



TGU-ECON Discussion Paper Series
#2026-1

Preferences for Domestic AI and Robots in Japan

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February 2026

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February 18, 2026

Abstract

Domestic AI and robotics have the potential to alleviate the household burden on married women in Japan, facilitating their labor market participation. In contrast to their industrial counterparts, domestic robots produce goods and services for direct household consumption, making safety, reliability, and data privacy paramount. This study investigates consumer preferences for home-cooking robots using an experimental vignette survey of 4,951 married individuals. A counterfactual policy simulation, based on a structural model estimated from stated preference data, reveals that a two-thirds price subsidy would have a negligible impact on adoption. Specifically, only 2% of respondents are identified as "compliers," whereas 22–29% are "always-takers." The results indicate that the majority are "never-takers" who resist adoption regardless of financial incentives. Our findings suggest that financial incentives alone cannot catalyze the adoption of domestic robots given the significant intrinsic disutility associated with their use.

Keywords: domestic AI and robots; household production; structural model estimation; stated preferences; vignette survey

Statements and Declarations: We are grateful to the Japan Science and Technology Agency, Research Institute of Science and Technology (JST RISTEX) for their financial support JPMJRX19H4. The authors have no relevant financial or non-financial interests to disclose. All authors contributed to the study conception and design. Data collection and organization were performed by Nobuko Nagase and Emiko Usui. Analysis and material preparations were performed by Yoshiaki Omori. The first draft of the manuscript was written by Yoshiaki Omori and Nobuko Nagase commented on previous versions of the manuscript.

Acknowledgements: We thank Jian Tianyou and Yoshiko Shimada for their excellent research assistance and participants at TG Economics workshops for their helpful and insightful comments.

JEL classification: D13, J22, O33, C99

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1. Introduction

The IT revolution has fundamentally reshaped production processes by enhancing input flexibility and boosting total factor productivity (Jorgenson, 2001; Jorgenson et al., 2008). However, while the productivity effects of IT are well-documented, the impact of Artificial Intelligence (AI) and robotics remains under-explored. Existing research focuses predominantly on labor market outcomes—such as employment and income inequality (Lu and Zhou, 2021)—leaving a critical gap in our understanding of how these technologies reshape the "home economy."

Japan presents a particularly compelling case for studying the adoption of domestic technology due to its persistent gender inequality in the division of household labor. Despite increasing female labor force participation, the gendered disparity in domestic responsibilities in Japan remains exceptionally high in comparison to other postindustrial societies (Brinton et al. 2018; OECD, 2021). Married men's contribution to housework and childcare continues to be disproportionately low, placing a "second shift" burden on married women that potentially hinders their career development and well-being (Cabinet Office, 2023). This unequal division of domestic labor has been identified as a critical factor hindering higher-order births in Japan (Nagase and Brinton, 2017).

Against this backdrop, there is growing interest in how the introduction of domestic robots might reshape the intra-household time allocation between husbands and wives. If these technologies can effectively substitute for human labor in time-intensive chores like cooking, they may not only reduce the total household workload but also trigger a reallocation of time that could alleviate the gendered disparity in domestic responsibilities.

Household production—comprising essential daily activities like childcare and elderly care—relies on a nexus of market inputs and domestic labor. As domestic AI and robots (hereafter "robots") become increasingly accessible, they promise to revolutionize household efficiency, potentially liberating individuals from domestic chores and reallocating time toward market labor or leisure. In Japan, where nearly 40% of married women are college-educated, robot adoption could serve as a pivotal lever to i the disproportionate burden of unpaid work and catalyze female labor force participation (Hertog et al., 2023).

The potential impact of domestic robots, however, hinges on a household's willingness to adopt them. Unlike industrial robots used by firms, household adoption may not be driven solely by price and productivity. Safety, reliability, and privacy concerns (e.g., data collection and leakage) create a complex web of "household preferences" that may impede adoption even when the technology is economically efficient.

This study analyzes Japanese households' preferences for domestic robots by addressing key counterfactual questions: If robots were commercially available, what would be the adoption rate? To what extent would government subsidies stimulate demand? Critically, we decompose potential adopters into "always-takers," "compliers," and "never-takers" to evaluate the cost-effectiveness of subsidy policies.

Answering these questions requires addressing a significant identification problem: when households have intrinsic preferences over production *factors* themselves (not just the output), standard demand functions are confounded. This challenge is analogous to estimating factor demand in the presence of employer discrimination (Becker, 1971; Gronau, 1977; Pollak and Wachter, 1975; Graham and Green, 1984; Kerkhofs and Kooreman, 2023). We resolve this by estimating a structural model using stated-preference data from an original vignette experimental survey of 4,951 married individuals in Japan. This experimental approach is vital—not only because robots are not yet widespread, but also to eliminate the endogeneity inherent in observational data, where the attributes of the robot are often confounded with unobserved intrinsic preferences and unobserved attributes of unchosen production factors.

Theoretically, we extend Becker’s (1965) household production model. Just as a firm’s discriminatory preference against minorities increases its effective marginal cost of labor (Becker, 1971), a household’s negative preference for a robot acts as a "shadow tax," raising its marginal cost and reducing demand despite its technical efficiency.

This study uses the stated-preference data to analyze the willingness to pay (hereafter referred to as “WTP”) or the shadow tax rate. In the vignette, respondents are presented with options for using a robot, a commercial human service, and a spouse’s domestic labor other than their own domestic labor (hereafter referred to as “own domestic labor”), each with various price and productivity combinations. They are then asked to choose one of those options to save own domestic labor or none.⁴

This paper contributes to the burgeoning literature using stated-preference data and structural utility models to examine household decision-making (e.g., Dosman and Adamowicz, 2006; Hill, 2009; Prabhu, 2010; Michaud et al., 2020). To our knowledge, this is the first study to investigate the household’s preferences for domestic robots by estimating a structural model of household production with stated-preference data.

The remainder of this study is organized as follows. Section 2 develops the theoretical framework, while Section 3 details the experimental vignette survey design and the resulting stated-preference data. Section 4 introduces empirical models, emphasizing a structural approach with minimal functional assumptions to identify the unobserved preference distributions necessary for counterfactual analysis. We also discuss why reduced-form models are insufficient for this purpose. Section 5 presents descriptive statistics and balance checks to confirm the experiment’s internal validity, justifying our use of random-effects models. Section 6 provides preliminary results using linear probability models to demonstrate that efficiency alone does not dictate household choices. Section 7 presents our main structural estimates for willingness to pay (WTP), and Section 8 conducts counterfactual policy simulations based on these results. Section 9 concludes.

⁴ It should be noted that data this study uses is on individual preferences stated by either husbands or wives rather than data on joint preferences stated by couples. Therefore, caution is warranted when interpreting the findings.

2. Theoretical Model

In this section, we develop a model of household production where a robot’s service, a commercial human service, and spousal domestic labor are available as alternatives to one’s own domestic labor. We contrast two scenarios: (i) a benchmark case where the household has no preference over how domestic goods are produced, and (ii) a generalized case where the household exhibits intrinsic preferences over production factors.

2.1. The Unitary Household Production Framework

We begin with a unitary household production model. The household utilizes four inputs—own domestic labor (ℓ_{OWN}), spousal domestic labor (ℓ_{SP}), a commercial human service (HS), and a robot service (R)—to produce a fixed quantity (\bar{q}) of domestic goods (e.g., meals). The household production function F represents the technical relationship between these inputs and the output:

$$q = F(R, HS, \ell_{SP}, \ell_{OWN})$$

We assume standard properties for F , including positive marginal products and a diminishing marginal rate of technical substitution (MRS) of the robot for own domestic labor.⁵

The respondent and the spouse are each subject to a total time endowment (T), which is allocated between domestic labor (ℓ_{OWN}, ℓ_{SP}), leisure (L_{OWN}, L_{SP}), and market labor supply ($T - \ell_{OWN} - L_{OWN}, T - \ell_{SP} - L_{SP}$) at hourly wages w_{OWN} and w_{SP} , respectively. Let P_R be the hourly rental price of the robot service and P_{HS} be the price of the commercial human service. The opportunity cost of domestic labor is defined by the respective hourly wages. For simplicity, we abstract from other market goods and focus on the trade-offs among these four domestic production factors. Given non-earned income I , the household faces the following budget constraint:

$$P_R R + P_{HS} HS \leq w_{OWN}(T - \ell_{OWN} - L_{OWN}) + w_{SP}(T - \ell_{SP} - L_{SP}) + I$$

2.2. Case 1: Neutral Preferences over Production Factors

⁵ Since robots are currently not widely used, we do not know for sure if the latter assumption will be met. To help evaluate the validity of the assumption, we consider production technology in which the marginal product of any factor of production does not depend on the other factors of production. In the absence of interactive effects among the four factors of production, the diminishing marginal rate of substitution assumption is fulfilled if the marginal product of the robot service does not increase, and the marginal products of other factors decrease in their hours. If the marginal product of the robot service increases, the assumption is satisfied if the marginal products of other factors decrease at a faster rate than the marginal product of the robot service increases.

Suppose the household derives utility u solely from the consumption of domestic goods and leisure, meaning the production process itself does not directly affect well-being. The utility maximization problem is:

$$\begin{aligned} & \text{Max } U[F(R, HS, \ell_{SP}, \ell_{OWN}), L_{SP}, L_{OWN}] \\ \text{subject to } & P_R R + P_{HS} HS \leq w_{OWN}(T - \ell_{OWN} - L_{OWN}) + w_{SP}(T - \ell_{SP} - L_{SP}) + I \\ & \bar{q} \leq F(R, HS, \ell_{SP}, \ell_{OWN}) \end{aligned}$$

The optimal allocation $(R^*, HS^*, \ell_{SP}^*, \ell_{OWN}^*)$ is characterized by the equimarginal principle, where the marginal cost is equalized across all factors: ⁶

$$\frac{P_R}{MP_R(R^*, HS^*, \ell_{SP}^*, \ell_{OWN}^*)} = \frac{P_{HS}}{MP_{HS}(R^*, HS^*, \ell_{SP}^*, \ell_{OWN}^*)} = \frac{w_{SP}}{MP_{SP}(R^*, HS^*, \ell_{SP}^*, \ell_{OWN}^*)} = \frac{w_{OWN}}{MP_{OWN}(R^*, HS^*, \ell_{SP}^*, \ell_{OWN}^*)}$$

Since domestic robots are nascent technology, assuming a specific functional form for F may be inappropriate.⁷ Therefore, we initially have the respondent consider a situation in which fixed units of domestic goods are to be produced by their own domestic labor. That is, we assume that an initial state is characterized by a corner solution $(0, 0, 0, 1)$, and that the robot service, the commercial human service, and the spouse's domestic labor are added to the options. We then observe whether the respondent uses any other factor for at least one hour when the options are made available. Under the diminishing marginal rate of substitution assumption we know that the optimal hours of the robot service (R^*) will be positive when the household chooses to use the robot service even a little at the corner:

$$\frac{P_R}{MP_R(0, 0, 0, \bar{\ell})} = \min \left[\frac{P_R}{MP_R(0, 0, 0, \bar{\ell})}, \frac{P_{HS}}{MP_{HS}(0, 0, 0, \bar{\ell})}, \frac{w_{SP}}{MP_{SP}(0, 0, 0, \bar{\ell})}, \frac{w_{OWN}}{MP_{OWN}(0, 0, 0, \bar{\ell})} \right]$$

or

$$\frac{P_R}{MRTS_{R,OWN}(0, 0, 0, \bar{\ell})} = \min \left(\frac{P_R}{MRTS_{R,OWN}(0, 0, 0, \bar{\ell})}, \frac{P_{HS}}{MRTS_{HS,OWN}(0, 0, 0, \bar{\ell})}, \frac{w_{SP}}{MRTS_{SP,OWN}(0, 0, 0, \bar{\ell})}, w_{OWN} \right)$$

In the remainder of this section MP_R , MP_{HS} , MP_{SP} , MP_{OWN} , $MRTS_{R,OWN}$, $MRTS_{HS,OWN}$, $MRTS_{SP,OWN}$ are evaluated at the corner $(0, 0, 0, \bar{\ell})$. The point of evaluation is not noted to avoid clutter.

2.3. Case 2: Intrinsic Preferences over Production Factors

In reality, households may have intrinsic preferences for (or against) specific production factors. In this case, the utility function depends directly on the inputs:

$$u = U(q, R, HS, \ell_{SP}, \ell_{OWN}, L_{SP}, L_{OWN}) = U[F(R, HS, \ell_{SP}, \ell_{OWN}), R, HS, \ell_{SP}, \ell_{OWN}, L_{SP}, L_{OWN}].$$

⁶ In the vignette survey, we choose to use thirty minutes instead of one hour. We use one hour for an expositional purpose here.

⁷ Even if the robot could independently produce the domestic good without the intervention of domestic labor and even if its marginal product remained constant, the marginal rates of technical substitution of the robot service for other factors would not remain constant since the marginal products of other factors are known to eventually diminish.

This formulation implies that the choice of factors affects utility independently of the output q . The condition for adopting the robot for at least one hour becomes:

$$\frac{P_R(1 - \delta_R)}{MP_R} = \min \left(\frac{P_R(1 - \delta_R)}{MP_R}, \frac{P_{HS}(1 - \delta_{HS})}{MP_{HS}}, \frac{w_{SP}(1 - \delta_{SP})}{MP_{SP}}, \frac{w_{OWN}(1 - \delta_{OWN})}{MP_{OWN}} \right)$$

or

$$\frac{P_R(1 - \delta_R)}{MRTS_{R,OWN}} = \min \left(\frac{P_R(1 - \delta_R)}{MRTS_{R,OWN}}, \frac{P_{HS}(1 - \delta_{HS})}{MRTS_{HS,OWN}}, \frac{w_{SP}(1 - \delta_{SP})}{MRTS_{SP,OWN}}, w_{OWN}(1 - \delta_{OWN}) \right)$$

where δ_j represents the coefficient for the marginal utility (or disutility) of factor j (hereafter referred to as “WTP coefficients” or “WTPs”). These coefficients can be interpreted as shadow subsidies or taxes. For instance, a negative δ_{OWN} indicates a distaste for housework (fatigue), while a positive δ_{SP} might reflect the respondent's preference for their spouse's contribution. When multiplied by the corresponding price, δ_j equals willingness to pay (WTP) for (or the monetary value of the marginal utility of) the factor j . We assume that $\delta_j < 1$. The adoption condition can be stated in terms of effective prices. The household chooses the robot service if its "shadow-price-adjusted" effective marginal cost is lower than that of any other alternative.

This structural framework allows us to identify WTPs by observing choices under varying price and productivity scenarios in our vignette experiments.

3. Data

We implement a rigorous online factorial survey experiment (vignette survey) grounded in our theoretical framework. Section 3.1 elucidates the construction of the vignettes, or hypothetical decision scenarios, which serve as the primary instrument for capturing respondent preferences. Section 3.2 details the experimental design used to extract a D-efficient fractional vignette sample from the vignette universe; this approach targets the identification of causal effects and maximum statistical precision by maintaining orthogonality among causal variables and level balance. Finally, Section 3.3 delineates the sampling strategy, which utilizes stratified randomization to eliminate potential confounding between causal variables and respondent-level characteristics.

We select "meal preparation" as the primary task for analysis. This choice is motivated by several factors: the output quantity is relatively fixed, the task allows for forward planning, and efficiency is a primary objective for households—all of which align with the assumptions of the household production model. In contrast, activities such as childcare or elder care are less suitable because their timing and required intensity are often unpredictable.

3.1 Experimental Vignette Survey

The architecture of the vignette survey is aligned with the theoretical framework. We prompt respondents to imagine a future scenario in which they are tasked with meal preparation, initially utilizing only their own domestic labor. To minimize the confounding effects of prior culinary knowledge, we provide a standardized description of the required tasks, including menu planning, preparation, and food storage.

