

Exercise 03

Exercise 3.1

a)

In this analysis, our group decided to analyze the data from Taiwan.

After data preparation, the original sample size was 1844 observations, while the final sample size was reduced to 990, following the deletion of cases with missing values on key variables. A significant portion of the cases (910 respondents) had no response for their spouse's social class, making up the majority of the cases cleansed.

b)

The sample statistics by gender are detailed in **Table 1**.

Table 1. The Sample Statistics by Gender			
	1-Men (N=507)	2-Women (N=483)	Overall (N=990)
CLASS			
1-unskilled workers	78 (15.4%)	128 (26.5%)	206 (20.8%)
2-skilled workers	253 (49.9%)	229 (47.4%)	482 (48.7%)
3-lower grade service	109 (21.5%)	105 (21.7%)	214 (21.6%)
4-Higher grade service	67 (13.2%)	21 (4.3%)	88 (8.9%)
CLASS_SPOUSE			
1-unskilled workers	147 (29.0%)	81 (16.8%)	228 (23.0%)
2-skilled workers	233 (46.0%)	230 (47.6%)	463 (46.8%)
3-lower grade service	107 (21.1%)	102 (21.1%)	209 (21.1%)
4-Higher grade service	20 (3.9%)	70 (14.5%)	90 (9.1%)
PCLASS			
Mean (SD)	3.02 (1.10)	2.92 (1.11)	2.97 (1.10)
Median [Min, Max]	3.00 [1.00, 6.00]	3.00 [1.00, 6.00]	3.00 [1.00, 6.00]
DEP			
Mean (SD)	0.241 (0.428)	0.238 (0.426)	0.239 (0.427)
Median [Min, Max]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]
GENDER			
1-Men	507 (100%)	0 (0%)	507 (51.2%)
2-Women	0 (0%)	483 (100%)	483 (48.8%)

Table 1 provides a detailed breakdown of sample statistics in Taiwan, categorizing data by gender (men and women). It includes information on Social Class, Social Class of Spouse, Perceived Social Class (PCLASS), Financial Hardship (DEP), and Gender for the 990 respondents. The table presents the CLASS of respondents and their spouses, showcasing proportions in various social classes. Notably, more women (26.5%) than men (15.4%) belong to "1-unskilled workers," and more men (13.2%) than women (4.3%) fall into the "4-Higher grade service" class. CLASS_SPOUSE exhibits a similar pattern but in reverse,

reflecting gender class distributions in the population. Additional granularity is provided through variables PCLASS and DEP, enabling a nuanced examination of variations within different Perceived Social Classes and Financial Hardship.

Exercise 3.2

a)

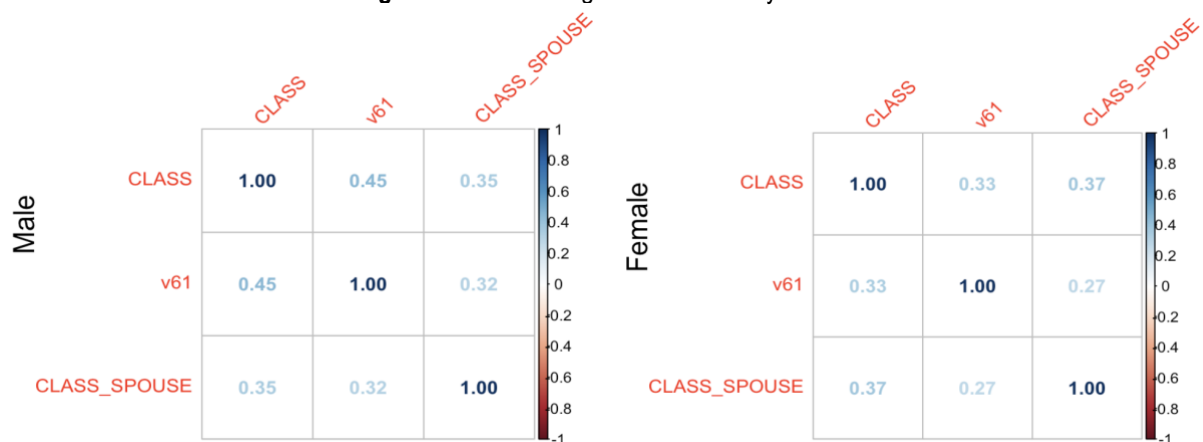
Using Spearman's rank correlation coefficient method, the correlation coefficients between social class (CLASS) and perceived social class (PCLASS) are moderate, with 0.45 for males and 0.33 for females, respectively.

b)

The data indicates that the correlation coefficients between spousal class (CLASS_SPOUSE) and perceived (own) social class (PCLASS) are comparatively lower than those between CLASS and PCLASS, with 0.32 for males and 0.27 for females, respectively.

