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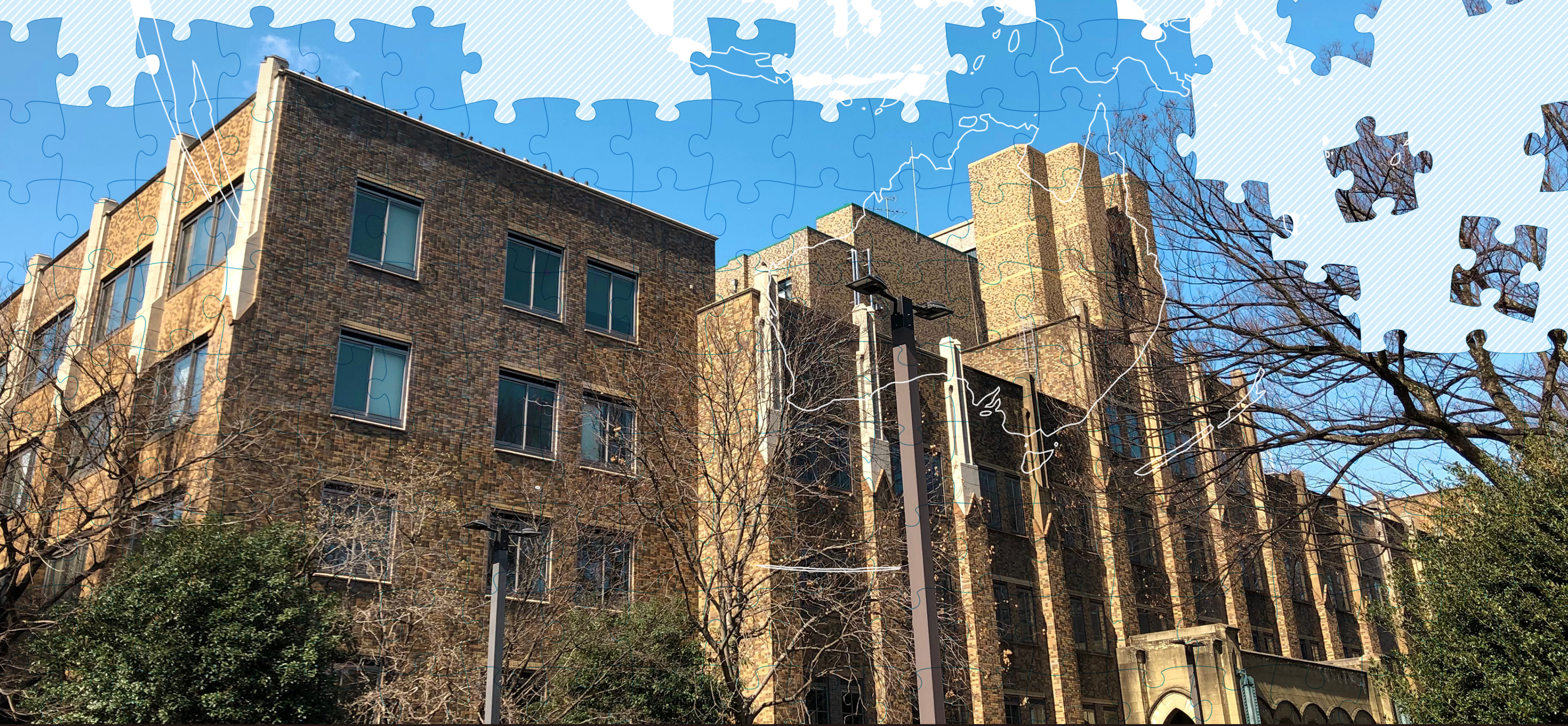
"As the boy, so the man?": Heterogeneous first-daughter effects on gender attitudes



No. 14

Date Apr. 2021

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“As the boy, so the man?”: Heterogeneous first-daughter effects on gender attitudes*

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Abstruct

The previous literature suggests that familial relationships play a fundamental role in developing social preferences, beliefs, and opinions. In particular, some studies have found that the sex of the first child has a causal effect on opinions about gender issues, which is referred to as the first-daughter effect. This paper provides evidence on the first-daughter effect in Japan with the most serious gender disparity among developed countries (World Economic Forum (2021)). Our estimation results show the average first-daughter effect to increases public support for the opinion “The best way for women to be independent is to have a job.” Additionally, significant heterogeneity is revealed by employing the causal inference with machine learning.

Keyword: First-daughter effect, Heterogeneous effects, Machine learning.

*This research was supported by KAKENHI Grant-in-Aid for Specially Promoted Research (Grant Numbers 25000001 and 18H05204) and Scientific Research (S) (Grant Numbers 18103003 and 22223005) from the Japan Society for the Promotion of Science (JSPS). The research support in conducting the panel surveys was obtained from the Institute of Social Science, University of Tokyo, and The Outscouring, Inc. The permission to use the panel data is obtained from the Management Committee of the Japanese Life Course Panel Surveys. We thank seminar participants at the Tokyo Labor Economics Workshop for their comments.