We then offer the respondent additional options of using (i) the robot service, (ii) the commercial human service, and (iii) the spouse's domestic labor for at least 30 minutes to reduce their own domestic labor. We provide the costs $(P_R, P_{HS}, w_{SP}, w_{OWN})$ and the productivity $(MRTS_{R,OWN}(0,0,0,\bar{\ell}), MRTS_{HS,OWN}(0,0,0,\bar{\ell}), \text{ and } MRTS_{SP,OWN}(0,0,0,\bar{\ell}))$ —representing the amount of own domestic labor saved for each option. To incorporate realistic time constraints, each vignette is further enriched with household context, including work hours, the presence and age of children, and eldercare responsibilities. Based on this high-dimensional information set, respondents execute a discrete choice: adopting the robot service ($R^* > 0$), utilizing a commercial service ($HS^* > 0$), requesting spouse assistance ($SP^* > 0$), or none of the additional options, performing the task entirely on their own ($R^* = 0, HS^* = 0, SP^* = 0$).

3.2 The Design of Experiment

Our experimental framework utilizes a $6^{10}2^1$ design, featuring ten causal variables with six levels and one causal variable with two levels. These "dimension variables" include the price and the MRTS of each option for own domestic labor based on the theory alongside the contextual factors. We use varied wage levels within the vignettes rather than observed wages to avoid endogeneity—as observed wages may correlate with unobserved domestic productivity—and assign potential wages to respondents out of the labor force. To ensure situational plausibility, we exclude implausible combinations, such as positive work hours paired with zero wages and zero work hours for both the respondent or the spouse.⁸ Table 1 presents the dimensions and level values.⁹

We utilize the D-efficiency criterion to select a fractional vignette sample containing $n_s = 144$ distinct vignettes from the vignette universe of $6^{10}2^1$ so that all unknown parameters of interest can be identified and estimated efficiently. A common challenge in designing experiments for nonlinear choice models is that the variance-covariance matrix of the estimated parameters depends on unknown true parameter values. Given the lack of prior empirical studies to inform these values, we adopt a second-best strategy: using a D-efficient fractional vignette sample that minimizes the variance-covariance matrix of estimated parameters of a factorial linear probability model (LPM).

⁸ In the analysis sample containing 14,853 vignettes, 1,959 vignettes are associated with positive own wage rates with no hours of own work, 2,084 vignettes are associated with positive spouse's wage rates with no hours of spouse's work.

⁹ We do not use "the MRTS of option j for own domestic labor" in vignettes and instead use "the number of hours of own domestic labor saved by using the option j for one hour" interpretation for better understanding.

The LPM offers distinct advantages for experimental design: its variance-covariance matrix of the estimated parameters is independent of true parameter values, it requires no distributional assumptions, and its coefficients provide a straightforward interpretation of causal effects. We specify the following factorial model (Specification 1):

$$\begin{aligned} \text{Ind}(R_{i,k}^* > 0) = & b_0 + \mathbf{b}_R \mathbf{P}_{R,i,k} + \mathbf{b}_{HS} \mathbf{P}_{HS,i,k} + \mathbf{b}_{SP} \mathbf{P}_{SP,i,k} + \mathbf{b}_{OWN} \mathbf{P}_{OWN,i,k} \\ & + \mathbf{c}_R \mathbf{MRTS}_{R,OWN,i,k} + \mathbf{c}_{HS} \mathbf{MRTS}_{HS,OWN,i,k} + \mathbf{c}_{SP} \mathbf{MRTS}_{SP,OWN,i,k} \\ & + \mathbf{d}_Z \mathbf{Z}_{i,k} + \varepsilon_{i,k} \end{aligned}$$

where $\text{Ind}(R_{i,k}^* > 0)$ serves as the dependent variable indicating that the respondent i chooses to use the robot service for at least thirty minutes in the vignette k , bolded vectors represent a semi-parametric specification using dummy variables for the levels of the dimension variables, and $\varepsilon_{i,k}$ is the error term.

The contextual factors appear as $\mathbf{Z}_{i,k}$. We denote by $\boldsymbol{\theta} = (b_0, \mathbf{b}_R, \mathbf{b}_{HS}, \mathbf{b}_{SP}, \mathbf{b}_{OWN}, \mathbf{c}_R, \mathbf{c}_{HS}, \mathbf{c}_{SP})$ a $p (= 1 + 5 \times 10 + 1 \times 1 = 52) \times 1$ vector of all unknown parameters. A fractional vignette sample is represented by an $n_s \times p$ design matrix \mathbf{X} .

We optimize the design matrix \mathbf{X} under the constraints to exclude the implausible vignettes, using the D-efficiency criterion defined as:

$$D = 100 \cdot \frac{1}{n_s} |\mathbf{X}'\mathbf{X}|^{\frac{1}{p}}$$

where $|\mathbf{X}'\mathbf{X}|$ is the determinant of the Fisher Information matrix.

Our design in Table 2 achieves a D-efficiency score of 95.93, which exceeds the standard benchmark of 90 used in social science research. An analysis of the inverse Fisher Information Matrix in Table 3 confirms the success of the design: 97% of the diagonal elements (variances) fall between $.007\sigma_\varepsilon^2$ to $.008\sigma_\varepsilon^2$ with off-diagonal elements near zero.

To mitigate respondent fatigue and ensure data integrity, we partitioned the n_s (=144) vignettes into d (=48) “decks,” each consisting of three vignettes. This blocking strategy was implemented to ensure that the deck effects are as orthogonal as possible to the dimension variables. Each respondent was randomly assigned to a single deck. Consequently, with n_r total respondents, each deck was evaluated by $\frac{n_r}{d}$ participants.

The resulting data matrix for our analysis is equivalent to the design matrix \mathbf{X} , with each row replicated $\frac{n_r}{d}$ times. Under this framework, the variance-covariance matrix of the OLS estimators for $\boldsymbol{\theta}$ is given by:

$$V(\boldsymbol{\theta}) = \frac{d}{n_r} \sigma_\varepsilon^2 (\mathbf{X}'\mathbf{X})^{-1},$$

where σ_ε^2 represents the variance of the error term.

This formulation implies that for a given \mathbf{X} and σ_ε^2 , the variance of the estimators can be reduced to any desired level of precision by sufficiently increasing the number of respondents per deck (n_r/d). Prior to the main survey, we conducted a pilot study to obtain an unbiased estimate of σ_ε^2 . Based on these pilot

results, we confirmed that our planned sample size (n_r) provides sufficient statistical power for the main analysis.

While the D-efficiency criterion ensures the identification and efficient estimation of parameters in a factorial or semi-parametric framework, representing dimension variables numerically is often more advantageous for rigorous hypothesis testing. However, transitioning to a parametric regression analysis requires further optimization of the specific level labels assigned to each dimension variable within the D-efficient sample. To achieve this, we computed the variance-covariance matrices for the coefficients estimated from a data matrix of numerical variables, which were generated using the level labels and the unbiased estimate of σ_ϵ^2 obtained from our pilot survey. We then strategically selected level labels for the key dimension variables to ensure two critical outcomes: first, that the variances of the estimated parameters remain sufficiently small for statistical precision, and second, that the resulting vignettes remain contextually plausible for the respondents.

3.3 Sampling Strategy

To ensure robust internal validity, we stratify the respondent population by sex and five age cohorts (25–29, 30–34, 35–39, 40–44, and 45–59). To eliminate any spurious correlation between these stratifying variables and the experimental treatments, we allocate multiples of the 48 decks evenly across each stratum. A large sample of respondents is randomly drawn from each stratum and subsequently assigned to the decks. This randomization procedure, supported by the law of large numbers, ensures that respondent characteristics—both observed and unobserved—remain uncorrelated with the dimension variables or deck effects within each stratum.

The data were collected through an online survey of married men and women in Japan, utilizing the monitor database of Rakuten Insight Corporation between March 15 and March 21 in 2022. The original data contains 5,199 respondents. After eliminating invalid responses, we obtain an analysis sample of 4,951 respondents with 2,466 men and 2,485 women. We verify the success of this randomization—the cornerstone of our experimental design—by performing a "balance check" against the respondents' observed characteristics obtained from a separate background survey. Passing this check justifies the use of random-effects models in our primary analysis. Furthermore, the absence of systematic correlation between respondent characteristics and treatments implies that including observed characteristics as control variables is not strictly necessary for obtaining unbiased estimates.

4. Empirical Models

In this section, we develop two complementary empirical approaches to analyze household preferences for domestic robot services. First, we construct a structural model based on the theoretical

framework presented in Section 3. The primary advantage of the structural approach over a reduced-form model is that it explicitly incorporates the underlying preference structure into the estimation. This allows us to identify the "deep parameters" of household preferences—specifically, the unobserved willingness-to-pay ($\delta_{j,i}$) for different production factors. By formally modeling how these preferences interact with technological and budget constraints, the structural model enables us to perform counterfactual policy simulations, such as evaluating the impact of price subsidies on the robot adoption.

Second, we employ a reduced-form Linear Probability Model (LPM). While the structural model is essential for identifying latent preferences and conducting policy analysis, the reduced-form approach provides a robust and intuitive test of our core hypotheses. Specifically, it allows us to examine whether the choice of the robot services is driven primarily by cost-minimization or whether significant psychological or technical barriers exist that financial incentives cannot easily overcome. By combining these two approaches, we provide both a rigorous estimation of the latent preference distributions and a transparent validation of the theoretical predictions derived from our model.

4.1 The Structural Model: Panel Random Effects Multinomial Logit Model

Section 4.1 constructs a structural model based on the theoretical framework and discusses a method for deriving the distribution of unobserved parameters that represent preferences for the robot service. A structural model explicitly incorporates the underlying preference structure, the constraints and decision-making principles faced by the decision-maker, enabling the identification and estimation of the "deep parameters" of the underlying theoretical model.

To implement the model using standard statistical software, we specify a functional form for an additive random utility model. Let i denote the household and k denote the vignette (hypothetical scenario).

The marginal utility (net of the marginal cost) that household i derives from choosing option j is given by:

$$U_{j,i,k} = V_{j,i,k} + \varepsilon_{j,i,k}, \quad j = R, HS, SP, OWN$$

where j represents the robot service (R), commercial human service (HS), spousal domestic labor (SP), or only one's own domestic labor (OWN). The error term $\varepsilon_{j,i,k}$ represents errors in evaluating marginal utility. We assume that $\varepsilon_{j,i,k}$ follows an independent extreme value distribution, which leads to a variant of the multinomial logit model. This distributional assumption is made primarily for computational feasibility.

We further specify the systematic component of utility as:

$$V_{j,i,k} = \beta \ln \frac{MP_{j,i,k}}{P_{j,i,k}(1 - \delta_{j,i})}$$

where $MP_{j,i,k}$ is the marginal product of factor j , $P_{j,i,k}$ is its price (using w_{SP} for spousal labor and w_{OWN} for own labor), and $\delta_{j,i}$ represents the WTP coefficient for factor j . Although $\delta_{j,i}$ can be positive or negative, we assume $1 - \delta_{j,i} > 0$ to facilitate the logarithmic transformation. If $1 - \delta_{j,i} < 0$, the effective price becomes negative, which would imply an extreme incentive to utilize factor j .¹⁰

Given that the logarithmic function is monotonically increasing and β is a constant, this formulation—in the absence of evaluation error $\varepsilon_{j,i,k}$ —is consistent with the theoretical marginal principle for selecting the option with the highest marginal utility (or lowest marginal cost). The logarithmic functional form and the inclusion of $(1 - \delta_{j,i})$ as a price multiplier are critical for maintaining the additive random utility structure.

Rewriting the equation yields:

$$\begin{aligned} V_{j,i,k} &= \beta \ln \frac{\frac{MP_{j,i,k}}{MP_{OWN,i}} MP_{OWN,i}}{P_{j,i,k}(1 - \delta_{j,i})} \\ &= \beta \ln \frac{MRTS_{j,OWN,i,k} MP_{OWN,i}}{P_{j,i,k}(1 - \delta_{j,i})} \\ &= \beta \ln \frac{MRTS_{j,OWN,i,k}}{P_{j,i,k}} + \beta \ln MP_{OWN,i} - \beta \ln(1 - \delta_{j,i}) \\ &= \alpha_i + \alpha_{j,i} + \beta \ln \frac{MRTS_{j,OWN,i,k}}{P_{j,i,k}} \end{aligned}$$

where $\alpha_i = \beta \ln MP_{OWN,i}$, $\alpha_{j,i} = -\beta \ln(1 - \delta_{j,i})$. Both terms are unobserved and are treated as random effects; α_i is specific to household i , while $\alpha_{j,i}$ is specific to household i and option j . We assume that WTP depends on the household and the option but remains invariant across vignettes (k). This assumption characterizes the model as a panel random-effects multinomial logit model. The $MRTS$ and price variables are numerical variables derived from the six-level dimension variables.

The marginal utility can be further extended to include other covariates:

$$V_{j,i,k} = \alpha_i + \alpha_{j,i} + \beta \ln \frac{MRTS_{j,OWN,i,k}}{P_{j,i,k}} + \gamma_j Z_{i,k}$$

$Z_{i,k}$ represents covariates that vary across vignettes for the same household, such as work hours and household needs (i.e., presence and age of children, eldercare requirements). We assume these covariates

¹⁰ In a separate work in progress, we develop another structural model without the constraints on δ_R , δ_{HS} , δ_{SP} , and δ_{OWN} . A distributional form assumption on δ_R , δ_{HS} , δ_{SP} , and δ_{OWN} allows us to express the probability of choice for each option based on these conditions. The resulting model is a non-additive random utility model, for which no existing estimation program is available.

do not directly affect WTP. To examine gender differences in WTP, we estimate the model separately by sex rather than including sex as a covariate.¹¹

The household chooses the robot service for at least thirty minutes if:

$$U_{R,i,k} = \max[U_{R,i,k}, U_{HS,i,k}, U_{SP,i,k}, U_{OWN,i,k}]$$

The distribution of α_i is not identified because it cancels out during within-household comparisons across options. Identification requires normalizing the parameters for one option to zero; we set $\alpha_{OWN,i} = \zeta_{OWN} = 0$. Assuming a multivariate normal distribution for the remaining random effects, $\alpha_i = (\alpha_{R,i}, \alpha_{HS,i}, \alpha_{SP,i}) \sim \mathcal{N}(\mu_\alpha, \Sigma_\alpha)$, the model can be estimated as a panel mixed multinomial logit model. Finally, we derive the distribution of $\delta_{j,i}$, by sampling from the estimated distributions of β and α_i using the transformation:

$$\delta_{j,i} = 1 - \exp(-\alpha_{j,i}/\beta)$$

4.2 The Reduced Form Model: LPM

Section 4.2 introduces a reduced-form choice model to test a specific hypothesis derived from the theory. Unlike the structural model, the reduced-form approach does not incorporate the underlying preference structure into the estimation and thus does not allow for counterfactual policy analysis. However, it remains a valuable tool for testing the absence of intrinsic preferences. If the household has no preference over production factors ($\delta_R = 0, \delta_{HS} = 0, \delta_{SP} = 0, \delta_{OWN} = 0$), the theory predicts that the robot service is chosen if it provides the lowest marginal cost:

$$\frac{P_R}{MRTS_{R,OWN}} = \min\left(\frac{P_R}{MRTS_{R,OWN}}, \frac{P_{HS}}{MRTS_{HS,OWN}}, \frac{w_{SP}}{MRTS_{SP,OWN}}, w_{OWN}\right)$$

or

$$\ln P_R - \ln MRTS_{R,OWN} = \min(\ln P_R - \ln MRTS_{R,OWN}, \ln P_{HS} - \ln MRTS_{HS,OWN}, \ln w_{SP} - \ln MRTS_{SP,OWN}, \ln w_{OWN}).$$

Therefore, a specification consistent with the absence of intrinsic preferences (hereafter referred to as Specification 2) is given by:

$$\begin{aligned} \text{Ind}(R_{i,k}^* > 0) &= b_0 \\ &+ b_R \text{Ind}[\ln P_R - \ln MRTS_{R,OWN} = \min(\ln P_R - \ln MRTS_{R,OWN}, \ln P_{HS} - \ln MRTS_{HS,OWN}, \ln w_{SP} - \ln MRTS_{SP,OWN}, \ln w_{OWN})] \\ &+ \mathbf{d}_Z \mathbf{Z}_{i,k} + \varepsilon_{i,k}. \end{aligned}$$

In this case, the dummy variable indicating that the robot service achieves the lowest marginal cost should be the primary determinant of the choice, with an expected effect size of 1.0:

¹¹We need not and do not want to control for the actual characteristics of households and their members, such as gender, age, educational background, and region of residence if the data passes the balance check. Their effects are absorbed in $\alpha_i + \alpha_{j,i}$, and hence, the distribution of $\delta_{j,i}$.

$$H^1: b_R = 1 \text{ and } \mathbf{d}_Z = \mathbf{0}^{12}$$

A naïve reduced-form specification (hereafter referred to as Specification 3) is formulated in the spirit of the aforementioned models as follows:

$$\begin{aligned} \text{Ind}(R_{i,k}^* > 0) = & b_0 + b_R \ln P_{R,i,k} + b_{HS} \ln P_{HS,i,k} + b_{SP} \ln w_{SP,i,k} + b_{OWN} \ln w_{OWN,i,k} \\ & + c_R \ln \text{MRTS}_{R,OWN,i,k} + c_{HS} \ln \text{MRTS}_{HS,OWN,i,k} + c_{SP} \ln \text{MRTS}_{SP,OWN,i,k} \\ & + \mathbf{d}_Z \mathbf{Z}_{i,k} + \varepsilon_{i,k}, \end{aligned}$$

where the coefficients $b_0, b_R, b_{HS}, b_{SP}, b_{OWN}, c_R, c_{HS}, c_{SP}$ are unknown and represent the causal effects of the corresponding variables on the use of the robot service.

