



Global Workforce Modeling for South Korea

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01

Business Value



1.1 Background

Employment rates vary across countries due to multiple factors
(e.g., economic growth, health crises, demographic shifts)

Key structural factors include:

- Aging populations
- Education levels
- Healthcare infrastructure

Understanding global employment strategies can provide useful policy insights for South Korea



Objectives

Compare employment-related factors across multiple countries using data-driven methods

Evaluate how key factors influence employment outcomes

Analyze policy responses to recent global challenges (e.g., pandemics, automation)



Goal

Implications for South Korea

Derive insights to enhance Korea's employment environment

Propose strategic, data-informed policy directions

Support sustainable and resilient workforce development

1.2 Problem Definition



Problem Definition

- South Korea is facing persistently low employment rates
- This threatens economic and social stability
- Key contributing factors:
 - Aging population
 - Declining birth rates
 - Global uncertainties (e.g., pandemics, market volatility)

1.2 Problem Definition & Value Proposition

Why Comparative Analysis?

- Advanced economies offer valuable lessons in labor market resilience
- Studying countries with higher employment rates helps identify:
 - Best practices
 - Adaptable strategies for Korea

1.2 Problem Definition & Value Proposition

Project Goals

- Perform comparative analysis of labor market factors across countries
- Extract actionable insights for South Korea
- Provide policy recommendations to:
 - Boost workforce participation
 - Reduce youth unemployment
 - Strengthen labor market resilience

02

Data Overview



Data Acquisition

- Collected on Kaggle
- Source: World Bank – World Development Indicators (WDI)
- Scope: 19 advanced economies (2011–2021)
- Key variables include:
 - Employment rates
 - Education levels
 - Health infrastructure
 - Population trends
 - Youth engagement

03

Techniques

Data Preprocessing

1. Change object types to int types

```
print(df_org['Time Code'].head())
print(df_org['Time Code'].dtype)
```

```
Time
2011    YR2011
2011    YR2011
2011    YR2011
2011    YR2011
2011    YR2011
Name: Time Code, dtype: object
object
```



```
df_org['Time Code'] = df_org['Time Code'].astype(str).str.extract('(\#d+)', expand=False).astype(int)
print(df_org['Time Code'].dtype)
```