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1 Introduction

Social scientists have emphasized the role of social beliefs and norms in economic and political behavior. Naturally, determinants of those beliefs and norms have been of interest in the literature. A large body of literature has investigated the connection between family relationships and gender-related beliefs and norms, for instance Sharrow et al. (2018)[1] in political science and Yu and Kuo (2018) in sociology.

This paper estimates the first-daughter effect (Sharrow et al. (2018)), which is interpreted as the "causal" effect of the first child being female rather than male. By employing the technique of causal inference with machine learning, not only the average effect but also heterogeneous effects are examined.

The estimation results show a clear average effect on norms related to females and work. The first-daughter effect increases the number of respondents supporting the opinion "The best way for women to be independent is to have a job" on average. The paper also estimates the first-daughter effect on the opinion "A man's job is to earn an income; a woman's job is to protect her home and family." While there are no clear average effects, we detect subgroups with a significant effect.

The remainder of this paper is follows. In Section 2 we discuss the our empirical approach including explanation of data, and identification and estimation strategy. Section 3 introduces the estimation results. We draw conclusions in Section 4.

2 Empirical approach

2.1 Data

We use the Japan Life Course Panel Study (JLPS), which is survey data including rich variables of the sex of the first child and gender attitude in addition to respondent background. Even though the survey is a long-period panel, the current analysis focuses on the survey data from 2018.

The outcome variable is gender attitude, which is measured by attitude toward opinion. The following three opinions are used;

1. A man's job is to earn an income; a woman's job is to protect her home and family.
2. The best way for women to be independent is to have a job.

The respondents chose from the following options: (1) strongly agree, (2) agree, (3) neutral, (4) disagree, and (5) strongly disagree.

The treatment variable is the sex of the first child, which is directly observed in our data. We focus on respondents with children and without missing values for gender attitude questions. The sample size is then 1900. Missing values for the background characteristics are imputed. For categorical variables, the level of missing data is used. For continuous variables, the missing values are imputed as the average, and a "missing" dummy is also used.

2.1.1 Descriptive difference

The following figure shows the non-adjusted distribution of gender attitude. The outcome variable is attitude toward the following opinion: "The best way for women to be independent is to have a job." The respondents chose "strongly agree," "agree," "neutral," "disagree," or "strongly disagree." Additionally, some respondents stated "no idea" or did not answer.

[1] Urbatsch (2020) reexamines Sharrow et al. (2018) and show non-robustness of their findings in terms of specification choices and coding.