However, Specification 3 is further limited by the fact that it ignores the inherent discontinuity of the decision-making process. Specifically, it fails to account for the fact that the indicator variable—which identifies whether the robot service achieves the lowest marginal cost—is not a continuous function of prices ($P_R, P_{HS}, w_{SP}, w_{OWN}$). The estimates for Specification 3 are available in the Appendix.

5. Descriptive Statistics and Balance Check

Our primary sample consists of 4,951 respondents (2,466 males and 2,485 females). Since each respondent evaluated three vignettes, the total number of vignette observations is 14,853. Columns 2–4 of Table 4 present the descriptive statistics for this sample.

To verify the internal validity of our experimental design, we performed a balance check to ensure that the random assignment of vignettes to respondents was executed successfully. Given that the dimension variables are orthogonal by design, it is sufficient to examine whether the mean characteristics of respondents are consistent across the levels of any single dimension variable. Specifically, we compare the means of continuous variables, such as age and working hours, and the distributions of categorical variables, such as employment status and educational attainment, across the six levels of the "own hourly wage" dimension variable. The statistical equivalence of these observed characteristics across levels supports the assumption of balanced unobserved characteristics, which is crucial for ensuring that our estimators are consistent.

The balance check results, reported in the remaining columns of Table 4, confirm that the randomization was successful. While the largest variation is observed in the "female" variable, the

¹² In the presence of intrinsic preferences, the correct specification corresponding to Specifications 2 would replace P_R, P_{HS}, w_{SP} and w with $P_R(1 - \delta_R), P_{HS}(1 - \delta_{HS}), w_{SP}(1 - \delta_{SP})$ and $w_{OWN}(1 - \delta_{OWN})$, respectively, if the preferences were observable. The model misspecification biases the estimated coefficients in unknown directions, making the hypothesis H^1 unlikely to hold. It is in this weak sense that we can learn about household preferences from the reduced form model estimates.

χ^2 statistic is 6.74 with a corresponding P-value of 0.24, indicating no statistically significant differences. This evidence validates our empirical strategy and justifies the use of random-effects models.

6. Reduced Form Model Estimates

Before analyzing WTP, we report the LPM estimates for the choice of the robot service. Section 6.1 presents the Analysis of Variance (ANOVA) results for the semi-parametric Specification 1, for which the D-efficient sample is designed. Section 6.2 discusses the regression results for the parametric Specification 2 of the reduced-form LPM. The results for the parametric Specification 3 are provided in the Appendix.

6.1 ANOVA

The ANOVA results in Table 5 demonstrate the relatively low explanatory power of the dimension variables considered in the experiment. The coefficient of determination (R^2) is 0.067, and the adjusted R^2 is 0.064. Such low R^2 values are frequently observed in demand functions for goods and services estimated from observational data. This finding suggests the influence of other factors, such as intrinsic preferences, that are not captured by the dimension variables. Given that the price variation in the experiment is sufficiently large exceeding the variability typically found in observational data, the low R^2 is unlikely to stem from insufficient variation in the independent variables. Furthermore, since the model accounts for the MRTS—data rarely available in observational studies—, the lack of consideration for productivity differences cannot be a cause for the low explanatory power.

6.2 Regression Analyses

We begin the regression analysis with Specification 2 of the reduced form LPM, which assumes an absence of household preferences. Theory predicts that the household uses the robot service when it offers the lowest marginal cost for producing domestic goods. Accordingly, we estimate the model using a dummy variable indicating whether the robot service attains the minimum marginal cost, alongside causal variables related to working hours, childcare, and eldercare as specified in the vignettes.

Table 6 presents the coefficients estimated via Ordinary Least Squares (OLS) and a Random Effects (RE) model. We treat the respondent as the grouping variable for the random intercepts. Robust standard errors are reported in parentheses.

The OLS and RE estimates are qualitatively and quantitatively similar. As expected, the RE estimates yield smaller standard errors than the OLS estimates; however, the differences are marginal, and the primary conclusions remain unaffected by the estimation method. Although not reported in the table, omitting the causal variables for working hours, childcare, and eldercare makes hardly any difference in the estimated

coefficient for the minimum marginal cost dummy. This robustness arises because the experimental design ensures that the underlying dimension variables are orthogonal to each other

The economic theory predicts that the option minimizing the marginal cost of household production is chosen, implying that the coefficient of the dummy variable is 1.0 and those of other variables are zero ($H^1: b_R = 1, d_Z = 0$). We reject this joint hypothesis ($p < 0.0001$) for both OLS and RE models, which is counter to the theory in the absence of household preferences. We subsequently test $b_R = 1$ and $d_Z = 0$ separately.

We reject the hypothesis that $b_R = 1$ ($p < 0.0001$). Nevertheless, the effect of the lowest marginal cost is substantial; the coefficients (0.150 for OLS and 0.154 for RE) are positive and precisely estimated. When the robot service minimizes the marginal cost of household production, the household's chance of using the robot service increases by 15.0 to 15.4 percentage points.

We reject the joint hypothesis $d_Z = 0$ ($p < 0.0001$) partly because working hours have positive effects. Increased working hours induce the household to use the robot service even when the marginal cost is held constant, suggesting that time constraints and/or fatigue increase the usage of the robot service. However, a 1% increase in either the individual's own hours of work or in the spouse's hours of work increases the household's chance of using the robot service by less than 0.01 percentage points. While statistically significant, these effects are quantitatively minor compared to the marginal cost effect. According to the RE estimates, own hours of work must increase by 1,166% to generate the 15.0 percentage point increase caused by the lowest marginal cost. For the spouse's hours of work, the required increase is 1,537%. The estimated coefficients for childcare and eldercare indicate statistically significant causal effects on the robot service use in the expected directions, though none has an impact comparable to the marginal cost effect.

As previously mentioned in Section 4.2, the rejection of the joint hypothesis ($H^1: b_R = 1, d_Z = 0$) suggests that household preferences lead to misspecification bias in the estimated coefficient b_R for the dummy variable indicating the lowest marginal cost attained by the robot service.

7. The Structural Model Estimates

The estimation results of the reduced form model in Section 6 are partially counter to the view that efficiency alone matters, and the household has no preference. In this section, we report the results from the structural model (the panel random effects multinomial model) to study household preferences explicitly.

Panel Random Effects Multinomial Model Estimates

We estimate a panel random-effects multinomial logit model that explicitly accounts for intrinsic preferences. The latent dependent variables represent alternative-specific marginal utility levels. The set of independent variables consists of two types: alternative-specific and case-specific variables. The

alternative-specific variables include the log-relative efficiency ($\ln MRTS / price$ or $\ln \frac{MRTS_{j,OWN,i,k}}{P_{j,i,k}}$) and the three alternative-specific intercepts (excluding own domestic labor). The case-specific variables encompass the hours of own and spousal market work, the presence of a child, the age of the youngest child, and the provision of eldercare. In addition to the full model, we estimate a version without case-specific variables for comparison. Our discussion focuses on the results of the model that controls for case-specific variables, hereafter referred to as Specification A. We employ the maximum simulated likelihood method for estimation, utilizing Hammersley's integration sequence with 664 points. This approach, similar to the Halton sequence, serves as an advanced alternative to pseudo-random sampling by achieving superior regularity in the distribution of integration points.

The structural estimation reveals that while technical efficiency significantly drives adoption, there exists substantial unobserved heterogeneity in intrinsic preferences across households. The estimates in Table 7 confirm that the coefficient for the log-relative efficiency per yen ($\ln \frac{MRTS_{j,OWN,i,k}}{P_{j,i,k}}$), β , is positive and statistically significant. However, the magnitude of the random-effects variances (σ_R^2 , σ_{HS}^2 , σ_{SP}^2) indicates substantial unobserved heterogeneity.

Willingness to Pay Coefficients

The structural model identifies substantial variation in the WTPs for all domestic labor alternatives, particularly for the robot service and the commercial human service. We generate the distributions of these WTPs using the estimated joint distribution of $\alpha_{j,i}$ and β through the transformation $\delta_{j,i} = 1 - \exp(-\alpha_{j,i}/\beta)$, applying the point estimates for the parameters of the estimated distribution. As presented in the variance-covariance matrix in Table 8, the estimated WTPs ($\widehat{\delta_{j,i}}$) exhibit significant dispersion across households. This statistical variation highlights that the perceived value of domestic automation and external services is not uniform but highly idiosyncratic, reflecting diverse household-specific preferences.

The observed volatility in WTP for the robot and commercial services stems from a small but distinct fraction of individuals who harbor extremely large negative preferences. Figures 1 and 2, which display the histograms for these WTPs, reveal that the distributions are heavily negatively skewed. While we truncate these histograms at -1000 and -50 respectively to maintain visual clarity for the majority of observations, the underlying data in Table 8 confirms that these extreme "never-takers" perceive a psychological or safety-related cost that far exceeds any potential economic gain. This structural resistance explains why the mean WTP remains suppressed despite the technical efficiency of the robot service.

Correlation analysis suggests that households tend to view the robot service and spousal domestic labor as economic substitutes, whereas commercial human services remain independent of these factors. According to the correlation matrix in Table 8, the correlation coefficient between the WTP for spousal labor and the WTP for the robot service is 0.171, indicating a moderate degree of substitutability between

these two modes of production. In contrast, the correlation coefficients between the WTP for commercial human services and both the robot service and spousal labor are effectively zero (0.000). These distinct correlation patterns imply that while automation may directly offset the need for a spouse's domestic contribution, it occupies a different market niche than traditional commercial outsourcing.¹³

Gender-based analysis in the Appendix shows that women possess a relatively higher valuation for the robot service than men, likely reflecting their greater burden in domestic production. The median WTP for the robot is slightly higher among women, suggesting that the daily demands of meal preparation increase the appeal of technological substitutes. In contrast, the valuation for spousal labor (δ_{SP}) follows a distinct pattern, highlighting the unique psychological and economic value assigned to human-provided domestic work. The median men's WTPs are -1,953,752 for robots, -348.739 for commercial services, -1.15e+09 for the spouse's domestic labor. The corresponding figures for the median women are -55,284.73, -4.78e+07, and -3,426.327, respectively. These structural parameters serve as the foundation for the counterfactual simulations that follow.

8. Simulation

In this section we perform counterfactual policy simulations using the structural model estimates in Sections 7. We look to answering the following questions. By how much will the government's subsidy for using the robot service increase the adoption? What fraction of those using robots in the presence of the government's subsidy will be "always takers" or will have used them with or without the subsidy? What fraction will be "compliers" or will use them with the subsidy, but will not use them without it? What fraction will be "never takers" or will not use them with or without the subsidy? The answers to these questions can help improve the cost-effectiveness of the subsidy policy.

8.1 The Method

We employ a counterfactual simulation method to evaluate how a two-thirds price subsidy influences the decision-making process regarding domestic labor by sex. To determine the choice probabilities under the subsidy, we utilize the estimated joint distribution of the preference parameters ($\alpha_i = (\alpha_{R,i}, \alpha_{HS,i}, \alpha_{SP,i})$)

¹³ According to a survey commissioned by the Ministry of Economy, Trade, and Industry (METI) in FY2022, the usage rate of housekeeping services in Japan is notably low at 1.8 percent (The Japan Research Institute, Limited, 2024). Several factors contribute to the limited prevalence of commercial human services, including a strong "Do-It-Yourself" ethos, a cultural emphasis on cleanliness, and a high valuation of household privacy. Additionally, psychological barriers such as guilt, social pressure, and stress over differing household methods, alongside economic factors like high costs and the availability of low-cost technological substitutes (e.g., robot vacuum cleaners and dishwashers), further hinder adoption. Labor shortages and restrictions on foreign workers also constrain the supply side. Furthermore, the COVID-19 pandemic appears to have reinforced these trends; post-pilot survey interviews reveal that some respondents remain reluctant to use such services due to lingering fears of infection from individuals entering their homes.

and β) and calculate the predicted choices for each respondent. Specifically, we compare the baseline scenario, where the price is set at the experimental level P_R , with the policy scenario, where the effective price is reduced to $P_R/3$.¹⁴ This structural approach allows us to identify the individual-level transitions between alternatives—own domestic labor, the robot service, the commercial human service, and the spousal labor—thereby isolating the causal effect of price incentives on technological adoption.

The simulation assumes baseline household characteristics and opportunity costs derived from representative survey data to ensure the empirical relevance of the predicted choices. Based on our background survey, we set the weekly market work hours at 36.80 for men and 16.28 for women, and the spousal weekly market work hours at 19.69 for men and 38.80 for women. We assume a household composition that includes an infant under six months old and no elderly dependents. Regarding the opportunity costs of domestic labor (w_{OWN}), we set the hourly wage at 1,800 yen (900 yen per 30 minutes) for men and 1,400 yen (700 yen per 30 minutes) for women, with spousal wage (w_{SP}) adjusted accordingly, reflecting the gender wage gap observed in the sample. Furthermore, we assume no gender difference in marginal productivity ($MRTS_{SP,OWN} = 1$), focusing the analysis on how gender-specific opportunity costs and intrinsic preferences drive the adoption of automation.

We determine the benchmark prices for the robot service based on expert projections, reflecting the anticipated market costs of cooking robots in the near future. Drawing on a Delphi survey (Nagase et al., 2024), which predicts an annual price range between 15,000 and 150,000 yen, we calculate the price per 30-minute use. Given that an average Japanese couple spends 404.42 hours on cooking annually—as derived from the Basic Survey on Social Life—the corresponding prices for a 30-minute service are set at 18.545 yen and 185.450 yen. These values provide a realistic economic framework for evaluating the sensitivity of households to both low-end and high-end technological scenarios.