Figure 1 displays the overall correlation coefficients among social class, spousal class, and perceived social class in the Correlogram.

Figure 1. The Correlogram of Classes by Gender



Exercise 3.3

a)

Table 2 presents the contingency table with CLASS (rows) by CLASS_SPOUSE (columns). Approximately 43% of couples in the same social class consist of homogeneous couples, while around 40% of couples have the man belonging to a higher social class than the woman.

Table 2. The contingency table with CLASS (row) by CLASS_SPOUSE (column)

	1	2	3	4
1	84	88	28	6
2	110	255	81	36

3	29	90	68	27
4	5	30	32	21

b)

The Spearman’s rank correlation between CLASS and CLASS_SPOUSE is 0.32, indicating a moderate correlation in Taiwan.

c)

For decades, the concept of social class has been intrinsically tied to the male head of the household, with the prevailing assumption that a man's social standing determined the overall class status of the family unit. The status of women in many places in the world is lower than that of men, which results in gender being a significant social division. (Warwick-Booth, 2022)

In traditional East Asian societies, including Taiwan, the patriarchal structure dictated that the man's social class served as a proxy for the entire household, simplifying matters with one classification to represent the collective. Yet, as societies evolve, so do their dynamics. These unequal social arrangements comprise inequalities on several axes, including—but not necessarily limited to—race/ethnicity, gender, and social class. (Valentino & Vaisey, 2022) This analysis provides a fresh perspective on the historical backdrop.

Notably, the ISSP 2019 data reveals a remarkable trend—17% of women in Taiwan occupy a higher social class than their spouses, challenging the notion that a woman's class status is inherently tied to her husband's. These women are carving their own paths, defying traditional norms, and achieving upward mobility. The correlation coefficient between a woman's social class and her spouse's is weaker than that of men, suggesting that women's class mobility is less influenced by their partner's status. Perhaps women are increasingly making independent strides, driven by education, career opportunities, and personal aspirations.

Approximately 43% of couples share the same social class, reflecting stability and continuity in adherence to the traditional model. The remaining 40% of couples exhibit intriguing dynamics where the man's social class surpasses that of the woman. This scenario challenges the historical norm, emphasizing that women are not merely passive recipients of their husband's status; instead, they actively contribute to the household's overall class position.

These findings underscore the importance of recognizing this evolving landscape for policymakers. Social programs, educational opportunities, and workforce policies must account for women's increasing agency in shaping household class dynamics. The results highlight the significance of gender equality in Taiwan, emphasizing the need to empower women economically, socially, and educationally to enhance their ability to influence household class trajectories.

In conclusion, Taiwan's households are breaking free from rigid gender roles, redefining social class in this context invites a celebration of the women who defy conventions and contribute to a more equitable and dynamic future.

Exercise 3.4

a)

Model 1 aims to explore the impact of social class, gender, and age on the likelihood of experiencing financial hardship (see **Table 3**).

Table 3. The Regression of Financial Hardship

Characteristic	Beta	95% CI ¹	p-value
CLASS			
1-unskilled workers	—	—	
2-skilled workers	-0.06	-0.13, 0.01	0.074
3-lower grade service	-0.22	-0.30, -0.14	<0.001
4-Higher grade service	-0.19	-0.30, -0.09	<0.001
GENDER			
1-Men	—	—	
2-Women	-0.03	-0.09, 0.02	0.2
Age of respondent	0.00	-0.01, 0.00	<0.001
¹ CI = Confidence Interval			

The analysis indicates that social class significantly influences the probability of facing financial hardship. Specifically, individuals in lower-grade service and higher-grade service classes are more and less likely, respectively, to experience financial hardship compared to unskilled workers. Additionally, increasing age is associated with a decreased likelihood of financial hardship. However, gender does not exhibit a statistically significant relationship with financial hardship in this model.