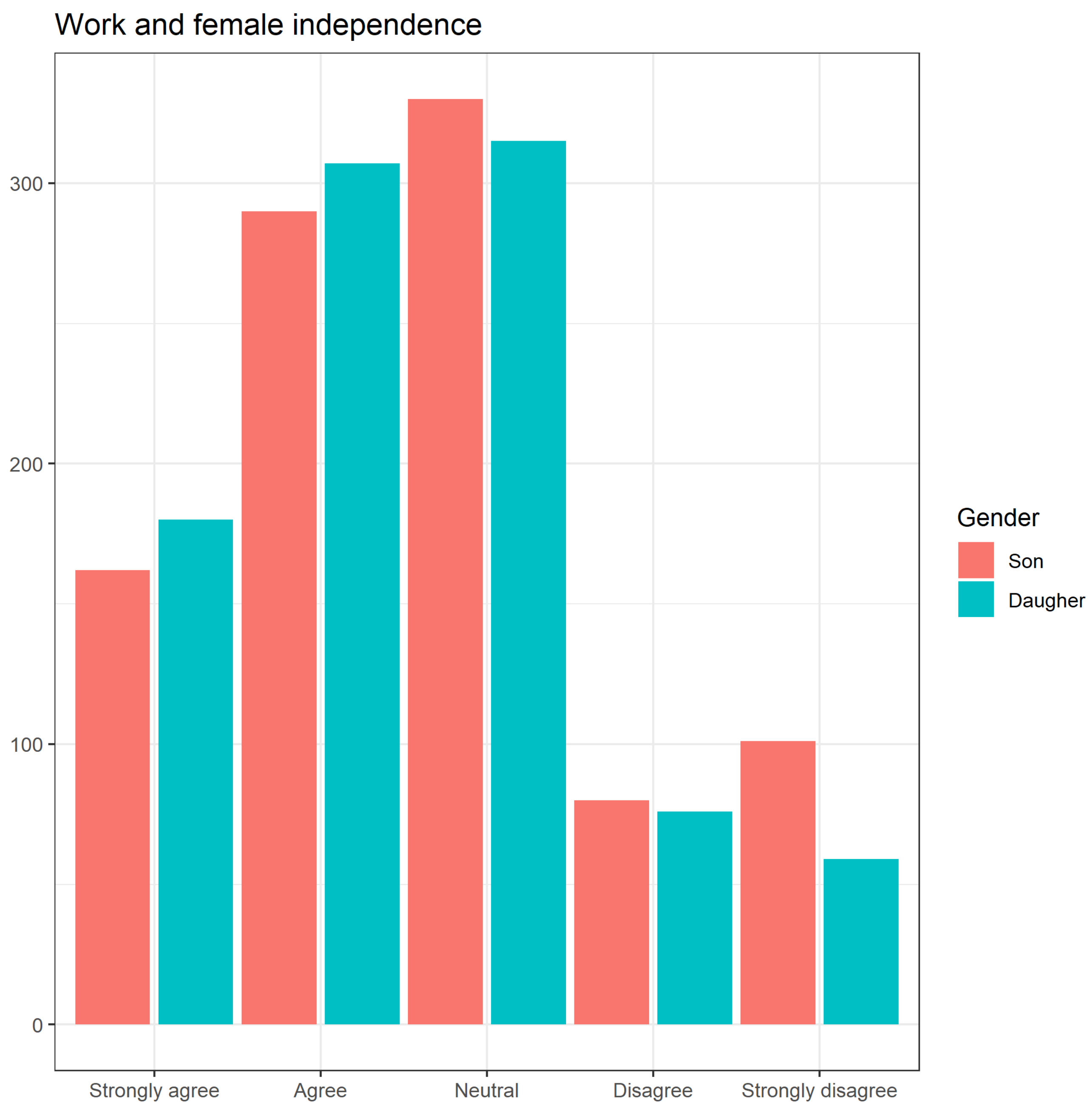

Figure 1. Attitude toward "A man's job is to earn an income; a woman's job is to protect her home and family."

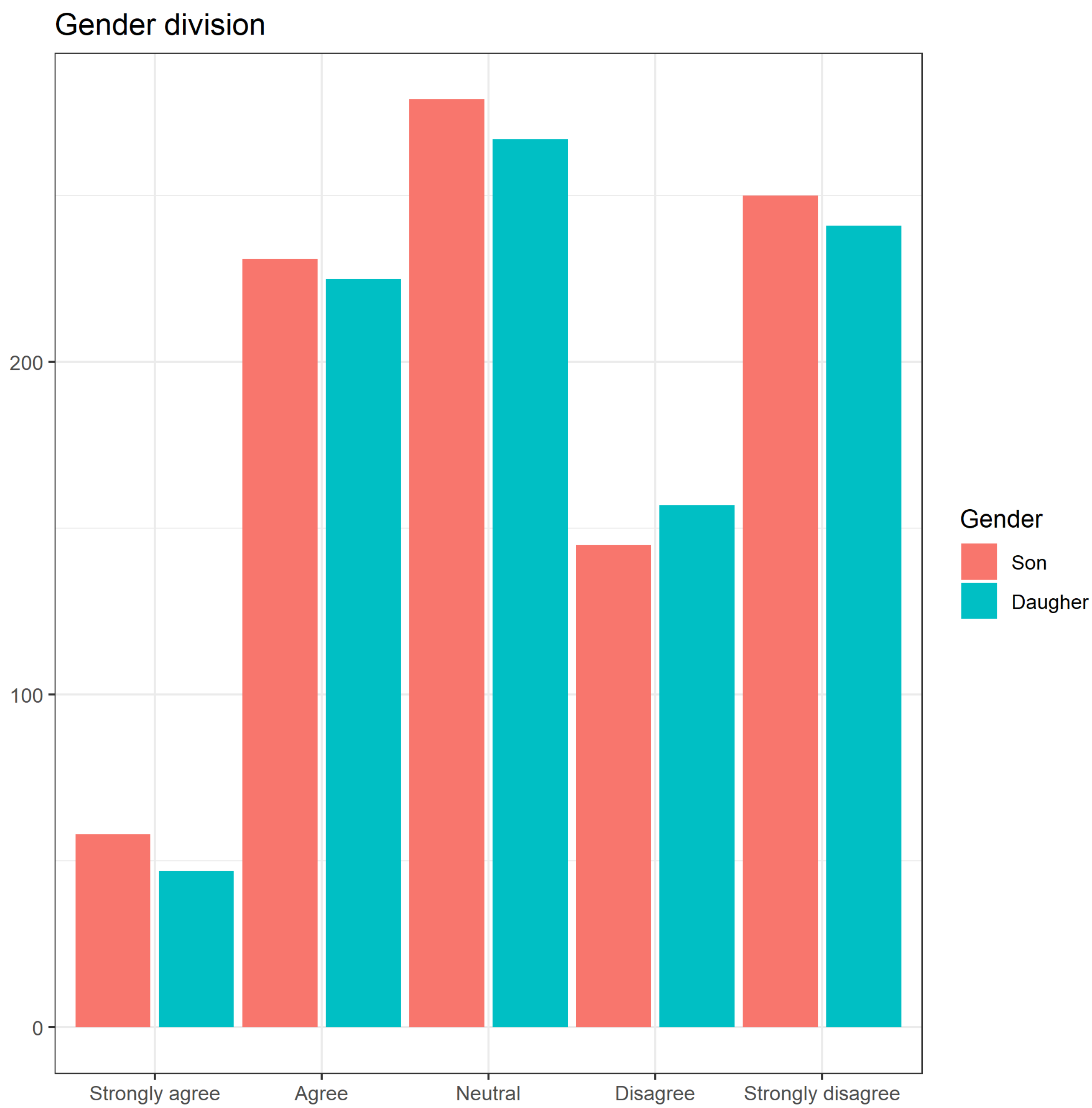

Figure 2. Attitude toward "The best way for women to be independent is to have a job."