The simulation incorporates specific parameters for time-saving efficiency and the cost of alternative commercial services to capture the relative advantages of each domestic production mode. Following Lehdonvirta et al. (2023), we assume that the robot service replaces 32.48% of the time spent on manual cooking ($MRTS_{R,OWN} = .3248$), meaning that 30 minutes of the robot use saves 9.7 minutes of own labor. For the commercial human service, we set the price (P_{HS}) at 1,750 yen per 30 minutes (3,500 yen per hour), assuming a higher marginal productivity where 30 minutes of service saves 60 minutes of own cooking time ($MRTS_{HS,OWN} = 2.0$). We summarize the values for the price and MRTS of each option assumed in each experiment in Table 9. These parameters allow for a rigorous comparison between nascent AI technology and established but costly human-provided services.

8.2 Findings

¹⁴ A fifty percent subsidy yields qualitatively similar results. The two-thirds and fifty percent subsidization rate often used in Japan.

The simulation results, reported in Tables 10a for $P_R=18.545$ and 11a for $P_R=185.450$, demonstrate that even a substantial price subsidy fails to achieve widespread adoption of domestic robots, as the resulting increase in adoption is remarkably small regardless of the baseline price. For instance, when the baseline price P_R is set at 185.450 yen, the predicted adoption rate for the robot service remains modest, 23.72% for men and 26.38% for women, even after a two-thirds reduction in the effective price. This outcome reinforces the earlier finding that for the majority of the population, economic incentives are secondary to the psychological and safety-related barriers identified in the WTP distribution. The structural resistance, represented by the large negative values of δ_R , acts as a "shadow tax" that effectively cancels out the benefits of the financial subsidy.

A decomposition of the population, reported in Tables 10b for $P_R=18.545$ and 11b for $P_R=185.450$, reveals that "never-takers" dominate the market, rendering price-based policies largely ineffective for the vast majority of households. Based on the transitions observed in the simulation at $P_R=185.450$ yen we classify respondents into three groups as shown in Table 11b. The "never-takers," who reject the robot service regardless of the subsidy, constitute the overwhelming majority of the sample, 76.28% for men and 73.17% for women. In contrast, "compliers"—those whose adoption decision is flipped by the two-thirds subsidy—comprise a mere 1.80% of men and 1.98% of women, while "always-takers" account for 21.92% of men and 24.5% of women. This stark contrast underscores that the diffusion of domestic AI and robots depends more on addressing intrinsic concerns than on lowering acquisition costs.

The simulation for specific demographic profiles, reported in Tables A4a, A4b, A5a and A5b in the Appendix, further confirms that even among groups with a higher opportunity cost of time, such as women who share common characteristics with men, the shift toward automation remains marginal. In the final simulation we assume that own weekly hours of work are 26.51 and that the spouse's weekly hours of work are 29.28 for both men and women. These are average hours reported by all respondents in the background survey. As for the opportunity costs of domestic labor, we assume that own hourly wage and the spouse's hourly wage are 1,600 yen (eight hundred yen for thirty minutes), respectively, for both men and women. The simulation for the high-price scenario ($P_R=185.450$) confirms that the vast majority of women remain unresponsive to price incentives, with 97.60% of those initially choosing own domestic labor refusing to switch despite the subsidy. As illustrated in Table A5a, 36.72% of women choose to cook for themselves in the absence of a subsidy. The introduction of a two-thirds subsidy shifts only 2.40% of these choices from "own domestic labor" to the "robot service," leaving the remaining 97.60% of women's decisions unaffected. This negligible shift highlights that even substantial financial support is insufficient to overcome the intrinsic disutility associated with domestic automation when the baseline cost is high.

8. Conclusions

Our structural analysis concludes that the 'shadow tax' associated with domestic robots represents a major barrier to alleviating household burdens through technology. The introduction of domestic robots into homes has the potential to reduce the burden of unpaid domestic work on married Japanese women, encouraging them to participate in the labor market. However, unlike the production of goods in factories, domestic robots produce domestic goods and services that are directly consumed by household members; therefore, safety and reliability are essential. There is also a risk of personal information being collected and leaked via AI and robots.

Understanding preferences for the use of domestic robots in households is important for future growth of the concept. This study conducted an experimental vignette survey of 4,951 married men and women in Japan to investigate Japanese preferences for the use of domestic AI and robots in home cooking.

The willingness-to-pay coefficients (WTPs) derived from the structural model estimates show that (i) substantial variation exists in all WTPs, but the variation is particularly large for the robot service and the commercial human service; (ii) the substantial variations in the WTPs for the robot's service and the commercial human service result from the presence of a small fraction of individuals with negative WTPs large in absolute value; (iii) individuals have a tendency to consider the robots' service and the spouse's domestic labor as substitutes; (iv) women are less unwilling to accept the robot and the spouse's domestic labor and less willing to accept the commercial human service than men.

Counterfactual policy stimulation to assess the effects of the two-thirds subsidy reveals that the effect of the subsidy on the adoption is quantitatively small. While "always-takers," who use robots with or without the subsidy, account for 22-29%, "compliers", who use robots with the subsidy, but do not use robots without the subsidy, account for approximately 2%. The majority are "never-takers," who do not use the robots with or without the subsidy.

Tables and Figures

Table 1: Dimension Variables and Levels

Variable	Definition	Levels	
		#	Level (value)
X1	Own hourly wage rate (w)	6	Your hourly wage is 1(0), 2(750), 3(1500), 4(2000), 5(3000), 6(5000) yen
X2	Own hours of work	6	Typical weekly work hours: 1(60), 2(55), 3(50), 4(15), 5(8), 6(0) hours
X3	The spouse's hourly wage rate (w_{SP})	6	Your spouse's hourly wage is 1(0), 2(750), 3(1500), 4(2000), 5(3000), 6(5000) yen
X4	The spouse's hours of work	6	Typical weekly work hours: 1(60), 2(55), 3(50), 4(15), 5(8), 6(0) hours
X5	Youngest child age	6	1(No children), 2(6 months), 3(2 years), 4(6 years), 5(12 years), 6(17 years)
X6	Eldercare responsibilities	2	Yes/no
X7	Price for robot/application for 30 minutes (P_R)	6	1(50), 2(100), 3(250), 4(1000), 5(2000), 6(4500) yen
X8	Relative productivity for robot/application ($MRTS_{R,\ell}$)	6	Using smart technology for 30 minutes saves 1(10), 2(15), 3(20), 4(25), 5(80), 6(100) minutes of your time
X9	Price for human services for 30 minutes (P_{HS})	6	1(100), 2(400), 3(750), 4(1000), 5(3000), 6(4000) yen
X10	Relative productivity for human service ($MRTS_{HS,\ell}$)	6	Using the human helper for 30 minutes saves 1(10), 2(15), 3(20), 4(25), 5(85), 6(100) minutes of your time
X11	Relative productivity for the spouse ($MRTS_{SP,\ell}$)	6	Using the spouse's help for 30 minutes saves 1(10), 2(15), 3(20), 4(25), 5(85), 6(100) minutes of your time

Notes : The fractional vignette sample size $N_S = 144$

The following constraints are imposed.

If $X2 = 65, 50, 40, 25, 10$, then $X1 \neq 0$; If $X4 = 65, 50, 45, 25, 10$, then $X3 \neq 0$; If $X2 = 0$, then $X4 \neq 0$; If $X4 = 0$, then $X2 \neq 0$.

Table 2: Efficiently Blocked D-efficient sample X

Block	Run	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
1	1	6	2	6	6	5	2	4	3	1	6	1
1	2	1	6	5	2	5	2	2	1	3	4	2
1	3	5	5	2	4	3	1	6	2	6	3	5
2	1	6	4	5	1	6	1	4	3	4	5	3
2	2	2	2	3	6	3	2	3	6	4	3	2
2	3	4	3	6	4	4	1	1	4	6	2	1
3	1	2	3	4	1	3	1	4	1	6	1	3
3	2	4	2	6	4	4	2	2	4	1	6	6
3	3	1	6	2	3	6	1	5	3	5	5	4
4	1	6	2	2	4	1	1	3	4	2	1	4
4	2	2	1	6	1	5	1	2	6	1	5	2
4	3	5	4	5	3	4	1	4	1	6	3	5
5	1	4	6	5	2	3	1	5	6	1	6	4
5	2	2	2	1	6	6	1	4	5	3	1	6
5	3	1	6	4	1	2	2	6	2	6	3	2
6	1	5	6	3	4	3	2	1	3	2	6	4
6	2	6	4	2	2	2	2	3	4	1	3	1
6	3	4	3	6	3	6	1	2	2	4	1	2
7	1	4	5	5	6	2	1	2	1	2	6	1
7	2	2	4	1	6	4	1	1	3	1	4	4
7	3	3	1	2	2	1	2	4	2	5	1	3
8	1	3	1	4	2	4	2	3	2	2	6	1
8	2	6	2	5	3	3	1	4	6	5	3	4
8	3	5	5	3	4	5	2	3	5	4	5	6

9	1	3	6	6	1	1	1	6	2	1	2	5
9	2	1	6	2	2	4	2	1	5	4	6	3
9	3	6	4	3	6	1	1	2	4	5	4	6
10	1	5	3	5	1	6	2	5	4	4	6	3
10	2	3	6	4	4	5	2	4	1	5	5	4
10	3	4	4	2	5	5	1	2	2	2	2	6
11	1	3	1	3	6	4	1	3	3	3	1	5
11	2	5	3	4	5	1	1	5	2	1	5	6
11	3	2	6	6	4	6	2	6	6	2	4	3
12	1	4	5	3	5	5	2	4	3	4	1	6
12	2	5	4	4	3	3	1	2	5	1	3	3
12	3	6	2	2	6	6	2	5	2	3	2	2
13	1	4	3	4	2	1	2	5	6	4	4	4
13	2	5	1	6	1	2	1	3	1	2	1	6
13	3	6	1	3	3	5	1	6	4	1	6	3
14	1	3	5	5	5	2	2	3	3	5	2	3
14	2	5	3	6	6	4	2	5	1	6	1	4
14	3	2	6	3	3	6	1	1	2	3	3	6
15	1	5	5	6	5	1	1	3	3	3	3	4
15	2	3	6	2	3	4	1	4	5	4	6	2
15	3	6	5	3	2	6	2	1	6	1	1	5
16	1	5	1	2	6	5	1	6	1	4	4	6
16	2	4	2	6	2	3	1	2	5	6	5	4
16	3	2	3	1	6	4	2	3	2	1	5	3
17	1	4	2	4	1	2	2	3	5	5	4	5
17	2	6	4	3	4	4	2	6	2	3	2	3

17	3	3	5	2	5	3	2	2	1	1	1	1
18	1	6	1	4	6	4	2	2	5	4	3	5
18	2	4	6	2	1	3	2	1	4	3	1	3
18	3	3	4	3	4	6	1	6	1	5	6	2
19	1	4	4	2	1	5	1	3	6	6	4	2
19	2	2	5	6	4	2	2	5	2	5	3	3
19	3	1	6	5	5	1	1	6	5	1	1	5
20	1	4	4	4	4	1	2	5	3	2	3	2
20	2	1	6	6	1	4	2	4	4	5	2	6
20	3	2	1	2	5	6	2	3	6	6	6	4
21	1	2	5	6	3	4	1	6	3	3	4	1
21	2	1	6	4	4	3	1	3	4	4	5	5
21	3	5	3	5	6	5	2	1	5	2	3	3
22	1	2	3	6	6	5	1	1	2	5	6	5
22	2	4	1	2	1	4	2	4	3	1	3	2
22	3	5	4	1	6	2	2	5	6	4	2	1
23	1	4	1	6	5	2	1	5	4	3	3	5
23	2	5	2	4	5	4	1	6	6	5	4	1
23	3	2	4	5	6	1	2	1	1	1	2	6
24	1	6	5	6	2	4	1	3	1	3	4	2
24	2	2	3	2	4	2	2	2	3	5	4	5
24	3	1	6	3	1	5	1	5	6	2	3	1
25	1	6	6	5	4	2	1	5	3	6	1	2
25	2	4	5	4	1	4	2	6	5	2	2	4
25	3	5	1	6	2	1	2	4	4	2	5	1
26	1	2	2	4	5	4	1	5	4	2	1	3

26	2	3	2	6	1	1	2	1	1	4	3	4
26	3	5	6	4	2	5	1	4	2	3	2	5
27	1	4	4	5	6	4	2	3	2	6	5	4
27	2	2	6	4	2	1	1	2	3	4	1	1
27	3	4	2	3	5	6	2	1	1	2	4	5
28	1	1	6	6	4	1	1	3	6	3	6	3
28	2	2	6	2	2	2	2	6	1	4	3	6
28	3	5	1	1	6	3	2	2	3	2	2	2
29	1	1	6	3	3	2	2	2	2	2	1	4
29	2	2	5	3	1	1	1	5	5	5	2	1
29	3	3	1	1	6	6	2	6	4	6	6	6
30	1	6	4	6	2	6	2	6	5	2	5	5
30	2	5	5	4	3	1	2	1	6	3	6	2
30	3	3	2	3	1	3	2	5	2	1	4	1
31	1	3	2	3	2	2	1	2	6	6	2	3
31	2	4	1	5	6	1	2	6	6	5	1	6
31	3	6	3	2	5	5	1	6	5	3	3	1
32	1	3	5	2	6	6	1	5	5	1	2	4
32	2	2	1	5	4	5	1	1	5	6	5	1
32	3	6	3	4	5	3	2	6	1	5	6	2
33	1	6	1	4	4	6	1	2	6	4	2	4
33	2	4	2	1	6	2	1	6	1	3	5	3
33	3	5	4	6	3	6	2	3	5	5	1	1
34	1	2	5	4	6	6	1	4	4	2	2	2
34	2	4	3	3	3	1	2	6	3	6	5	1
34	3	6	6	2	1	4	1	1	6	5	5	6

35	1	2	1	3	5	4	1	5	1	4	5	5
35	2	3	5	1	6	5	2	2	4	5	3	4
35	3	6	3	4	1	2	1	3	3	2	6	6
36	1	1	6	4	4	6	2	4	1	1	4	1
36	2	3	2	5	3	1	1	1	4	6	2	2
36	3	4	4	3	2	3	1	5	5	5	6	6
37	1	5	2	5	1	6	1	2	2	4	6	1
37	2	3	3	1	6	1	1	3	5	2	4	2
37	3	1	6	6	5	3	2	1	3	6	2	6
38	1	6	5	1	6	5	2	5	6	6	1	5
38	2	3	4	6	6	3	1	6	3	4	4	3
38	3	5	6	3	5	4	2	2	4	5	5	2
39	1	3	4	4	6	2	1	1	4	3	5	1
39	2	6	5	5	3	3	2	4	2	2	4	6
39	3	5	2	5	2	5	2	6	3	5	2	5
40	1	4	6	4	3	5	1	3	1	1	2	3
40	2	3	4	2	5	2	1	4	6	2	6	5
40	3	2	5	5	2	3	1	6	4	2	5	2
41	1	2	3	2	3	3	2	3	4	4	2	5
41	2	6	6	3	5	1	2	2	5	6	4	3
41	3	4	1	4	2	6	1	1	3	5	3	3
42	1	6	1	1	6	3	1	1	1	5	2	1
42	2	3	3	5	1	6	2	2	3	3	5	5
42	3	5	3	3	2	2	1	4	4	1	4	4
43	1	3	1	5	4	3	2	5	5	3	4	6
43	2	6	2	2	3	1	2	5	1	2	5	3