b)

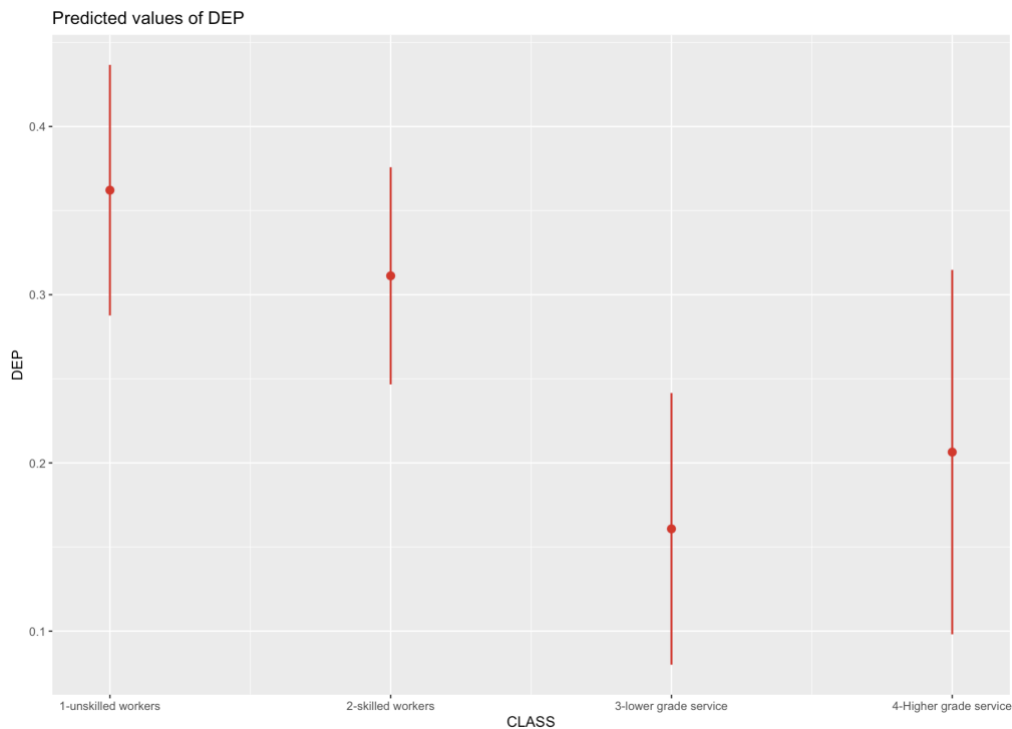
The results from the Model 2 regression analysis, particularly the plot (see **Figure 2**) depicting the probabilities of financial hardship for different social classes in the context of the labor market, provide insights into the potential emergence of new social cleavages.

The plot reveals distinct patterns among social classes, suggesting that the digital transformation of the labor market might indeed be contributing to new social cleavages. Notably, "unskilled workers" and "skilled workers" exhibit higher probabilities of experiencing financial hardship, indicating potential vulnerabilities within these segments of the labor force.

This aligns with the notion that digital transformation, characterized by automation, technological advancements, and evolving skill requirements, could be creating disparities that transcend traditional class boundaries. The differential impact on various social classes underscores the complexity of contemporary labor market dynamics, where factors such as skill levels and adaptability may play a crucial role in determining economic well-being.

In conclusion, the analyses support the idea that the digital transformation of the labor market has led to new social cleavages, as evidenced by distinct financial hardship patterns among different social classes. This highlights the need for further exploration and policy considerations to address the evolving dynamics of inequality in the context of technological advancements.

Figure 2. The Predicted Values of DEP by Class



Exercise 3.5

a)

In investigating the connection between social class and financial hardship, separate analyses were conducted for men and women, both with and without considering the social class of the spouse (CLASS_SPOUSE). For women, the initial model (MODEL 2a) revealed significant associations between lower-grade service, higher-grade service, increasing age, and financial hardship. However, when CLASS_SPOUSE was included (MODEL 2b), the robustness of the significance of individual social classes weakened. Initially, three social classes (lower-grade service, higher-grade service, and skilled workers) demonstrated statistical significance, but upon including CLASS_SPOUSE, only lower-grade service retained significance. This suggests that the initial effect size of individual social classes may not be as robust, and financial hardship outcomes for women could be influenced by the social class of their spouses.