The above figures show that respondents with first daughter tend to support non-traditional opinions.

2.2 Identification

Our identification strategy crucially depends on the randomness of the sex of the first child. Even though decision-making about having children is endogenous, the sex of the first child can be supposed to be random within households with children.

Formally, let $Y_i(1)$ and $Y_i(0)$ be the potential gender attitude of respondent's i toward the first daughter and son, respectively. $Y_i(w) = 1$ if her/she agrees "non traditional opinion" and $= 0$ otherwise. Therefore

$Y_i(w) = 1$ if "disagree" or "strongly disagree" is chosen on "A man's job is to earn an income; a woman's job is to protect her home and family." On "The best way for women to be independent is to have a job," $Y_i(w) = 1$ if "agree" or "strongly agree" is chosen.

The treatment status is denoted by W_i has a value of one if the first child is a girl and zero if the child is a boy. X_i is observable characteristics, including the respondents' demographic and education status, experience at 15 years old, father's and mother's educational background, and their job status.

We assume the conditional independence, $\{Y_i(1), Y_i(0)\} \perp W_i | X_i$. The assumption is justified by the randomness of the sex of the first child. Under conditional independence, various causal estimands are identified. The most informative estimated is the individual treatment effect:

$$\tau_i = Y_i(1) - Y_i(0).$$

However, the individual treatment effect cannot be estimated due to the fundamental problem of causal inference Holland (1986).

A popular alternative is the conditional average first-daughter effect:

$$\tau(x) = E[\tau_i | X_i = x] = E[Y_i(1)|X_i = x] - E[Y_i(0)|X_i = x].$$

The conditional average first-daughter effect is the difference of average values of potential outcomes. The conditional independence assumption identifies the conditional average value of potential outcome as

$$E[Y_i(1)|X_i = x] = E[Y_i|W_i = 1, X_i = x]$$

$$E[Y_i(0)|X_i = x] = E[Y_i|W_i = 0, X_i = x]$$

and the conditional average first-daughter effect is also identified as

$$\tau(x) = E[Y_i|W_i = 1, X_i = x] - E[Y_i|W_i = 0, X_i = x].$$

Identification results require to estimate the conditional average and it's difference. We employ the augmented inverse propensity weighted estimator (Robins, Rotnitzky, and Zhao (1994)) with the machine learning method.

Let define score functions as

$$\mu_i(0) = f(0, X_i) + \frac{(1 - W_i) \times (Y_i - f(0, X_i))}{1 - e(X_i)},$$

and

$$\mu_i(1) = f(1, X_i) + \frac{W_i \times (Y_i - f(1, X_i))}{e(X_i)},$$

where $f(0, X_i) = E[Y_i|W_i = 0, X_i]$, $f(1, X_i) = E[Y_i|W_i = 1, X_i]$, and $e(X_i) = E[W_i|X_i]$. Additional identification results are obtained as

$$E[Y_i(1)|X_i = x] = E[\mu_i(1)|X_i = x],$$

and

$$E[Y_i(0)|X_i = x] = E[\mu_i(0)|X_i = x].$$

The first-daughter effect is then identified as $\tau(x) = E[\mu_i(1) - \mu_0(1)|X_i = x]$. The identification results imply a simple estimation strategy; (1) estimate score functions $\mu_i(1)$ and $\mu_i(0)$, and (2) aggregate estimated score functions.

2.3 Estimation

A straight-forward strategy is the plug-in approach as

$$\tilde{\mu}_i(1, x) = \tilde{f}(1, x) + \frac{W_i \times (Y_i - \tilde{f}(1, x))}{\tilde{e}(x)},$$

and

$$\tilde{\mu}_i(0, x) = \tilde{f}(0, x) + \frac{(1 - W_i) \times (Y_i - \tilde{f}(0, x))}{1 - \tilde{e}(x)},$$

where $\tilde{f}(w, x)$ and $\tilde{e}(x)$ are estimated nuisance functions.

To avoid the over-fitting problem, nuisance functions are estimated by a machine learning method, boosting Chen et al. (2015)[2]. Farrell (2015), Chernozhukov et al. (2017), Chernozhukov et al. (2018), and Semenova and Chernozhukov (2017) examine the finite sample and asymptotic property of the AIPW with the machine learning estimators. Their results require to cross-fitted values. Each respondent i is randomly assigned into one of 20 sub-samples $k = 1, ..., 20$. $k(i)$ be the sub-sample assigned a respondent i.