43	3	4	5	1	6	1	1	4	2	4	6	5
44	1	4	6	5	5	6	2	3	4	1	3	1
44	2	3	5	4	3	2	2	1	6	1	5	6
44	3	2	4	2	1	1	2	2	1	3	6	5
45	1	3	3	5	4	4	1	2	6	2	3	6
45	2	2	4	4	1	5	2	6	4	3	1	4
45	3	6	6	6	5	2	2	4	5	6	6	2
46	1	5	5	2	6	6	1	2	4	6	4	3
46	2	2	1	3	3	2	2	4	5	3	2	4
46	3	3	4	6	5	5	2	1	2	4	1	2
47	1	4	3	2	6	3	2	4	6	3	5	1
47	2	6	1	5	5	2	1	1	2	4	4	4
47	3	2	2	4	3	5	2	5	3	6	6	6
48	1	5	2	2	4	2	1	1	5	1	1	2
48	2	3	3	3	2	6	1	3	1	6	3	6
48	3	3	6	6	3	5	2	5	4	2	4	5

Table 3 Inverse of the Fisher Information Matrix $(\mathbf{X}'\mathbf{X})^{-1}$

	β_0	β_{11}	β_{12}	β_{13}	β_{14}	β_{15}	β_{21}	β_{22}	β_{23}	β_{24}	β_{25}	β_{31}	β_{32}	β_{33}	β_{34}	β_{35}	β_{41}	β_{42}	β_{43}	β_{44}	β_{45}	β_{51}	β_{52}	β_{53}	β_{54}	β_{55}	β_{61}	
β_0	0.010	0.004	(0.002)	(0.002)	(0.001)	(0.001)	0.002	0.001	0.001	0.001	0.000	0.004	(0.002)	(0.002)	(0.002)	(0.001)	0.002	0.002	0.001	0.001	0.001	0.000	(0.000)	(0.000)	0.000	0.000	0.000	0.000
β_{11}	0.004	0.024	(0.004)	(0.003)	(0.002)	(0.002)	0.005	0.003	0.002	0.001	0.001	0.000	0.000	(0.000)	(0.000)	0.000	(0.000)	0.000	0.000	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000
β_{12}	(0.002)	(0.004)	0.009	0.002	0.001	0.001	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	0.000	(0.000)	(0.000)	0.001	(0.000)	0.000	(0.000)	0.000	0.000	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)
β_{13}	(0.002)	(0.003)	0.002	0.008	0.001	0.001	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)	(0.000)	0.000	0.000	0.000	0.000	0.000	0.000
β_{14}	(0.001)	(0.002)	0.001	0.001	0.007	0.001	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	0.000	0.000	(0.000)	0.000	(0.000)	(0.000)	(0.000)	0.000	(0.000)	0.000	0.000	(0.000)	(0.000)	0.000	0.000	0.000	0.000
β_{15}	(0.001)	(0.002)	0.001	0.001	0.001	0.007	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_{21}	0.002	0.005	(0.003)	(0.002)	(0.001)	(0.001)	0.009	0.000	0.001	0.000	0.000	(0.000)	0.000	0.000	0.000	(0.000)	0.001	0.001	0.001	0.000	0.000	0.000	0.000	(0.000)	(0.000)	0.000	(0.000)	0.000
β_{22}	0.001	0.003	(0.001)	(0.001)	(0.001)	0.001	0.003	0.000	0.008	0.000	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	0.001	(0.000)	0.000	0.000	0.000	0.000	0.000	(0.000)	0.000	0.000	0.000
β_{23}	0.001	0.002	(0.001)	(0.001)	(0.001)	(0.001)	0.001	0.000	0.008	0.000	0.000	0.000	(0.000)	0.000	(0.000)	(0.000)	0.000	0.001	0.000	0.000	0.000	(0.000)	0.000	(0.000)	0.000	0.000	0.000	0.000
β_{24}	0.001	0.001	(0.001)	(0.001)	(0.001)	(0.000)	0.000	0.000	0.000	0.008	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.001	0.001	0.000	0.000	0.000	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	(0.000)
β_{25}	0.000	0.001	(0.001)	(0.001)	(0.000)	(0.001)	0.000	0.000	0.000	0.000	0.000	0.008	(0.000)	0.000	0.000	0.000	0.001	0.000	(0.000)	0.000	(0.000)	0.000	0.000	(0.000)	(0.000)	0.000	0.000	0.000
β_{31}	0.004	0.000	(0.000)	(0.000)	0.000	0.000	(0.000)	0.000	0.000	0.000	0.000	(0.000)	0.014	(0.004)	(0.003)	(0.003)	(0.002)	0.004	0.002	0.002	0.001	0.001	0.000	(0.000)	(0.000)	0.001	0.000	(0.000)
β_{32}	(0.002)	0.000	0.000	0.000	(0.000)	0.000	0.000	0.000	(0.000)	(0.000)	0.000	(0.004)	0.009	0.002	0.001	0.001	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	0.000	0.000	(0.000)	0.000	0.000	0.000	0.000
β_{33}	(0.002)	0.000	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.003)	0.002	0.008	0.001	0.001	(0.002)	(0.002)	(0.001)	(0.000)	(0.001)	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000
β_{34}	(0.002)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	0.000	(0.003)	0.001	0.001	0.007	0.001	(0.002)	(0.001)	(0.001)	(0.001)	0.000	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)
β_{35}	(0.001)	0.000	0.001	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.002)	0.001	0.001	0.001	0.007	(0.001)	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	(0.000)
β_{41}	0.002	(0.000)	(0.000)	0.000	(0.000)	0.000	0.001	0.000	0.000	0.001	0.001	0.004	(0.002)	(0.002)	(0.002)	(0.001)	0.008	0.001	0.000	0.000	0.000	(0.000)	(0.000)	0.000	0.000	0.000	0.000	0.000
β_{42}	0.002	0.000	0.000	(0.000)	(0.000)	(0.000)	0.001	0.001	0.001	0.001	0.000	0.002	(0.001)	(0.002)	(0.001)	(0.000)	0.001	0.008	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)
β_{43}	0.001	0.000	(0.000)	(0.000)	0.000	(0.000)	0.001	0.001	0.000	0.000	(0.000)	0.002	(0.001)	(0.001)	(0.001)	0.000	0.000	0.000	0.008	0.000	0.000	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	(0.000)
β_{44}	0.001	(0.000)	0.000	0.000	0.000	(0.000)	0.000	0.000	0.000	0.000	0.000	0.001	(0.001)	(0.000)	(0.001)	0.000	0.000	0.000	0.000	0.008	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)
β_{45}	0.001	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	0.000	(0.000)	0.001	(0.001)	(0.001)	(0.000)	(0.000)	0.000	0.000	(0.000)	0.000	0.008	(0.000)	(0.000)	0.000	(0.000)	0.000	0.000	0.000
β_{51}	0.000	(0.000)	0.000	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	0.000	(0.000)	0.007	(0.000)	(0.000)	(0.000)	(0.000)	0.000
β_{52}	(0.000)	0.000	0.000	0.000	0.000	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	(0.000)	0.000	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	(0.000)	0.007	(0.000)	(0.000)	(0.000)	(0.000)	0.000
β_{53}	0.000	(0.000)	(0.000)	0.000	0.000	(0.000)	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.007	0.007	(0.000)	(0.000)	0.000	0.000
β_{54}	0.000	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	0.000	0.001	0.000	(0.000)	(0.000)	0.000	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.007	0.000	0.000	0.000
β_{55}	0.000	0.000	(0.000)	0.000	0.000	(0.000)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	0.007	0.000	0.000
β_{61}	0.000	0.000	(0.000)	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	(0.000)	0.000	0.000	0.000	0.000	0.000	0.000	0.007	0.000
β_{71}	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	0.000	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	(0.000)	0.000	0.000	(0.000)	0.000	0.000	(0.000)	(0.000)	0.000	0.000	0.000	0.000
β_{72}	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	0.000	0.000	0.000	0.000	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)
β_{73}	(0.000)	(0.000)	0.000	(0.000)	(0.000)	0.000	0.000	(0.000)	(0.000)	0.001	0.000	(0.000)	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	(0.000)	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	0.000
β_{74}	0.000	0.000	0.000	0.000	(0.000)	(0.000)	0.000	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.001	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000
β_{75}	(0.000)	(0.000)	(0.000)	0.000	(0.000)	0.000	0.000	(0.001)	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	0.000
β_{81}	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000
β_{82}	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	0.000	0.000	(0.000)	(0.000)	0.000	0.000	0.000	0.000	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)	0.000	0.000
β_{83}	(0.000)	(0.000)	(0.000)	0.000	0.000	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	0.000
β_{84}	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	0.000	0.000	0.000	(0.000)	0.000	0.000	0.000	0.000	0.000	(0.000)	0.000	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	(0.000)
β_{85}	(0.000)	0.000	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_{91}	0.000	0.000	(0.000)	(0.000)	0.000	(0.000)	0.000	0.000	0.001	0.000	(0.000)	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	0.000	0.000	0.000	(0.000)	0.000	0.000	0.000	0.000	0.000	0.000
β_{92}	(0.000)	0.000	0.000	0.000	0.000	(0.000)	(0.000)	0.000	0.000	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	(0.000)	0.000	0.000	0.000	0.000
β_{93}	0.000	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	0.000	0.000	0.000	(0.000)	0.000	(0.000)	(0.000)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	(0.000)	0.000	0.000	0.000	0.000	0.000	(0.000)
β_{94}	0.000	(0.000)	(0.000)	0.000	0.000	(0.000)	0.000	0.000	0.000	0.000	0.000	0.000	(0.000)															

	β_{71}	β_{72}	β_{73}	β_{74}	β_{75}	β_{81}	β_{82}	β_{83}	β_{84}	β_{85}	β_{91}	β_{92}	β_{93}	β_{94}	β_{95}	β_{101}	β_{102}	β_{103}	β_{104}	β_{105}	β_{111}	β_{112}	β_{113}	β_{114}	β_{115}
β_0	0.000	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)	0.000	0.000	(0.000)	0.000	0.000	0.000	0.000	(0.000)
β_{11}	0.000	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	0.001	0.000	(0.000)
β_{12}	(0.000)	0.000	0.000	0.000	(0.000)	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)	(0.000)	0.000	0.000	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)
β_{13}	(0.000)	(0.000)	(0.000)	0.000	0.000	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	0.000	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
β_{14}	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	(0.000)	(0.000)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	(0.000)	0.000	(0.000)	0.000	0.000	0.000	0.000	(0.000)
β_{15}	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	0.000	(0.000)	0.000	0.000	(0.000)	0.000
β_{21}	0.000	(0.000)	(0.000)	0.000	0.000	0.000	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	0.001	0.000	(0.000)	(0.000)
β_{22}	(0.000)	(0.000)	(0.000)	0.000	(0.001)	(0.000)	0.000	0.000	0.000	(0.000)	0.000	0.000	0.000	0.000	(0.000)	(0.000)	0.000	0.000	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000
β_{23}	0.000	(0.000)	(0.001)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	0.000	0.000
β_{24}	0.000	0.000	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	(0.000)
β_{25}	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	(0.000)	(0.000)	0.000	(0.000)	(0.000)
β_{31}	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	0.000	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	0.000	(0.000)	0.000	0.000	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)
β_{32}	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	0.000	0.000	0.000	(0.000)	0.000	(0.000)
β_{33}	(0.000)	(0.000)	0.000	0.000	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	0.001	0.000	0.000	0.000
β_{34}	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	0.000	0.000	(0.000)	0.000	0.000	(0.000)	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000
β_{35}	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	0.000	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	0.000	0.000
β_{41}	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	0.000	0.000	(0.000)	(0.000)	0.000	0.000	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)
β_{42}	0.000	0.000	(0.000)	(0.000)	0.000	0.000	0.000	0.000	0.000	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	0.000	0.000	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_{43}	(0.000)	0.000	0.000	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	0.000	0.000	0.000	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	(0.000)	(0.000)	0.000
β_{44}	0.000	0.000	(0.000)	0.001	(0.000)	0.000	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	0.000	(0.000)	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	0.000
β_{45}	0.000	0.000	0.000	0.000	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	0.000	(0.000)	0.000	(0.000)	(0.000)	0.000	0.000	(0.000)
β_{51}	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	0.000	0.000	0.000	0.000	(0.000)
β_{52}	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	0.000	0.000	0.000	0.000	(0.000)	0.000	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	0.000	(0.000)	(0.000)
β_{53}	0.000	0.000	0.000	0.000	0.000	(0.000)	0.000	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000
β_{54}	0.000	0.000	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	0.000	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	(0.000)
β_{55}	0.000	0.000	0.000	(0.000)	(0.000)	0.000	0.000	0.000	0.000	(0.000)	0.000	0.000	0.000	0.000	0.000	(0.000)	0.000	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	0.000	(0.000)
β_{61}	0.000	(0.000)	0.000	0.000	0.000	0.000	0.000	0.000	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	(0.000)
β_{71}	0.007	0.000	(0.000)	0.000	0.000	0.000	0.000	(0.000)	0.000	0.000	(0.000)	0.000	0.000	(0.000)	0.000	(0.000)	(0.000)	0.000	0.000	(0.000)	0.000	0.000	0.000	0.000	(0.000)
β_{72}	0.000	0.007	0.000	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	0.000	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)	0.000
β_{73}	(0.000)	0.000	0.007	(0.000)	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	0.000	(0.000)	0.000	0.000	(0.000)	0.000	0.000	(0.000)	(0.000)
β_{74}	0.000	0.000	(0.000)	0.007	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	0.000	(0.000)	(0.000)	0.000	0.000	(0.000)	(0.000)
β_{75}	0.000	0.000	0.000	(0.000)	0.007	0.000	(0.000)	0.000	0.000	0.000	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	(0.000)	(0.000)	0.000	0.000	(0.000)	0.000	(0.000)	(0.000)	(0.000)
β_{81}	0.000	0.000	0.000	0.000	0.000	0.007	0.000	0.000	0.000	0.000	0.000	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	0.000
β_{82}	0.000	(0.000)	0.000	(0.000)	(0.000)	0.000	0.007	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	0.000	0.000	0.000	0.000	(0.000)	(0.000)	0.000	(0.000)
β_{83}	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	0.007	0.000	0.000	0.000	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000
β_{84}	0.000	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	0.000	0.007	0.000	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	0.000	(0.000)	(0.000)	0.000	0.000	0.000
β_{85}	0.000	0.000	(0.000)	(0.000)	0.000	0.000	(0.000)	0.000	0.000	0.007	0.000	0.000	(0.000)	0.000	0.000	(0.000)	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000
β_{91}	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)	0.000	0.007	0.000	0.000	0.000	0.000	0.000	0.000	(0.000)	(0.000)	0.000	(0.000)	0.001	0.000	0.000	0.000
β_{92}	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	0.007	0.000	0.000	0.000	0.000	0.000	0.000	(0.000)	(0.000)	0.000	(0.000)	0.000	0.000	(0.000)
β_{93}	0.000	0.000	0.000	(0.000)	0.000	(0.000)	(0.000)	(0.000)	0.000	(0.000)	0.000	0.000	0.007	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.001)
β_{94}	(0.000)	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.000)	0.000	0.000	0.000	0.000	0.000	(0.000)	0.007	(0.000)	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)
β_{95}	0.000	0.000	0.000	(0.000)	0.000	0.000	0.000	(0.000)	0.000	0.000	0.000	0.000	(0.000)	(0.000)	0.007	0.000	0.000	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	(0.000)
β_{101}	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	(0.000)	0.000	0.000	0.007	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	(0.000)	(0.000)	(0.000)
β_{102}	(0.000)	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	0.000	(0.000)	0.000	(0.000)	(0.000)	0.007	(0.000)	(0.000)	0.000	(0.000)	0.000	(0.000)	(0.000)	(0.000)
β_{103}	0.000	0.000	(0.000)	0.000	(0.000)	0.000	0.000	0.000	0.000	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.007	0.000	0.000	(0.000)	0.000	(0.000)	(0.000)	0.000
β_{104}	0.00																								

Note : β_0 is an intercept, β_{mn} is the coefficient for the dummy variable indicating the level n of the dimension variable X_m .