A similar pattern emerged for men, where the inclusion of CLASS_SPOUSE (MODEL 3b) resulted in only lower-grade service maintaining statistical significance. This points to a

potential attenuation in the robustness of the effect size of individual social classes when considering the social class of the spouse.

Table 4. The Regression of Financial Hardship by GENDER

Characteristic	Own Class(Female)			With Spouse's Class(Female)		
	Beta	95% CI ¹	p-value	Beta	95% CI ¹	p-value
CLASS01						
1-unskilled workers	—	—		—	—	
2-skilled workers	-0.05	-0.14, 0.04	0.3	-0.06	-0.17, 0.05	0.3
3-lower grade service	-0.25	-0.36, -0.14	<0.001	-0.16	-0.28, -0.03	0.017
4-Higher grade service	-0.29	-0.49, -0.10	0.003	-0.10	-0.24, 0.05	0.2
Age of respondent	0.00	-0.01, 0.00	0.068	0.00	-0.01, 0.00	<0.001
CLASS02						
1-unskilled workers				—	—	
2-skilled workers				-0.05	-0.14, 0.04	0.3
3-lower grade service				-0.09	-0.20, 0.02	0.12
4-Higher grade service				-0.20	-0.41, 0.01	0.057
¹ CI = Confidence Interval						
Characteristic	Own Class(Male)			With Spouse's Class(Male)		
	Beta	95% CI ¹	p-value	Beta	95% CI ¹	p-value
CLASS01						
1-unskilled workers	—	—		—	—	
2-skilled workers	-0.07	-0.18, 0.04	0.2	-0.06	-0.17, 0.05	0.3
3-lower grade service	-0.18	-0.31, -0.06	0.004	-0.16	-0.28, -0.03	0.017
4-Higher grade service	-0.15	-0.29, -0.01	0.032	-0.10	-0.24, 0.05	0.2
Age of respondent	0.00	-0.01, 0.00	0.002	0.00	-0.01, 0.00	<0.001
CLASS02						
1-unskilled workers				—	—	
2-skilled workers				-0.05	-0.14, 0.04	0.3
3-lower grade service				-0.09	-0.20, 0.02	0.12
4-Higher grade service				-0.20	-0.41, 0.01	0.057
¹ CI = Confidence Interval						

The observed change in significance may be attributed to multicollinearity, where the interdependence of individual social classes and the social class of spouses masks the distinct impact of each variable when included together. This underscores the importance of considering intricate relationships among variables and being cautious about drawing definitive conclusions in the presence of multicollinearity.

References:

- ISSP Research Group (2022). International Social Survey Programme: Social Inequality V - ISSP 2019. GESIS, Köln. ZA7600 Datenfile Version 3.0.0, 1(<https://doi.org/10.4232/1.14009>).
- Valentino, L., & Vaisey, S. (2022). Culture and Durable Inequality. *Annual Review of Sociology*, 48(1), 109–129. <https://doi.org/10.1146/annurev-soc-030320-102739>
- Warwick-Booth, L. (2022). *Social inequality 3e* (Third edition). SAGE.

R Packages:

- Enzmann JAIRscadwbD, Schwartz M, Jain N, Kraft S (2023). `_descr: Descriptive Statistics_`. R package version 1.1.8, <<https://CRAN.R-project.org/package=descr>>.
- Lüdecke D (2023). `_sjPlot: Data Visualization for Statistics in Social Science_`. R package version 2.8.15, <<https://CRAN.R-project.org/package=sjPlot>>.
- Rich B (2023). `_table1: Tables of Descriptive Statistics in HTML_`. R package version 1.4.3, <<https://CRAN.R-project.org/package=table1>>.
- Sjoberg DD, Whiting K, Curry M, Lavery JA, Larmarange J. Reproducible summary tables with the gtsummary package. *The R Journal* 2021;13:570–80. <https://doi.org/10.32614/RJ-2021-053>.
- Taiyun Wei and Viliam Simko (2021). R package 'corrplot': Visualization of a Correlation Matrix (Version 0.92). Available from <https://github.com/taiyun/corrplot>

Warnes GR, Bolker B, Lumley T, SAIC-Frederick RCJfRCJaC, Program IFbtIR, NIH ot,
Institute NC, NO1-CO-12400.CfCRuNC (2022). *_gmodels: Various R Programming
Tools for Model Fitting_*. R package version 2.18.1.1,
<<https://CRAN.R-project.org/package=gmodels>>.