Estimated score functions are then

$$\tilde{\mu}_i(1, x) = \tilde{f}^{-k(i)}(1, x) + \frac{W_i \times (Y_i - \tilde{f}^{-k(i)}(1, x))}{\tilde{e}^{-k(i)}(x)},$$

and

$$\tilde{\mu}(0, x) = \tilde{f}^{-k(i)}(0, x) + \frac{(1 - W_i) \times (Y_i - \tilde{f}^{-k(i)}(0, x))}{1 - \tilde{e}^{-k(i)}(x)},$$

where $\tilde{f}_{Y1}^{-k(i)}(x)$, $\tilde{f}_{Y0}^{-k(i)}(x)$, and $\tilde{f}_{W}^{-k(i)}(x)$ are nuisance functions estimated by sample excluding sub-sample $k(i)$.

In the following analysis, we report marginalized effects. The first quantity is the average first-daughter effect, $E_x[\tau(x)]$, which is estimated as $\frac{1}{N}\sum_i[\tilde{\mu}_i(1, x) - \tilde{\mu}_i(0, x)]$.

The second quantity is the group average effects; $E[\tau_i(x)|G_i] = \sum_g \gamma_g \times G_i$, where G_i is a group indicator. The group indicator is defined by a data-drive approach. We fit a shallow greedy tree of $\tilde{f}^{-k(i)}(1, x) - \tilde{f}^{-k(i)}(0, x)$ on X, which define group indicators to minimize the within-sample MSE of $\tilde{f}^{-k(i)}(1, x) - \tilde{f}^{-k(i)}(0, x)$.

3 Results

3.1 Estimated propencity score

We first report the estimated propensity score $\tilde{f}_W(x)$. The following figure shows gender-specific key summary statistics by the boxplot.

[2]All hyper-parameters are default values, excepting shrinkage parameter and iterations. Shrinkage parameter is set to 0.01. The iteration is determined by the cross-validation with 100 folds.

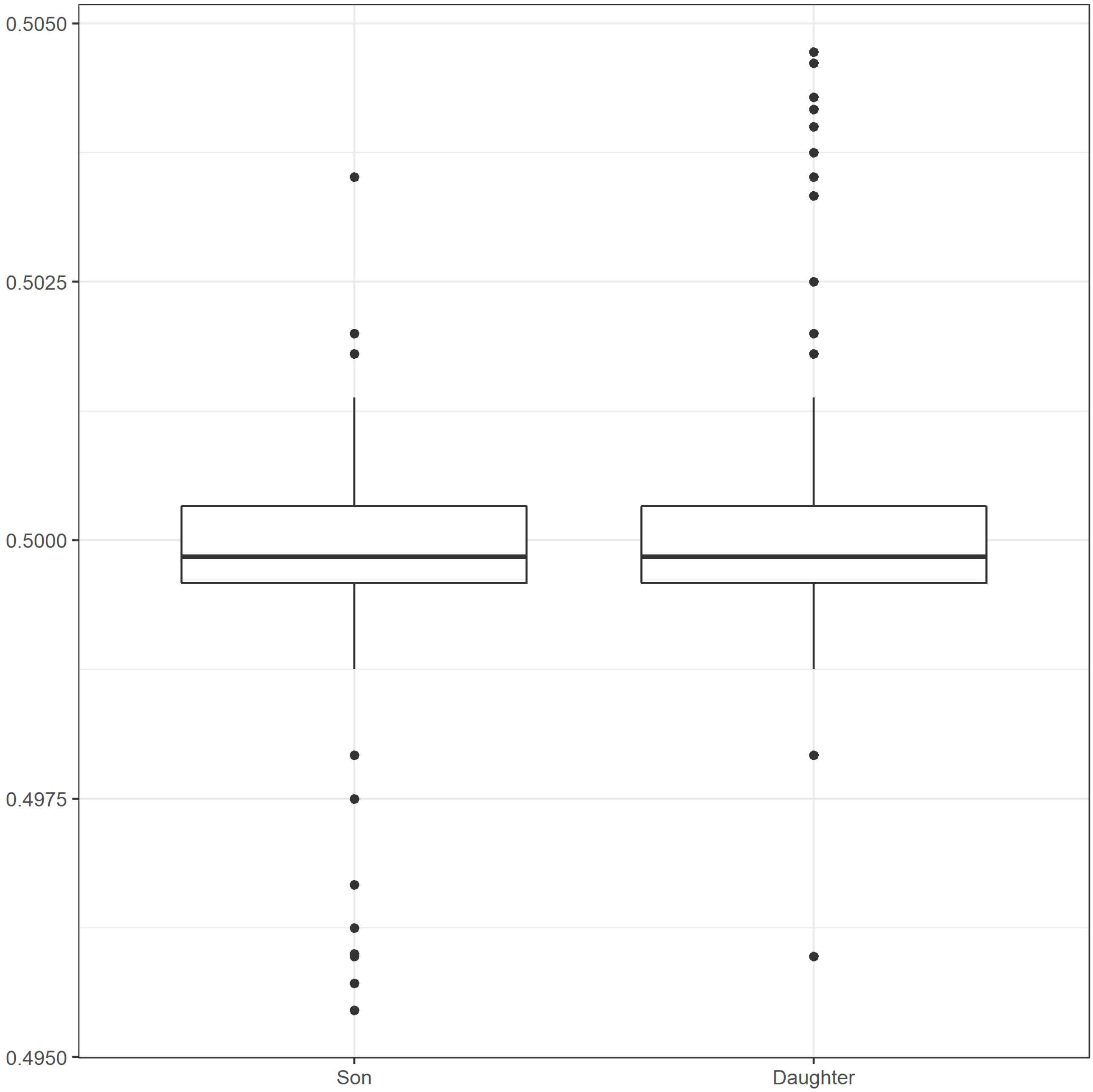

Figure 3. Estimated propensity score.