The numbers in red parentheses indicate negative values

Table 4 Descriptive Statistics and Balance Check across Own Wage Levels

Own wage level	All			1	2	3	4	5	6	<i>F</i> [<i>P</i> – <i>value</i>]	χ^2 [<i>P</i> – <i>value</i>]
	Men	Women	Total								
Female	.00	1.00	.50	.51	.51	.49	.52	.49	.49		6.74 [.24]
Own Age	45.31 (12.52)	44.22 (12.25)	44.76 (12.40)	44.61 (12.22)	44.69 (12.45)	44.89 (12.29)	44.71 (12.49)	44.84 (12.34)	44.76 (12.50)	.14 [.98]	
Spouse's Age	43.53 (12.23)	46.23 (12.97)	44.89 (12.68)	44.85 (12.73)	44.77 (12.71)	44.99 (12.58)	44.89 (12.79)	44.97 (12.58)	44.85 (12.68)	.11 [.99]	
Living in:											16.65 [.68]
large cities	.32	.31	.32	.31	.33	.32	.31	.31	.31		
mid-size cities	.28	.25	.26	.26	.26	.25	.27	.28	.27		
small cities	.28	.27	.27	.29	.27	.27	.28	.27	.27		
towns and villages				.10	.10	.12	.10	.10	.11		
municipalities of unknown size				.05	.04	.04	.04	.04	.04		
Number of children	1.45 (1.03)	1.44 (1.05)	1.44 (1.04)	1.47 (1.04)	1.44 (1.03)	1.43 (1.05)	1.45 (1.05)	1.43 (1.03)	1.44 (1.06)	.35 [.88]	
Have children	.77	.77	.77	.78	.77	.77	.77	.77	.76		4.37 [.50]
Age of the youngest child	1.49 (7.56)	1.39 (7.89)	1.44 (7.73)	1.48 (7.69)	1.18 (7.74)	1.62 (7.73)	1.24 (7.68)	1.57 (7.72)	1.60 (7.76)	1.33 [.25]	
Living with:											-

spouse	.979	.967	.973	.97	.97	.98	.97	.97	.97		5.37 [.37]
children	.599	.592	.595	.61	.60	.60	.60	.60	.58		2.55 [.77]
father	.039	.018	.028	.03	.03	.03	.03	.03	.03		5.19 [.39]
mother	.054	.037	.046	.04	.04	.05	.04	.04	.05		4.65 [.46]
father-in-law	.015	.022	.019	.02	.02	.02	.02	.02	.02		3.05 [.69]
mother-in-law	.027	.035	.031	.03	.03	.04	.03	.03	.03		6.62 [.25]
Household size	3.07 (1.31)	3.00 (1.19)	3.03 (1.25)	3.08 (1.28)	3.01 (1.21)	3.06 (1.31)	3.17 (1.49)	3.02 (1.24)	3.04 (1.27)	.50 [.78]	
Family members requiring long-term care:											9.06 [.87]
in-home long-term care	.03	.02	.03	.02	.03	.03	.03	.02	.03		
local long-term care (within a 30-minute radius of home)	.04	.03	.03	.04	.04	.04	.03	.03	.03		
long-term care at a distance	.06	.07	.07	.06	.06	.07	.06	.07	.07		
no family members requiring long-term care	.88	.87	.87	.88	.87	.87	.88	.87	.87		
Own education:											13.43 [1.00]
High school dropout	.02	.02	.02	.02	.02	.02	.02	.02	.02		

High school	.23	.23	.23	.23	.23	.23	.23	.23	.23		
Junior college	.02	.18	.10	.11	.10	.10	.10	.10	.10		
Vocational school	.11	.15	.13	.12	.13	.13	.14	.12	.12		
Technical college	.02	.02	.02	.02	.02	.02	.02	.02	.02		
Four-year college	.52	.36	.44	.45	.45	.43	.44	.45	.44		
Graduate school	.09	.03	.06	.05	.06	.06	.05	.06	.06		
Spouse's education:										2.68	
										[.90]	
High school dropout	.02	.05	.04	.04	.04	.04	.04	.04	.03		
High school	.27	.25	.26	.25	.25	.27	.27	.25	.27		
Junior college	.17	.02	.10	.11	.09	.10	.10	.09	.10		
Vocational school	.16	.11	.13	.14	.13	.13	.13	.14	.13		
Technical college	.03	.02	.02	.02	.02	.02	.02	.02	.02		
Four-year college	.32	.46	.39	.39	.40	.38	.40	.40	.38		
Graduate school	.03	.09	.06	.05	.06	.06	.06	.06	.06		
Own employment status:										36.20	
										[.93]	
regular employee	.76	.23	.49	.49	.48	.50	.48	.51	.49		
part-time worker ("paato")	.02	.23	.13	.14	.13	.12	.14	.12	.13		
part-time worker ("arubaito")	.01	.02	.02	.02	.02	.02	.02	.02	.02		
contract employee	.03	.02	.03	.02	.03	.03	.02	.03	.03		
re-hired employee	.01	.01	.01	.01	.01	.01	.01	.01	.01		
dispatched employee	.00	.02	.01	.01	.01	.01	.01	.01	.01		
other types of employment	.00	.00	.00	.00	.00	.00	.00	.01	.00		

self-employed	.07	.02	.04	.05	.04	.04	.04	.04	.04		
unpaid family worker	.00	.02	.01	.01	.01	.01	.01	.01	.01		
on leave	.00	.05	.03	.03	.03	.03	.03	.03	.03		
not employed	.09	.37	.23	.24	.23	.23	.24	.23	.23		
Spouse's employment status:										3.94	
										[.98]	
regular employee	.31	.73	.52	.52	.52	.50	.53	.51	.52		
part-time worker ("paato")	.25	.02	.14	.14	.14	.14	.13	.13	.14		
part-time worker ("arubaito")	.03	.01	.02	.02	.02	.02	.01	.02	.02		
contract employee	.02	.02	.02	.03	.01	.02	.02	.02	.02		
re-hired employee	.01	.01	.01	.01	.01	.01	.01	.01	.01		
dispatched employee	.01	.00	.01	.01	.01	.01	.01	.01	.01		
other types of employment	.01	.01	.01	.01	.01	.01	.01	.01	.01		
self-employed	.03	.10	.07	.06	.07	.07	.07	.07	.07		
unpaid family worker	.02	.00	.01	.01	.01	.01	.01	.01	.01		
on leave	.02	.00	.01	.01	.01	.01	.01	.01	.01		
not employed	.29	.09	.19	.19	.18	.19	.19	.19	.19		
Own annual earnings:										4.10	
										[1.00]	
0 yen	.03	.24	.14	.14	.14	.14	.14	.13	.14		
below 500,000 yen	.01	.10	.06	.06	.06	.05	.06	.06	.06		
500,000–1,000,000 yen	.01	.18	.10	.10	.10	.09	.10	.10	.10		
1,000,000–1,500,000 yen	.02	.11	.07	.07	.07	.07	.07	.06	.06		
1,500,000–2,000,000 yen	.04	.06	.05	.05	.05	.05	.05	.05	.05		

2,000,000–2,500,000 yen	.04	.06	.05	.05	.05	.05	.05	.05	.06	
2,500,000–3,000,000 yen	.06	.05	.05	.06	.06	.06	.06	.05	.05	
3,000,000–4,000,000 yen	.15	.08	.12	.12	.12	.12	.12	.11	.11	
4,000,000–5,000,000 yen	.16	.05	.11	.10	.11	.11	.10	.11	.11	
5,000,000–6,000,000 yen.	.14	.03	.09	.09	.09	.08	.09	.09	.09	
6,000,000–7,000,000 yen	.10	.01	.06	.06	.05	.06	.05	.06	.06	
7,000,000–8,000,000 yen	.07	.01	.04	.04	.04	.04	.03	.04	.04	
8,000,000–9,000,000 yen	.05	.00	.03	.02	.03	.03	.03	.03	.03	
9,000,000–10,000,000 yen	.03	.00	.02	.02	.02	.02	.02	.02	.02	
10,000,000–12,000,000 yen	.03	.00	.02	.02	.02	.02	.02	.02	.02	
12,000,000–15,000,000 yen	.02	.00	.01	.01	.01	.01	.01	.01	.01	
over 15,000,000 yen	.02	.00	.01	.01	.01	.01	.01	.01	.01	
							.			
Spouse's annual earnings:										3.34
										[1.00]
0 yen	.24	.03	.13	.13	.13	.13	.13	.13	.13	
below 500,000 yen	.08	.01	.04	.05	.04	.04	.05	.05	.05	
500,000–1,000,000 yen	.17	.02	.09	.09	.09	.10	.09	.09	.10	
1,000,000–1,500,000 yen	.11	.02	.06	.06	.06	.07	.06	.06	.06	
1,500,000–2,000,000 yen	.07	.04	.05	.06	.05	.06	.05	.05	.05	
2,000,000–2,500,000 yen	.05	.04	.05	.05	.05	.05	.05	.05	.05	
2,500,000–3,000,000 yen	.05	.07	.06	.06	.06	.06	.06	.06	.06	
3,000,000–4,000,000 yen	.09	.14	.12	.11	.12	.12	.12	.12	.12	
4,000,000–5,000,000 yen	.06	.15	.11	.12	.12	.10	.11	.11	.10	
5,000,000–6,000,000 yen.	.03	.15	.09	.09	.08	.09	.09	.09	.09	
6,000,000–7,000,000 yen	.02	.10	.06	.05	.06	.06	.06	.06	.05	

7,000,000–8,000,000 yen	.01	.08	.05	.05	.05	.04	.05	.04	.04		
8,000,000–9,000,000 yen	.01	.04	.02	.02	.02	.03	.02	.03	.02		
9,000,000–10,000,000 yen	.00	.04	.02	.02	.02	.02	.02	.02	.02		
10,000,000–12,000,000 yen	.01	.04	.02	.02	.02	.02	.02	.02	.02		
12,000,000–15,000,000 yen	.00	.02	.01	.01	.01	.01	.01	.01	.01		
over 15,000,000 yen	.00	.02	.01	.01	.02	.01	.02	.02	.01		
Own hours of work	36.80 (19.57)	16.28 (17.90)	26.51 (21.38)	26.75 (21.67)	26.17 (21.42)	26.59 (21.44)	26.08 (21.36)	26.97 (21.27)	26.66 (21.24)	.67 [.64]	
Spouse's hours of work	19.69 (19.15)	38.80 (2.21)	29.28 (21.89)	29.75 (22.01)	29.67 (21.91)	28.68 (21.83)	29.60 (21.92)	29.10 (21.98)	29.13 (21.73)	.88 [.49]	
Own frequency working at home:											13.83
not at all	.66	.80	.72	.76	.72	.72	.73	.71	.71		[.84]
occasionally	.13	.06	.10	.10	.11	.10	.10	.10	.11		
1–2 days a week	.07	.03	.06	.05	.05	.05	.06	.06	.06		
3–4 days a week	.04	.03	.03	.03	.04	.04	.03	.04	.03		
almost always	.09	.08	.09	.07	.09	.09	.08	.09	.09		
Spouse frequency working at home:											8.90
not at all	.81	.74	.77	.71	.79	.77	.77	.77	.76		[.98]
occasionally	.07	.11	.09	.11	.09	.09	.09	.10	.09		
1–2 days a week	.04	.05	.04	.06	.04	.04	.04	.04	.05		
3–4 days a week	.02	.02	.02	.03	.02	.02	.02	.02	.02		

almost always	.06	.07	.06	.09	.06	.07	.07	.07	.07		
Own hours of housework on a weekday:											24.99 [1.00]
0 min	.10	.01	.06	.05	.06	.05	.06	.06	.05		
1–30 min.	.25	.01	.13	.13	.12	.14	.13	.13	.13		
30 min–1 hr.	.28	.06	.17	.16	.17	.17	.16	.16	.18		
1–2 hrs.	.24	.23	.24	.22	.24	.25	.24	.25	.24		
2–3 hrs.	.09	.30	.20	.20	.20	.19	.19	.19	.19		
3–4 hrs.	.02	.18	.10	.11	.10	.10	.10	.10	.10		
4–5 hrs.	.01	.10	.05	.05	.05	.05	.05	.05	.05		
5–6 hrs.	.00	.05	.03	.03	.03	.03	.03	.03	.03		
6–7 hrs.	.00	.01	.01	.01	.01	.01	.01	.01	.01		
7–8 hrs.	.00	.01	.01	.00	.01	.01	.01	.00	.00		
over 8 hrs.	.00	.02	.01	.01	.01	.01	.01	.01	.01		
Spouse's hours of housework on a weekday:											4.40 [.83]
0 min	.03	.26	.15	.16	.15	.14	.15	.15	.14		
1–30 min.	.06	.38	.22	.21	.21	.21	.23	.21	.22		
30 min–1 hr.	.12	.18	.15	.16	.15	.15	.16	.14	.15		
1–2 hrs.	.25	.12	.18	.19	.17	.18	.17	.18	.19		
2–3 hrs.	.24	.04	.14	.14	.14	.15	.13	.15	.14		
3–4 hrs.	.15	.01	.08	.08	.08	.07	.08	.08	.07		
4–5 hrs.	.07	.01	.04	.03	.04	.04	.04	.04	.04		
5–6 hrs.	.03	.00	.02	.01	.02	.02	.02	.02	.01		

6–7 hrs.	.01	.00	.01	.01	.01	.01	.00	.00	.01		
7–8 hrs.	.01	.00	.01	.01	.01	.01	.01	.01	.01		
over 8 hrs.	.04	.00	.01	.02	.02	.02	.02	.02	.02		
Own hours of child- and long-term care work on a weekday:										33.24	
										[.97]	
0 min	.37	.38	.37	.36	.36	.38	.37	.38	.38		
1–30 min.	.14	.09	.12	.12	.11	.12	.12	.11	.11		
30 min–1 hr.	.14	.07	.10	.11	.11	.10	.10	.11	.10		
1–2 hrs.	.18	.12	.15	.15	.15	.15	.15	.15	.14		
2–3 hrs.	.09	.09	.09	.09	.08	.08	.09	.09	.09		
3–4 hrs.	.04	.06	.05	.06	.05	.05	.05	.04	.05		
4–5 hrs.	.02	.04	.03	.03	.03	.03	.03	.03	.03		
5–6 hrs.	.01	.03	.02	.01	.02	.02	.02	.02	.02		
6–7 hrs.	.01	.02	.02	.01	.02	.01	.02	.02	.02		
7–8 hrs.	.01	.01	.01	.01	.01	.01	.01	.01	.01		
over 8 hrs.	.01	.10	.05	.06	.06	.05	.05	.05	.05		
Spouse's hours of child- and long-term care work on a weekday:										37.14	
										[.91]	
0 min	.35	.50	.42	.42	.41	.43	.42	.42	.43		
1–30 min.	.06	.20	.13	.14	.13	.12	.13	.13	.12		
30 min–1 hr.	.09	.12	.11	.09	.10	.11	.11	.10	.11		
1–2 hrs.	.15	.11	.13	.13	.13	.12	.13	.12	.13		
2–3 hrs.	.13	.04	.09	.08	.09	.09	.08	.09	.08		
3–4 hrs.	.09	.02	.05	.05	.05	.04	.05	.05	.05		