Wickham H, Miller E, Smith D (2023). *_haven: Import and Export 'SPSS', 'Stata' and 'SAS'
Files_*. *R package version 2.5.4*, <<https://CRAN.R-project.org/package=haven>>.


```

library(haven)
library(descr)
library(table1)
library(gmodels)
library(corrplot)
library(gtsummary)
library(sjPlot)

#### Step 1: data preparation ####
rm(list=ls())
# Read in data & select the analytical sample
ISSP2019 <- read_dta("assets/ISSP2019_EX3.dta") # 44975 obs.
# Select Taiwan and relevant variables
DATA01 <- subset(ISSP2019, ISSP2019$country == 158,
                 select = c(CLASS, CLASS_SPOUSE, AGE, SEX, v53,
                             v61)) # 1926 obs. from Taiwan
# remove ISSP2019 from memory
rm(ISSP2019)

# Remove missing values
DATA02 <- subset(DATA01, !(is.na(DATA01$CLASS))) # 1844 obs.
DATA03 <- subset(DATA02, DATA02$v53 > 0) # 1837 obs.
DATA04 <- subset(DATA03, DATA03$v61 > 0) # 1803 obs.
DATA05 <- subset(DATA04, !(is.na(DATA04$CLASS_SPOUSE))) # 990
obs.

#### Step 2: variables construction ####
#Construct Variables
#Var: GENDER
DATA05$GENDER<-NA
DATA05$GENDER[DATA05$SEX==1]<-"1-Men"
DATA05$GENDER[DATA05$SEX==2]<-"2-Women"
DATA05$GENDER<-as.factor(DATA05$GENDER)

#Var: SOCIAL CLASS
DATA05$CLASS01<-NA
DATA05$CLASS01[DATA05$CLASS==1]<-"1-unskilled workers"
DATA05$CLASS01[DATA05$CLASS==2]<-"2-skilled workers"
DATA05$CLASS01[DATA05$CLASS==3]<-"3-lower grade service"
DATA05$CLASS01[DATA05$CLASS==4]<-"4-Higher grade service"
DATA05$CLASS01<-as.factor(DATA05$CLASS01)