The figure support the conditional independence assumption. The median and quantile values are almost balanced between respondents with first son and daughter. Moreover, the propensity score is distributed near 50%.

3.2 Average first-daughter effect

We next show estimated average first-daughter effects with confidence interval. The following analysis focuses on the share of respondents supporting non-traditionalism. The average effects are as follows.

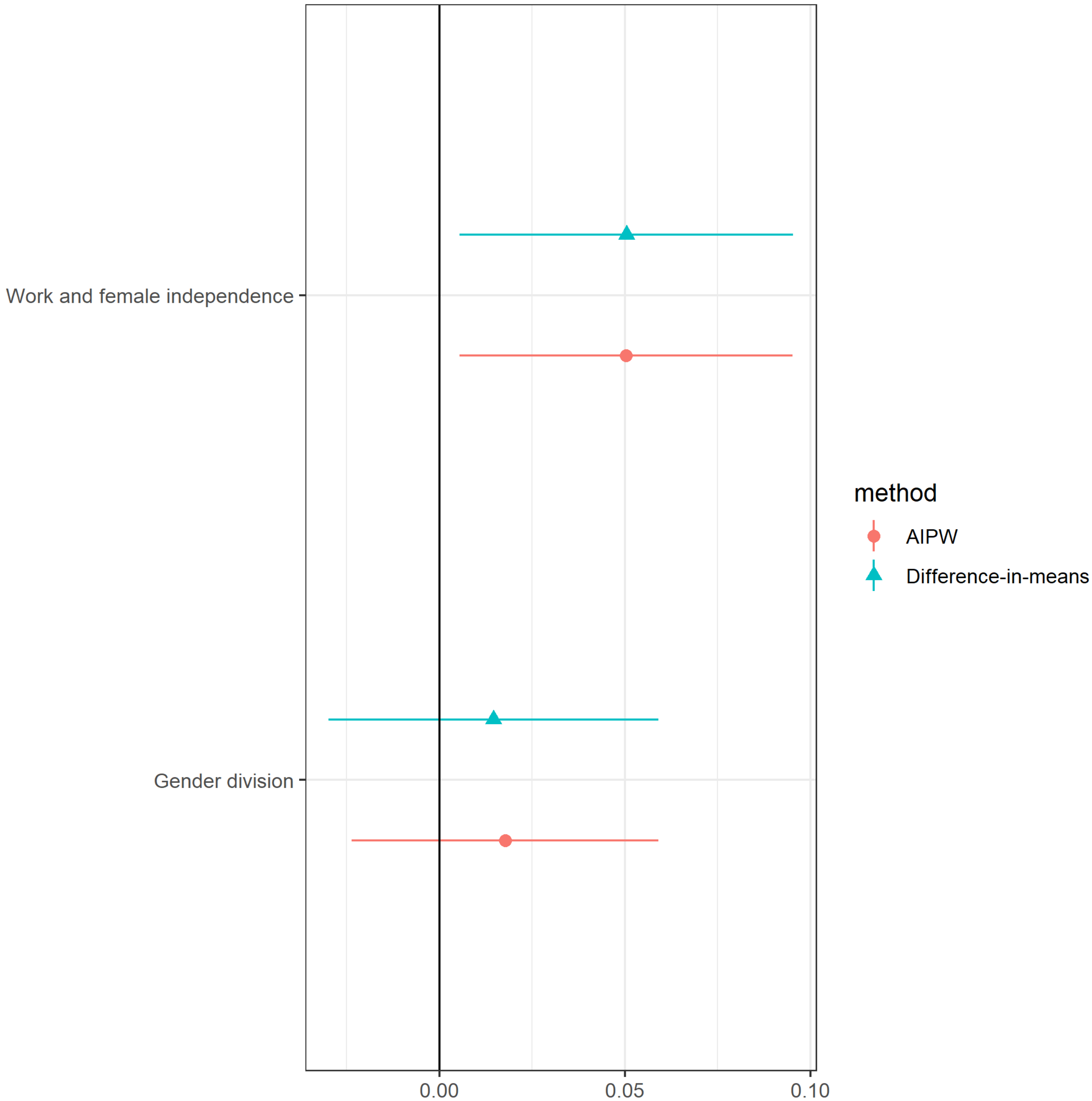

Figure 4. Average first-daughter effects.

Note that each point is a point estimator, and each bar is the 95% confidence interval. The term gender_division refers to "A man's job is to earn an income; a woman's job is to protect her home and family," and work and female independence is "The best way for women to be independent is to have a job."