4–5 hrs.	.05	.01	.03	.03	.03	.03	.03	.04	.03		
5–6 hrs.	.02	.00	.01	.01	.01	.01	.01	.01	.01		
6–7 hrs.	.01	.00	.01	.01	.00	.01	.01	.01	.01		
7–8 hrs.	.01	.00	.01	.01	.01	.01	.01	.01	.01		
over 8 hrs.	.05	.00	.03	.03	.03	.03	.03	.03	.03		
Person primarily responsible for housework:											15.52
											[.93]
always myself	.04	.49	.27	.28	.27	.25	.27	.26	.26		
mostly myself	.06	.36	.21	.21	.22	.22	.22	.20	.21		
the spouse and I	.29	.12	.20	.19	.20	.20	.20	.21	.21		
mostly the spouse	.45	.01	.23	.23	.22	.24	.23	.24	.23		
always the spouse	.15	.00	.07	.07	.08	.08	.07	.08	.08		
others	.01	.01	.01	.01	.01	.01	.01	.01	.01		
Person primarily responsible for child- and long-term care:											22.49
											[.84]
always myself	.02	.30	.16	.18	.17	.15	.17	.16	.16		
mostly myself	.04	.27	.15	.14	.15	.15	.16	.15	.15		
the spouse and I	.21	.07	.13	.14	.14	.14	.14	.14	.14		
mostly the spouse	.30	.01	.15	.16	.15	.15	.15	.16	.15		
always the spouse	.07	.00	.00	.04	.04	.04	.04	.04	.04		
others	.01	.01	.01	.01	.01	.01	.01	.01	.01		
Type of dwelling:											13.99
											[.96]

owner-occupied housing	.55	.53	.54	.56	.54	.55	.54	.54	.54	
an owner-occupied condominium	.14	.16	.15	.15	.16	.14	.15	.15	.15	
private rental housing	.25	.26	.25	.24	.25	.25	.25	.26	.26	
UR or public rental housing	.02	.02	.02	.02	.02	.02	.03	.02	.02	
employer-provided housing	.03	.03	.03	.03	.03	.03	.03	.03	.03	
other types of housing	.00	.01	.00	.00	.00	.01	.00	.00	.00	
Gender attitude:										
Men's duty is to earn income; women's duty is housework and to take care of family.	3.29	3.53	3.41	3.40	3.42	3.43	3.40	3.41	3.41	.23
strongly agree (1)–do not think so (5)	(1.18)	(1.18)	(1.18)	(1.19)	(1.18)	(1.17)	(1.19)	(1.19)	(1.19)	[.95]
Mother should focus on child rearing till child becomes three-year-old.	2.78	3.04	2.91	2.91	2.94	2.91	2.93	2.89	2.90	.65
strongly agree (1)–do not think so (5)	(1.22)	(1.29)	(1.26)	(1.26)	(1.27)	(1.25)	(1.26)	(1.26)	(1.27)	[.66]
Husband should share the burden of housework and childcare equally.	2.32	2.01	2.16	2.16	2.15	2.15	2.17	2.15	2.18	.60
strongly agree (1) – do not think so (5)	(1.02)	(.94)	(.99)	(1.01)	(.99)	(.98)	(.99)	(.97)	(1.02)	[.70]
Attitude toward technology:										
Eager to try out new digital technology at home.	2.79	3.03	2.91	2.94	2.89	2.94	2.91	2.92	2.90	.74
strongly agree (1) – do not think so (5)	(1.08)	(1.06)	(1.08)	(1.09)	(1.08)	(1.09)	(1.07)	(1.07)	(1.08)	[.59]
Feel anxious or worried about privacy when using digital devices.	2.70	2.46	2.58	2.55	2.56	2.57	2.60	2.59	2.59	.71
very much worried (1) – not worried at all (5)	(.98)	(.92)	(.96)	(.95)	(.96)	(.96)	(.95)	(.96)	(.96)	[.62]

Satisfaction:											
with life	6.60	6.73	6.67	6.65	6.67	6.65	6.64	6.69	6.69	.28	
not satisfied (1) – satisfied (10)	(2.02)	(2.01)	(2.02)	(2.06)	(2.02)	(2.04)	(2.01)	(1.98)	(2.02)	[.92]	
with job	5.64	4.99	5.31	5.22	5.28	5.32	5.29	5.38	5.36	1.12	
not satisfied (1) – satisfied (10)	(2.26)	(2.54)	(2.43)	(2.45)	(2.44)	(2.44)	(2.43)	(2.41)	(2.41)	[.35]	
with family relationship	7.22	7.26	7.24	7.24	7.25	7.23	7.21	7.26	7.26	.20	
not satisfied (1) – satisfied (10)	(2.18)	(2.30)	(2.24)	(2.26)	(2.24)	(2.26)	(2.27)	(2.21)	(2.23)	[.96]	
Number of vignette observations	7,398	7,455	14,853	1,226	2,806	2,781	2,788	2,572	2,680		

The standard deviation in parentheses. The P-values in brackets.

Table 5 ANOVA Estimates for the Linear Probability Model

Dependent Variable = 1 if the Robot Service Chosen

Specification 1

Number of Vignette Observations=14,853

 $R^2=.067$

Root Mean Square=.3903

Adjusted $R^2=.064$

Source	Partial SS	df	MS	<i>F</i>	P-value
Model	161.143	51.000	3.160	2.750	.000
The price of the robot service	8.332	5.000	16.066	105.490	.000
The price of the commercial human service	8.501	5.000	1.700	11.160	.000
The spouse's wage	2.608	5.000	.522	3.430	.004
Own wage	4.264	5.000	.853	5.600	.000
The MRTS of the robot service	15.276	5.000	3.055	2.060	.000
The MRTS of the commercial human service	4.618	5.000	.924	6.060	.000
The MRTS of the spouse's domestic labor	.410	5.000	.082	.540	.747
Own hours of work	16.570	5.000	3.314	21.760	.000
The spouse's hours of work	1.107	5.000	2.021	13.270	.000
The youngest child's age	1.039	5.000	.208	1.360	.234
Eldercare	2.051	1.000	2.051	13.470	.000
Residual	2254.289	14801.000	.152	2254.289	14801.000
Total	2415.432	14852.000	.163		

Notes: The data contain 14,853 vignette observations responded by 4,951 respondents.

The robust standard errors are reported in parentheses.

Table 6 The Estimated Coefficients for the Linear Probability Model

Dependent Variable = 1 if the Robot Service Chosen

Estimation Method	Specification 3	
	OLS	RE
Constant	.075 (.010)	.068 (.010)
The lowest marginal cost for household production attained by the robot service	.150 (.007)	.154 (.007)
Log of own hours of work	.013 (.001)	.013 (.001)
Log of the spouse's hours of work	.010 (.001)	.010 (.001)
The youngest child is 6 months old	.030 (.011)	.037 (.011)
The youngest child 2-years-old	.038 (.011)	.043 (.011)
The youngest child 6-years-old	.007 (.011)	.016 (.011)
The youngest child 12-years-old	.020 (.011)	.030 (.011)
The youngest child 17-years-old	.010 (.011)	.011 (.010)
Eldercare	.022 (.006)	.020 (.006)
Variance (Constant)		.032 (.002)
Variance (Residual)		.123 (.002)
Adjusted R^2	.045	
Log Pseudo Likelihood		-6954.971

Notes: The data contain 14,853 vignette observations responded by 4,951 respondents.

The robust standard errors are reported in parentheses.

Table 7 The Estimated Coefficients for the Panel Random Effects Multinomial Logit Model

Latent Dependent Variable = Latent Marginal Utility of Each Alternative

	Specification A				Specification B			
	Common Coefficients	Alternative-Specific Coefficients			Common Coefficients	Alternative-Specific Coefficients		
		Robot's service	Commercial human service	Spouse's domestic labor		Robot's service	Commercial human service	Spouse's domestic labor
<u>Alternative-specific variables</u>								
Log of [MRTS / Price]	.136 (.007)				.194 (.006)			
<u>Alternative-specific intercepts</u>								
Mean (Intercept)		-1.705 (.099)	-2.593 (.126)	-.956 (.087)		-1.003 (.0445)	-1.861 (.067)	-.693 (.039)
Variance (Intercept)								
Robot's service	3.499 (.222)				3.251 (.205)			
Commercial human service	3.884 (.295)				3.642 (.280)			
Spouse's domestic labor	2.662 (.187)				2.440 (.169)			
Covariance (Intercepts)								
Robot's service, Commercial human service	3.237 (.217)				2.983 (.199)			
Robot's service, Spouse's domestic labor	1.791 (.157)				1.612 (.142)			
Commercial human service, Spouse's domestic labor	1.658				1.479			

	(.181)				(.164)			
<u>Case-specific variables</u>								
Own hours of work		.182 (.013)	.203 (.017)	.156 (.013)				
The spouse's hours of work		.039 (.013)	.051 (.016)	-.124 (.012)				
The youngest child is 6 months old		.275 (.099)	.136 (.121)	.216 (.093)				
The youngest child is 2 years old		.183 (.099)	.109 (.121)	.055 (.097)				
The youngest child is 6 years old		.071 (.099)	-.015 (.119)	.243 (.092)				
The youngest child is 12 years old		.088 (.100)	-.064 (.126)	.057 (.095)				
The youngest child is 17 years old		.108 (.094)	.111 (.119)	.098 (.094)				
Eldercare		.246 (.057)	.238 (.071)	.107 (.055)				
Wald chi square	2247.91				2084.63			
P-value	<.0001				<.0001			
Log Simulated Pseudo Likelihood	-16944.696				-17230.881			

Notes: The data contain 14,853 vignette observations responded by 4,951 respondents.

The robust standard errors are reported in parentheses.

Table 8 Variance, Covariance and Correlation Matrix for Willingness to Pay

	Robot's Service	Commercial Human Service	Spouse's Domestic Labor
Robot's Service	[4.2e+57]	-0.000	0.171
Commercial Human Service	-1.9e+45	[2.6e+43]	-0.000
Spouse's Domestic Labor	1.5e+60	-1.1e+49	[1.8e+64]

Notes: 1. Diagonal elements in [brackets] represent variances (σ_R^2 , σ_{HS}^2 , σ_{SP}^2).

2. Elements below the diagonal represent covariances.

3. Elements above the diagonal represent correlation coefficients ($\rho_{R,HS}$, $\rho_{R,SP}$, $\rho_{HS,SP}$).

4. Results are based on the structural model estimates (Specification A).

Table 9. The Assumed Values of Prices and MRTSs.

Sex	Scenario	$P_{OWN,k}$	$P_{R,k}$	$MRTS_{R,OWN}$	$P_{HS,k}$	$MRTS_{HS,OWN}$	$P_{SP,k}$	$MRTS_{SP,OWN}$
Men	1	900	18.545	.3248	1,750	2.0	700	1.0
	2	900	185.450	.3248	1,750	2.0	700	1.0
Women	1	700	18.545	.3248	1,750	2.0	900	1.0
	2	700	185.450	.3248	1,750	2.0	900	1.0

Table 10a Impact of a Two-Thirds Price Subsidy on Household Choices when $P_R = 18.545$

<div>With Subsidy</div> <div>No subsidy</div>	Men					Women				
	OWN	R	HS	SP	Total	OWN	R	HS	SP	Total
OWN	98.00	2.05	0	0	100.00	97.31	2.69	0	0	100.00
	100.00	2.87	0	0	38.75	100.00	3.16	0	0	36.75
R	0	100.00	0	0	100.00	0	100.00	0	0	100.00
	0	93.13	0	0	25.77	0	93.09	0	0	29.13
HS	0	4.55	95.45	0	100.00	0	4.95	95.05	0	100.00
	0	1.60	100.00	0	9.73	0	0.74	100.00	0	4.67
SP	0	2.57	0	97.00	100.00	0	3.19	0	96.81	100.00
	0	2.40	0	100.00	25.75	0	3.01	0	100.00	29.45
Total	38.00	27.67	9.00	25.00	100.00	35.76	31.29	4.44	28.51	100.00
	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Note: The first value in each cell shows the row percentage, and the second value shows the column percentage.

Table 10b Classification of Individuals when $P_R = 18.545$

Type	Percent	
	Men	Women
never-takers	72.33	68.71
compliers	1.90	2.16
always-takers	25.77	29.13
total	100.00	100.00

Table 12a Impact of a Two-Thirds Price Subsidy on Household Choices for Men when $P_R = 185.450$

With Subsidy No subsidy	Men					Women				
	OWN	R	HS	SP	Total	OWN	R	HS	SP	Total
OWN	98.14	1.86	0	0	100.00	97.71	2.29	0	0	100.00
	100.00	3.16	0	0	40.36	100.00	3.30	0	0	38.65
R	0	100.00	0	0	100.00	0	100.00	0	0	100.00
	0	92.40	0	0	21.92	0	92.63	0	0	24.85
HS	0	4.10	95.90	0	100.00	0	4.54	95.46	0	100.00
	0	1.84	100.00	0	10.65	0	0.88	100.00	0	5.17
SP	0	2.27	0	97.73	100.00	0	2.74	0	97.26	100.00
	0	2.60	0	100.00	27.08	0	3.20	0	100.00	31.33
Total	39.61	23.72	10.21	26.46	100.00	37.77	26.83	4.94	30.47	100.00
	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Note: The first value in each cell shows the row percentage, and the second value shows the column percentage.

Table 12b Classification of Individuals when $P_R = 185.450$

Type	Percent	
	Men	Women
never-takers	76.28	73.17
compliers	1.80	1.98
always-takers	21.92	24.85
total	100.00	100.00

Figure 1: 3D Histograms of Three Deltas for Cooking

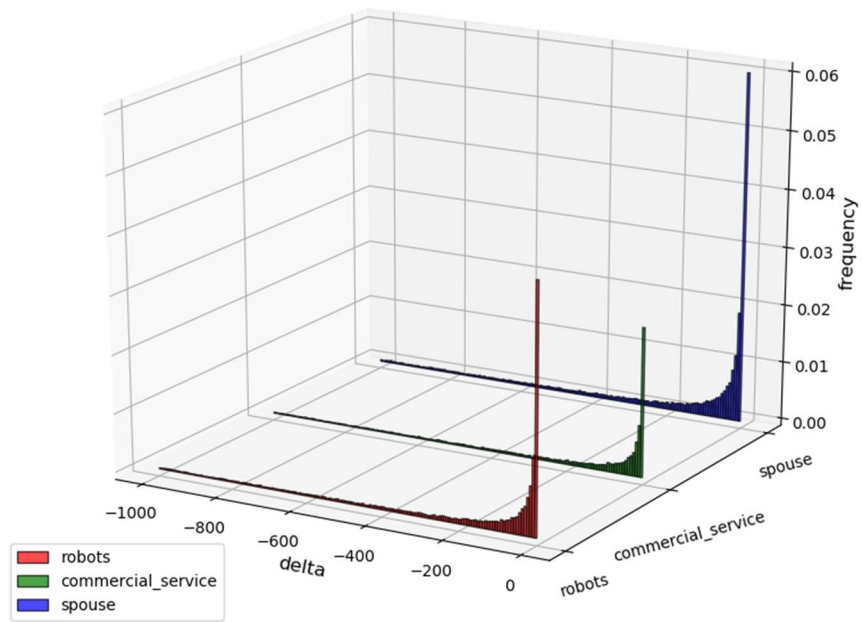
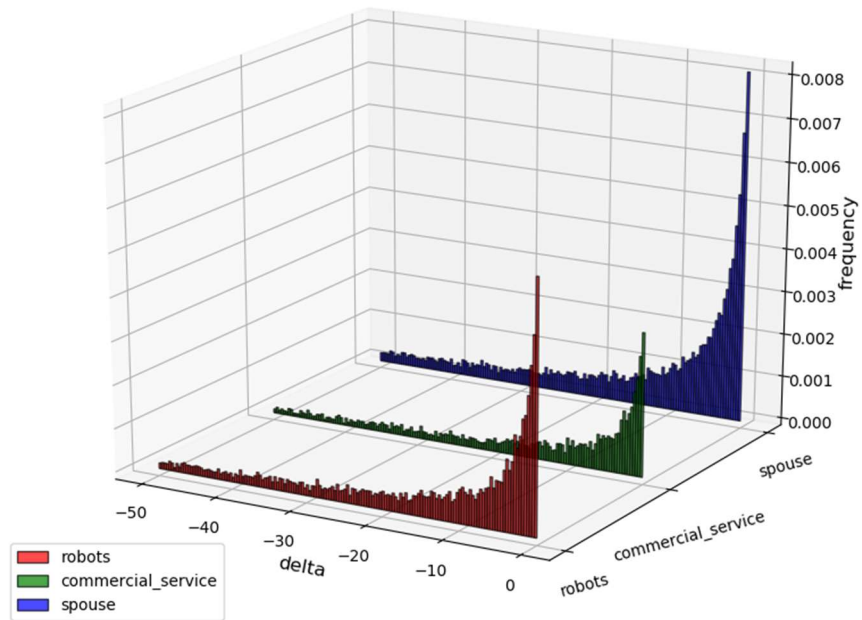