```

```
#Var: Spouse's Social Class
DATA05$CLASS02<-NA
DATA05$CLASS02[DATA05$CLASS_SPOUSE==1]<-"1-unskilled workers"
DATA05$CLASS02[DATA05$CLASS_SPOUSE==2]<-"2-skilled workers"
DATA05$CLASS02[DATA05$CLASS_SPOUSE==3]<-"3-lower grade service"
DATA05$CLASS02[DATA05$CLASS_SPOUSE==4]<-"4-Higher grade service"
DATA05$CLASS02<-as.factor(DATA05$CLASS02)
```

```
#Var: DEP
DATA05$DEP<-NA
DATA05$DEP[DATA05$v53<=2] <- 1
DATA05$DEP[DATA05$v53>=3] <- 0
DATA05$DEP <- as.numeric(DATA05$DEP)
```

```
#FINAL DATA SETS
ALL <- DATA05
FEMALE <- subset(DATA05,DATA05$SEX==2)
MALE <- subset(DATA05,DATA05$SEX==1)
```

```
#Summmary Statistics
table1::label(ALL$CLASS01) <- "CLASS"
table1::label(ALL$CLASS02) <- "CLASS_SPOUSE"
table1::label(ALL$v61) <- "PCLASS"
table1(~ CLASS01 + CLASS02 + v61 + DEP + GENDER | GENDER, data =
ALL)
```

```
#### Step 3: Analysis ####
```

```
# Exercise 3.2
# Correlation between CLASS and PCLASS
round(cor(MALE$CLASS, MALE$v61, method = "spearman"), 2) # 0.45
round(cor(FEMALE$CLASS, FEMALE$v61, method = "spearman"), 2) #
0.33
```

```
# Correlation between CLASS_SPOUSE and PCLASS
round(cor(MALE$CLASS_SPOUSE, MALE$v61, method = "spearman"), 2) #
0.32
round(cor(FEMALE$CLASS_SPOUSE, FEMALE$v61, method = "spearman"),
2) # 0.27
```

```
# Correlogram
CORR_M<-subset(MALE,select=c(CLASS,v61,CLASS_SPOUSE))
```

```
corrplot(corr=cor(CORR_M, use="complete.obs", method =  
"spearman"), method="number", tl.srt = 45)  
title_1 <- "Male"  
mtext(title_1, side = 2, cex = 1.5, col = "black")
```

```
CORR_F<-subset(FEMALE,select=c(CLASS,v61,CLASS_SPOUSE))  
corrplot(corr=cor(CORR_F, use="complete.obs", method =  
"spearman"), method="number", tl.srt = 45)  
title_2 <- "Female"  
mtext(title_2, side = 2, cex = 1.5, col = "black")
```

```
# Exercise 3.3
```

```
# Generate a contingency table with social class by social class  
of partner
```

```
table(ALL$CLASS, ALL$CLASS_SPOUSE)
```

```
# Calculate the fraction of class homogeneous couples
```

```
round(sum(ALL$CLASS == ALL$CLASS_SPOUSE)/nrow(ALL), 2) # 0.43
```

```
# Calculate the fraction of couples where the man belongs to a  
higher social class than the woman
```

```
round((sum(MALE$CLASS > MALE$CLASS_SPOUSE) + sum(FEMALE$CLASS <  
FEMALE$CLASS_SPOUSE)) / nrow(ALL), 2) # 0.40
```

```
# Calculate Spearman's rank correlation coefficient between CLASS  
and CLASS_SPOUSE
```

```
round(cor(ALL$CLASS, ALL$CLASS_SPOUSE, method = "spearman"), 2) #  
0.32
```

```
# Calculate the fraction of couples where the women belongs to a  
higher social class than the men
```

```
round((sum(MALE$CLASS < MALE$CLASS_SPOUSE) + sum(FEMALE$CLASS >  
FEMALE$CLASS_SPOUSE)) / nrow(ALL), 2) # 0.17
```

```
round(cor(FEMALE$CLASS_SPOUSE, FEMALE$v61, method = "spearman"),  
2) # 0.27
```

```
# Exercise 3.4
```

```
#Linear Regression
```

```
MODEL01 <- lm(DEP ~ CLASS01 + GENDER + AGE, data = ALL)
```

```
# display the regression results
```

```
tbl_regression(MODEL01)
```

```
MODEL02 <- lm(DEP ~ CLASS01 + GENDER + AGE + CLASS02, data = ALL)
```

```

OUTPUT01 <-tbl_regression(MODEL01)
OUTPUT02 <-tbl_regression(MODEL02)
tbl_merge(tbls = list(OUTPUT01, OUTPUT02), tab_spanner =
c("Model1", "Model2"))

plot_model(MODEL02, type = "pred", terms = c("CLASS01"))

# Exercise 3.5
# Conduct the analysis by gender
MODEL03F_A <- lm(DEP ~ CLASS01 + AGE, data = FEMALE)
MODEL03F_B <- lm(DEP ~ CLASS01 + AGE + CLASS02, data = MALE)

MODEL03M_A <- lm(DEP ~ CLASS01 + AGE, data = MALE)
MODEL03M_B <- lm(DEP ~ CLASS01 + AGE + CLASS02, data = MALE)

OUTPUT03F_A <-tbl_regression(MODEL03F_A)
OUTPUT03M_A <-tbl_regression(MODEL03M_A)

OUTPUT03F_B <-tbl_regression(MODEL03F_B)
OUTPUT03M_B <-tbl_regression(MODEL03M_B)

tbl_merge(tbls = list(OUTPUT03F_A, OUTPUT03F_B), tab_spanner =
c("Own Class(Female)", "With Spouse's Class(Female)"))
tbl_merge(tbls = list(OUTPUT03M_A, OUTPUT03M_B), tab_spanner =
c("Own Class(Male)", "With Spouse's Class(Male)"))

```