Figure 4 reports that the average first-daughter are consistently estimated with simple difference-in-means and the AIPW. Both estimators shows that the first-daughter effect clearly increases respondents who agree "The best way for women to be independent is to have a job." The point estimator is 5 percent, which implies that the first-daughter effect increase respondents who agree "The best way for women to be independent is to have a job." as 5 percent.

The first-daughter effect on the gender division is not clear. Even the point estimator is positive, it's size is smaller than the confidence interval.

3.3 Heterogeneous effect

While the average first-daughter effect on “Having a job is best for female independence” is clearly positive, the average effect on “gender division” is not clear. A possibility is the heterogeneity of first daughter effects, and the group average first-daughter effects are useful to detect it’s heterogeneity.

3.3.1 Gender group

We first examine the group average first-daughter effect with pre-specified groups. Sharrow et al. (2018) and Yu and Kuo (2018) emphasize heterogeneity between father and mother. The next figure then reports the gender-specific effects, $E[\tau(x)|male]$ and $E[\tau(x)|female]$.

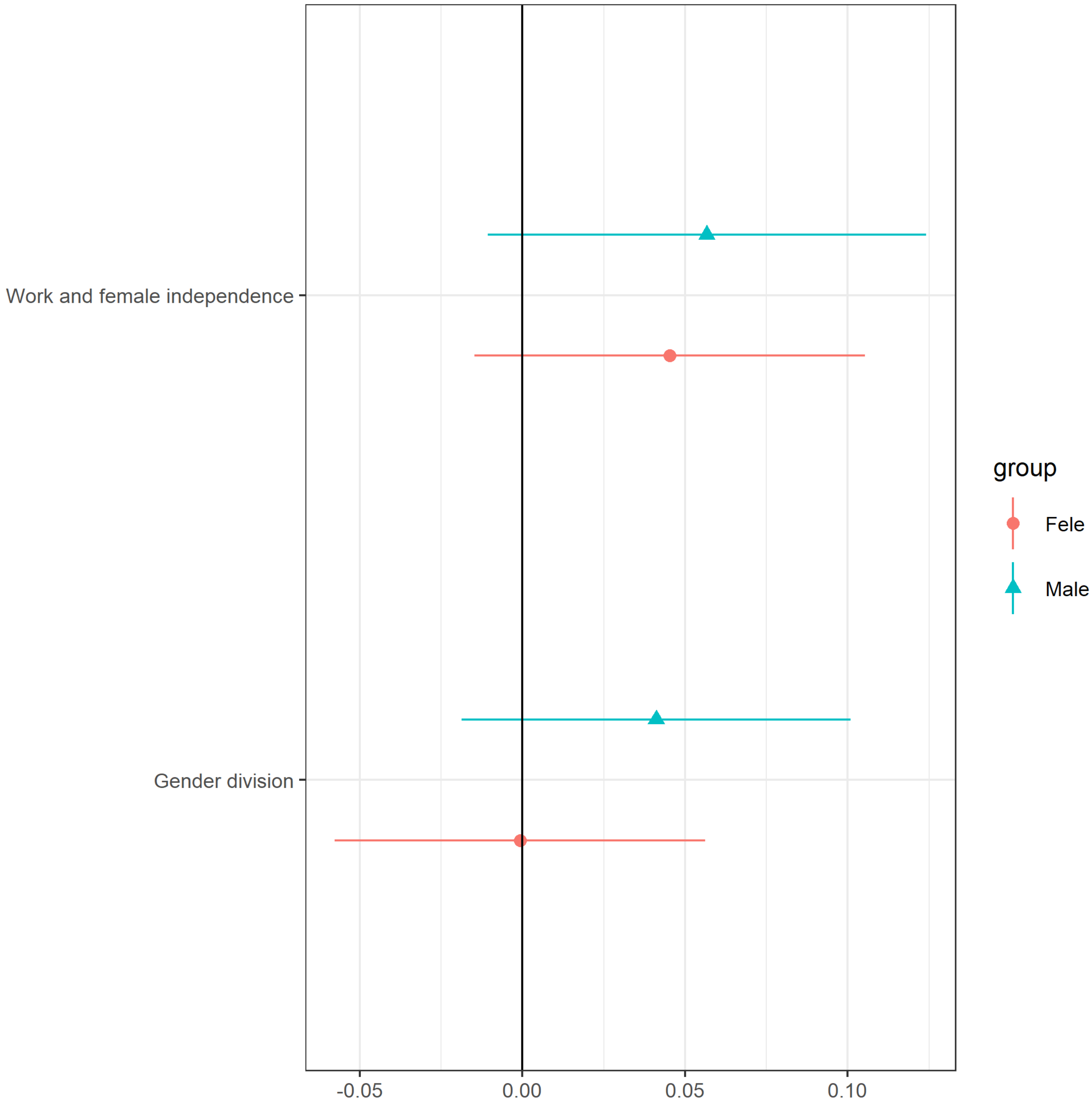

Figure 5. Gender-specific first daughter effects.

Note that each point is a point estimator, and each bar is the 95% confidence interval. The term gender_division refers to "A man's job is to earn an income; a woman's job is to protect her home and family," and work and female independence is "The best way for women to be independent is to have a job."