Figure 2: 3D Histograms of Three Deltas for Cooking



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Appendix

Table A1 The Estimated Coefficients for the Linear Probability Model

Dependent Variable = 1 if the Robot Service Chosen

Estimation Method	Specification 3	
	OLS	RE
Constant	.235 (.024)	.227 (.023)
Log of the price of the robot service	-.046 (.002)	-.045 (.002)
Log of the price of the commercial human service	.020 (.003)	.019 (.002)
Log of the spouse's wage	.004 (.001)	.005 (.001)
Log of own wage	.004 (.001)	.004 (.001)
Log of the MRTS of the robot service	.038 (.004)	.037 (.004)
Log of the MRTS of the commercial human service	-.017 (.004)	-.017 (.004)
Log of the MRTS of the spouse's domestic labor	-.006 (.004)	-.006 (.003)
Log of own hours of work	.015 (.002)	.015 (.001)
Log of the spouse's hours of work	.012 (.002)	.012 (.001)
The youngest child is 6 months old	.014 (.011)	.018 (.011)
The youngest child is 2 years old	.013 (.011)	.014 (.011)
The youngest child is 6 years old	-.009 (.011)	-.005 (.010)
The youngest child is 12 years old	.006 (.011)	.010 (.011)
The youngest child is 17 years old	.008 (.011)	.010 (.010)

Eldercare	.023 (.006)	.022 (.006)
Variance (Constant)		.0317 (.002)
Variance (Residual)		.121 (.002)
Adjusted R^2	.061	
Log Pseudo Likelihood		-6830.938

Notes: The data contain 14,853 vignette observations responded by 4,951 respondents.

The robust standard errors are reported in parentheses.

Table A2 The Estimated Coefficients for the Panel Random Effects Multinomial Logit Model, Men

Latent Dependent Variable = Latent Marginal Utility of Each Alternative

	Specification A				Specification B			
	Common Coefficients	Alternative-Specific Coefficients			Common Coefficients	Alternative-Specific Coefficients		
		Robot's service	Commercial human service	Spouse's domestic labor		Robot's service	Commercial human service	Spouse's domestic labor
<u>Alternative-specific variables</u>								
Log of [MRTS / Price]	.119 (.010)				.163 (.009)			
<u>Alternative-specific intercepts</u>								
Mean (Intercept)		-1.721 (.145)	-2.465 (.181)	-.691 (.119)		-1.130 (.0681)	-1.880 (.096)	-.585 (.0529)
Variance (Intercept)								
Robot's service	3.987 (.357)				3.672 (.330)			
Commercial human service	4.093 (.435)				3.810 (.407)			
Spouse's domestic labor	2.616 (.252)				2.480 (.237)			
Covariance (Intercepts)								
Robot's service, Commercial human service	3.531 (.330)				3.234 (.303)			
Robot's service, Spouse's domestic labor	1.677 (.225)				1.497 (.207)			
Commercial human service, Spouse's domestic labor	1.540				1.367			

	(.251)				(.230)			
<u>Case-specific variables</u>								
Own hours of work		.172 (.020)	.182 (.024)	.120 (.017)				
The spouse's hours of work		.048 (.018)	.039 (.023)	-.082 (.016)				
The youngest child is 6 months old		.028 (.144)	.018 (.170)	-.017 (.127)				
The youngest child is 2 years old		.042 (.143)	-.171 (.175)	-.100 (.133)				
The youngest child is 6 years old		-.004 (.147)	-.232 (.170)	.164 (.127)				
The youngest child is 12 years old		-.115 (.147)	-.164 (.177)	-.107 (.129)				
The youngest child is 17 years old		.113 (.138)	.047 (.171)	.181 (.130)				
Eldercare		.207 (.083)	.325 (.103)	.009 (.075)				
Wald chi square	979.95				900.59			
P-value	<.0001				<.0001			
Log Simulated Pseudo Likelihood	-8,518.182				-8,622.661			

Notes: The data contain 7,398 vignette observations responded by 2,466 male respondents.

The robust standard errors are reported in parentheses.

Table A3 The Estimated Coefficients for the Panel Random Effects Multinomial Logit Model, Women

Latent Dependent Variable = Latent Marginal Utility of Each Alternative

	Specification A				Specification B			
	Common Coefficients	Alternative-Specific Coefficients			Common Coefficients	Alternative-Specific Coefficients		
		Robot's service	Commercial human service	Spouse's domestic labor		Robot's service	Commercial human service	Spouse's domestic labor
<u>Alternative-specific variables</u>								
Log of [MRTS / Price]	.155 (.010)				.223 (.009)			
<u>Alternative-specific intercepts</u>								
Mean (Intercept)		-1.695 (.136)	-2.730 (.177)	-1.257 (.130)		-.905 (.059)	-1.847 (.093)	-.798 (.057)
Variance (Intercept)								
Robot's service	3.157 (.285)				2.949 (.260)			
Commercial human service	3.733 (.404)				3.492 (.380)			
Spouse's domestic labor	2.678 (.272)				2.336 (.233)			
Covariance (Intercepts)								
Robot's service, Commercial human service	3.035 (.293)				2.809 (.268)			
Robot's service, Spouse's domestic labor	1.921 (.223)				1.717 (.196)			
Commercial human service, Spouse's domestic labor	1.780				1.577			

	(.261)				(.230)			
<u>Case-specific variables</u>								
Own hours of work		.195 (.018)	.224 (.024)	.203 (.020)				
The spouse's hours of work		.027 (.017)	.061 (.023)	-.166 (.017)				
The youngest child is 6 months old		.491 (.136)	.246 (.173)	.449 (.137)				
The youngest child is 2 years old		.314 (.137)	.378 (.169)	.205 (.143)				
The youngest child is 6 years old		.118 (.135)	.182 (.167)	.300 (.133)				
The youngest child is 12 years old		.263 (.137)	.019 (.181)	.218 (.139)				
The youngest child is 17 years old		.083 (.130)	.166 (.165)	-.017 (.137)				
Eldercare		.284 (.078)	.161 (.100)	.218 (.081)				
Wald chi square	1,302.97				1,215.10			
P-value	<.0001				<.0001			
Log Simulated Pseudo Likelihood	-8,350.645				- 8,566.86			

Notes: The data contain 7,455 vignette observations responded by 2,485 female respondents.

The robust standard errors are reported in parentheses.

Table A4a Impact of a Two-Thirds Price Subsidy on Household Choices for Men and Women Sharing Common Characteristics when $P_R = 18.545$

With Subsidy No subsidy	Men					Women				
	OWN	R	HS	SP	Total	OWN	R	HS	SP	Total
OWN	97.89	2.11	0	0	100.00	97.26	2.74	0	0	100.00
	100.00	3.06	0	0	40.00	100.00	3.00	0	0	34.84
R	0	100.00	0	0	100.00	0	100	0	0	100.00
	0	93.21	0	0	25.75	0	93.12	0	0	29.65
HS	0	4.52	95.48	0	100.00	0	5.03	94.97	0	100.00
	0	1.58	100.00	0	9.66	0	0.79	100.00	0	4.97
SP	0	2.00	0	97.58	100.00	0	3.23	0	96.77	100.00
	0	2.15	0	100.00	24.58	0	3.10	0	100.00	30.53
Total	39.00	27.63	9.23	23.98	100.00	33.89	31.84	4.72	29.55	100.00
	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Note: The first value in each cell shows the row percentage, and the second value shows the column percentage.

Table A4b Classification of Men and Women Sharing Common Characteristics when $P_R = 18.545$

Type	Percent	
	Men	Women
never-takers	72.37	68.16
compliers	1.88	2.19
always-takers	25.75	29.65
total	100.00	100.00

Table A5a Impact of a Two-Thirds Price Subsidy on Household Choices for Men and Women Sharing Common Characteristics when $P_R = 185450$

With Subsidy No subsidy	Men					Women				
	OWN	R	HS	SP	Total	OWN	R	HS	SP	Total
OWN	98.18	1.82	0	0	100.00	97.60	2.40	0	0	100.00
	100.00	3.21	0	0	41.67	100.00	3.22	0	0	36.72
R	0	100	0	0	100.00	0	100.00	0	0	100.00
	0	92.36	0	0	21.87	0	92.49	0	0	25.28
HS	0	4.19	95.81	0	100.00	0	4.86	95.14	0	100.00
	0	1.87	100.00	0	10.58	0	0.98	100.00	0	5.52
SP	0	2.34	0	97.66	100.00	0	2.79	0	97.21	100.00
	0	2.56	0	100.00	25.88	0	3.31	0	100.00	32.49
Total	40.91	23.68	10.14	25.27	100.00	35.84	27.33	5.25	31.58	100.00
	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Note: The first value in each cell shows the row percentage, and the second value shows the column percentage.

Table A5b Classification of Men and Women Sharing Common Characteristics when $P_R = 185450$

Type	Percent	
	Men	Women
never-takers	76.32	72.67
compliers	1.81	2.05
always-takers	21.87	25.28
total	100.00	100.00

Figure A-1: 3D Histograms of Three Deltas for Cooking, Men

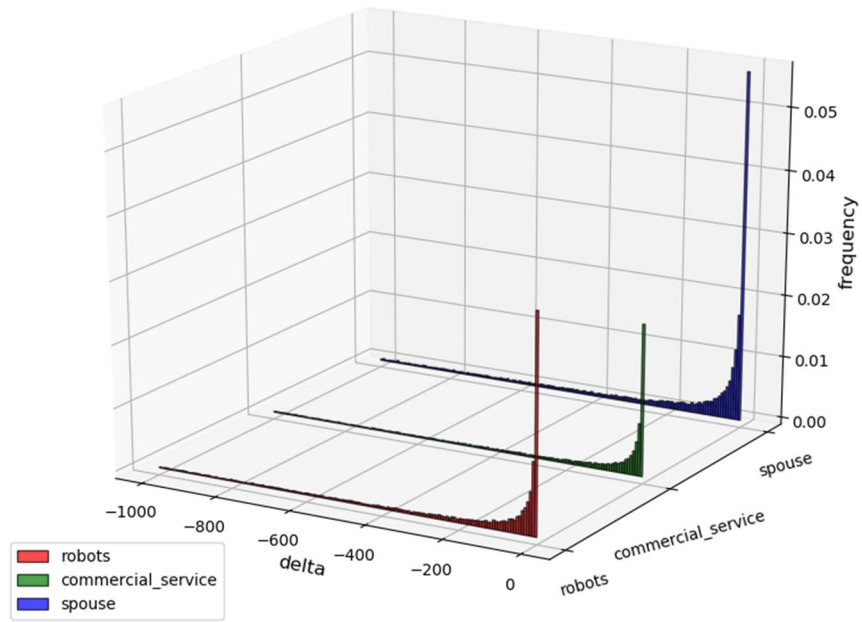


Figure A-2: 3D Histograms of Three Deltas for Cooking, Men

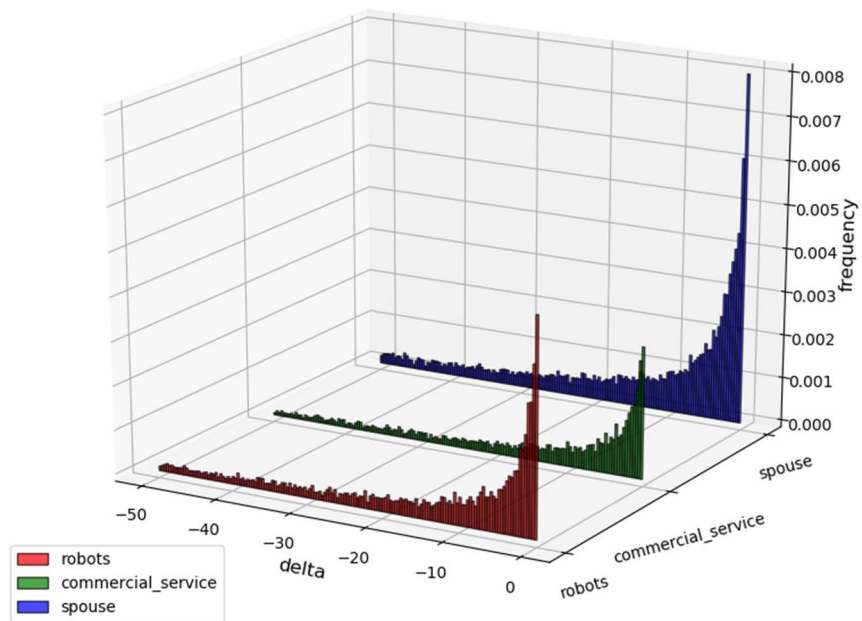


Figure A-3: 3D Histograms of Three Deltas for Cooking, Women

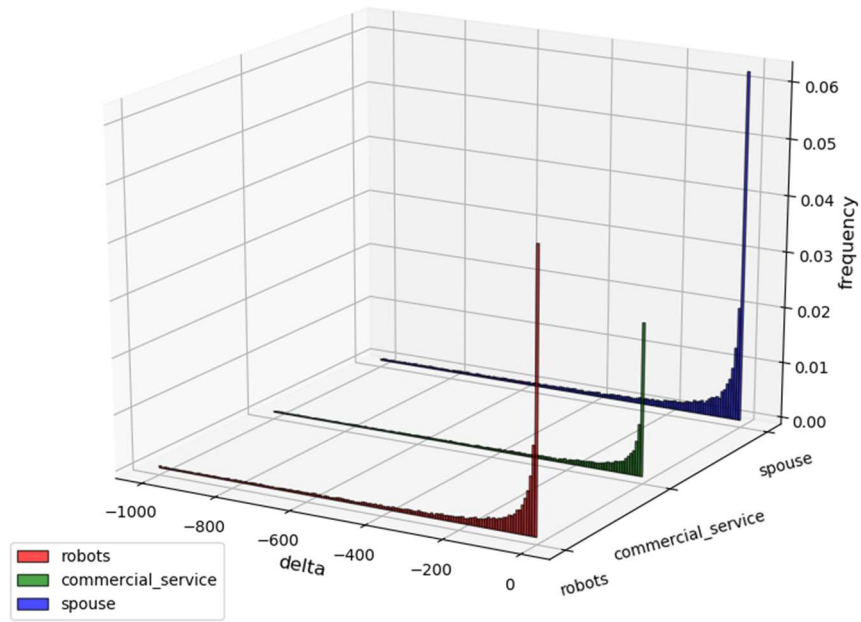


Figure A-4: 3D Histograms of Three Deltas for Cooking, Women

