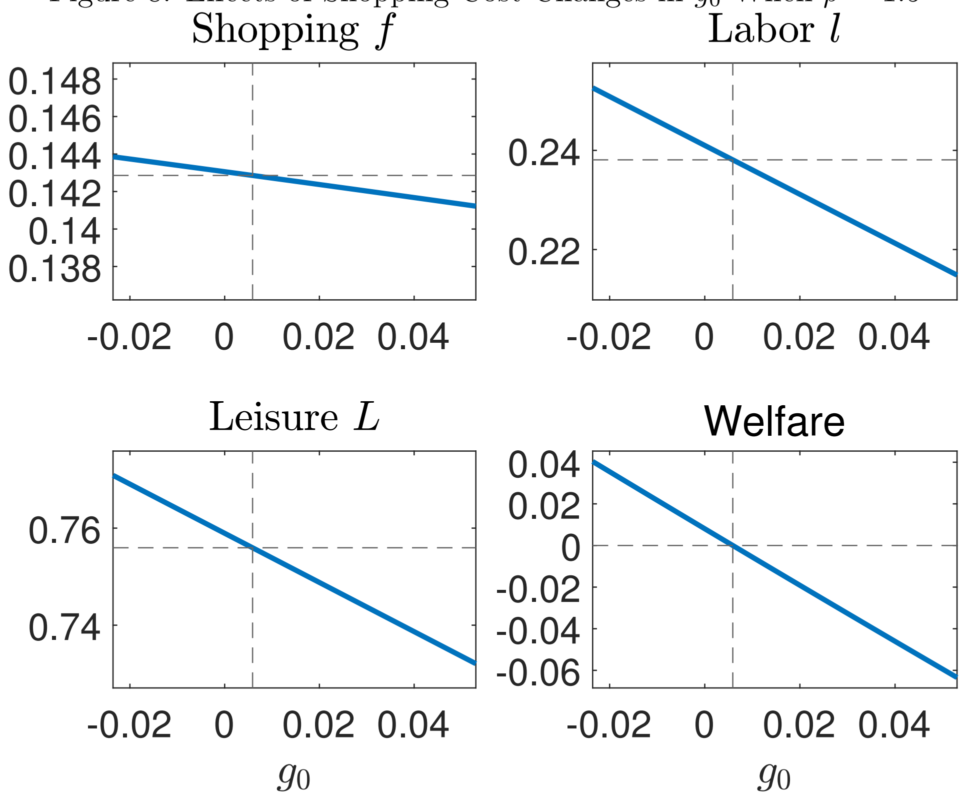
Figure 7 illustrates changes in time allocation and welfare when the first-derivative component of the shopping cost function, $g_1 = g'(0)$, varies. The results are both qualitatively and quantitatively similar to those obtained when varying g_2.

Figure 7: Effects of Shopping Cost Changes in $g'(0)$



Note: This figure illustrates changes in shopping frequency f, labor l, leisure L, and welfare (measured in consumption units) as the first-derivative component of the shopping cost function, $g_1 = g'(0)$, varies along the horizontal axis. The vertical and horizontal dashed lines indicate the baseline values.

Figure 8: Effects of Shopping Cost Changes in g_0 When $\rho = 1.5$



Note: This figure illustrates changes in shopping frequency f, labor l, leisure L, and welfare (measured in consumption units) as the zeroth-derivative component of the shopping cost function, g_0, varies along the horizontal axis. The vertical and horizontal dashed lines indicate the baseline values.

E.2 When the Elasticity of Substitution between Time and Market Goods is Large

For robustness, we consider an alternative value for the estimated elasticity of substitution between time and market goods, ρ. Specifically, we set $\rho = 1.5$, instead of the baseline value of 0.316. Figure 6 shows that the simulation results are virtually unchanged.