The figure reports no clear evidence of gender heterogeneity. On the job and independence, the point estimator of male is higher than female. However, the difference is not statistically significant.

3.3.2 Data-driven approach

The next figure reports the group average first-daughter effects with the data-driven group indicator. The tree algorithm with depth 1 detects subgroups in terms of age on “Having a job is best for female independence” and spouse’s education level on “gender division.”

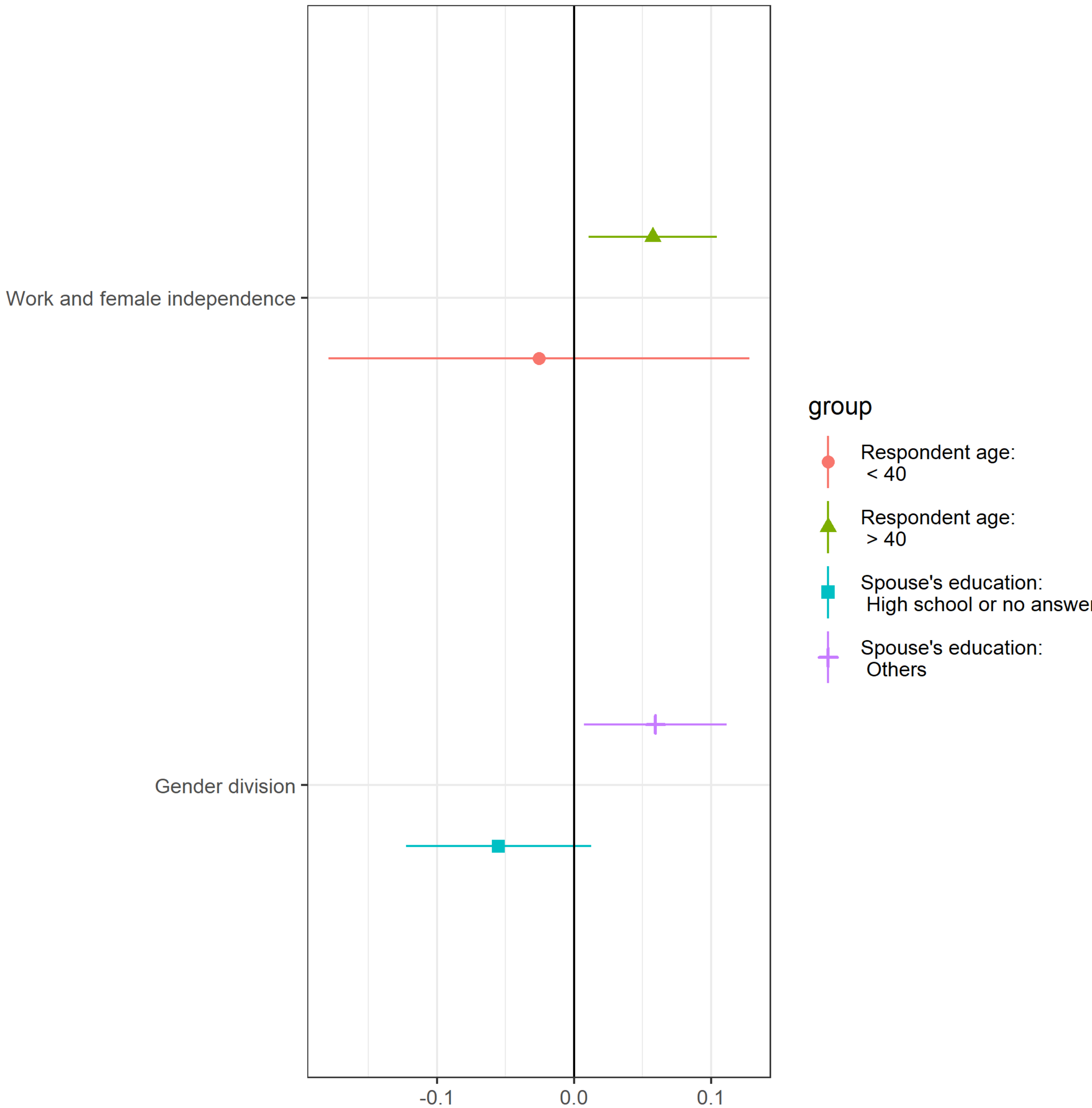

Figure 6. Conditional first-daughter effects.

Note that each point is a point estimator, and each bar is the 95% confidence interval. The term gender_division refers to “A man’s job is to earn an income; a woman’s job is to protect her home and family,” and work and female independence is “The best way for women to be independent is to have a job.”

The figure detect subgroups with clear first-daughter effects. On Gender divisions, positive and clear first-daughter effect is observed among respondents with spouses whose education level is not high school and not answered.

4 Conclusion

The paper investigates the first-daughter effect in Japan. Our estimation results show that the first-daughter effect increases support on the non-traditional opinions as “The best way for women to be independent is to have a job.” Additionally, heterogeneity of the effects is found. Among respondents with not high-school graduated spouse, we find the positive first-daughter effect on “A man’s job is to earn an income; a woman’s job is to protect her home and family.”

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