int64

2. Sort columns order

Time Code	209 non-null object
1 Country Name	209 non-null object
2 Country Code	209 non-null object
3 Current education expenditure, primary (% of total expenditure in primary public institutions) [SE.XPD.CPRM.ZS]	160 i
4 Current education expenditure, secondary (% of total expenditure in secondary public institutions) [SE.XPD.CSEC.ZS]	155 i
5 Current education expenditure, tertiary (% of total expenditure in tertiary public institutions) [SE.XPD.CTER.ZS]	165 non-n
6 Current education expenditure, total (% of total expenditure in public institutions) [SE.XPD.CTOT.ZS]	164 non-n
7 Current health expenditure (% of GDP) [SH.XPD.CHEX.GD.ZS]	209 non-null float64
8 Domestic general government health expenditure (% of GDP) [SH.XPD.GHED.GD.ZS]	209 non-null float64
9 Educational attainment, at least Bachelor's or equivalent, population 25+, female (%) (cumulative) [SE.SEC.CUAT.BA.FE.ZS]	18
10 Educational attainment, at least Bachelor's or equivalent, population 25+, male (%) (cumulative) [SE.TER.CUAT.BA.MA.ZS]	1
11 Educational attainment, at least Bachelor's or equivalent, population 25+, total (%) (cumulative) [SE.TOT.CUAT.BA.ZS]	18
12 Educational attainment, at least completed lower secondary, population 25+, female (%) (cumulative) [SE.SEC.CCUAT.LO.FE.ZS]	18
13 Educational attainment, at least completed lower secondary, population 25+, male (%) (cumulative) [SE.SEC.CUAT.LO.MA.ZS]	1
14 Educational attainment, at least completed lower secondary, population 25+, total (%) (cumulative) [SE.SEC.CUAT.LO.ZS]	1
15 Educational attainment, at least completed post-secondary, population 25+, female (%) (cumulative) [SE.SEC.CUAT.PO.FE.ZS]	18
16 Educational attainment, at least completed post-secondary, population 25+, male (%) (cumulative) [SE.SEC.CUAT.PO.MA.ZS]	18
17 Educational attainment, at least completed post-secondary, population 25+, total (%) (cumulative) [SE.SEC.CUAT.PO.ZS]	18
18 Educational attainment, at least completed primary, population 25+ years, female (%) (cumulative) [SE.PRM.CUAT.FE.ZS]	1
19 Educational attainment, at least completed primary, population 25+ years, male (%) (cumulative) [SE.PRM.CUAT.MA.ZS]	1
20 Educational attainment, at least completed primary, population 25+ years, total (%) (cumulative) [SE.PRM.CUAT.ZS]	1
21 Educational attainment, at least completed primary, population 25+ years, total [SH.MED.BEDS.ZS]	1
22 Educational attainment, at least completed short-cycle tertiary, population 25+, 2 International migrant stock (% of population) [SM.POP.TOTL.ZS]	1
23 Educational attainment, at least completed short-cycle tertiary, population 25+, 3 Net migration [SM.POP.NETM]	1
24 Educational attainment, at least completed upper secondary, population 25+, 4 Nurses and midwives (per 1,000 people) [SH.MED.NUMW.P3]	192 non-null float64
25 Educational attainment, at least completed upper secondary, population 25+, 5 Part time employment, female (% of total female employment) [SL.TLF.PART.FE.ZS]	209 non-null int64
26 Educational attainment, at least completed upper secondary, population 25+, 6 Part time employment, male (% of total male employment) [SL.TLF.PART.MA.ZS]	200 non-null float64
27 Employment in agriculture, female (% of total employment) [SL.UEM.NEET.FE.ZS]	189 non-null int64
28 Employment in agriculture, female (% of total employment) [SL.UEM.NEET.MA.ZS]	189 non-null float64
29 Employment in agriculture, male (% of total employment) [SL.UEM.NEET.FE.ZS]	189 non-null float64
30 Educational attainment, at least Master's or equivalent, population 25+, total (%) (cumulative) [SE.POP.GROW]	193 non-null float64
31 Educational attainment, Doctoral or equivalent, population 25+, female (% of total population), female (% of population) [SP.POP.TOTL.FE.ZN]	209 non-null int64
32 Educational attainment, Doctoral or equivalent, population 25+, male (% of total population), male (% of population) [SP.POP.TOTL.MA.ZN]	209 non-null int64
33 Employers, female (% of female employment) (modeled ILO estimate) [SLEM.FP.EMPF.GD.ZS]	209 non-null int64
34 Employers, male (% of male employment) (modeled ILO estimate) [SLEM.FP.EMPM.GD.ZS]	194 non-null float64
35 Employers, total (% of total employment) (modeled ILO estimate) [SLEM.FP.EPTL.GD.ZS]	181 non-null float64
36 Employment in agriculture, female (% of total employment) (modeled ILO estimate) [SLEM.FP.AGRIC.ZS]	209 non-null float64
37 Employment in agriculture, female (% of female employment) (modeled ILO estimate) [SLEM.FP.SELF.FE.ZS]	209 non-null float64
38 Employment in agriculture, male (% of male employment) (modeled ILO estimate) [SLEM.FP.SELF.MA.ZS]	209 non-null float64
39 Employment in industry (% of total employment) (modeled ILO estimate) [SLEM.FP.INDU.ZS]	209 non-null float64
40 Employment in industry, female (% of female employment) (modeled ILO estimate) [SLEM.FP.INDU.FE.ZS]	209 non-null float64
41 Employment in industry, male (% of male employment) (modeled ILO estimate) [SLEM.FP.INDU.MA.ZS]	209 non-null float64
42 Employment in services (% of total employment) (modeled ILO estimate) [SLEM.FP.SERV.ZS]	209 non-null float64
43 Employment in services, female (% of female employment) (modeled ILO estimate) [SLEM.FP.SERV.FE.ZS]	209 non-null float64
44 Employment in services, male (% of male employment) (modeled ILO estimate) [SLEM.FP.SERV.MA.ZS]	209 non-null float64
45 Employment to population ratio, 15+ (% of population) (modeled ILO estimate) [SL.DYN.RE15]	209 non-null float64
46 Employment to population ratio, 15+ (% of population) (modeled ILO estimate) [SL.DYN.RE15.ZS]	209 non-null float64
47 Employment to population ratio, 15+–total (%) (modeled ILO estimate) [SL.UEM]	209 non-null float64
48 Employment to population ratio, ages 15–24, female (%) (modeled ILO estimate) [SL.UEM]	209 non-null float64
49 Employment to population ratio, ages 15–24, male (%) (modeled ILO estimate) [SL.UEM]	209 non-null float64
50 Employment to population ratio, ages 15–24, total (%) (modeled ILO estimate) [SL.UEM]	209 non-null float64
51 Unemployment, female (% of female labor force with basic education) [SL.UEM.BASC.FE.ZS]	190 non-null float64
52 Unemployment with advanced education, female (% of female labor force with advanced education) [SL.UEM.ADVN.FE.ZS]	1
53 Unemployment with basic education, male (% of male labor force with basic education) [SL.UEM.BASC.MA.ZS]	1
54 Unemployment with intermediate education, female (% of female labor force with basic education) [SL.UEM.INTM.FE.ZS]	1
55 Unemployment with intermediate education, male (% of male labor force with basic education) [SL.UEM.INTM.MA.ZS]	1
56 Unemployment with intermediate education, female (% of female labor force with intermediate education) [SL.UEM.INTM.ZS]	209 non-null float64
57 Unemployment with intermediate education, male (% of male labor force with intermediate education) [SL.UEM.INTM.ZS]	209 non-null float64
58 Unemployment, female (% of female labor force) (modeled ILO estimate) [SL.UEM.TOTL.FE.ZS]	209 non-null float64
59 Unemployment, male (% of male labor force) (modeled ILO estimate) [SL.UEM.TOTL.MA.ZS]	209 non-null float64
60 Unemployment, total (% of total labor force) (modeled ILO estimate) [SL.UEM.TOTL.ZS]	209 non-null float64
61 Unemployment, youth female (% of female labor force ages 15–24) (modeled ILO estimate) [SL.UEM.I524.FE.ZS]	209 non-null float64
62 Unemployment, youth male (% of male labor force ages 15–24) (modeled ILO estimate) [SL.UEM.I524.MA.ZS]	209 non-null float64
63 Unemployment, youth total (% of total labor force ages 15–24) (modeled ILO estimate) [SL.UEM.I524.ZS]	209 non-null float64
64 Vulnerable employment, female (% of female employment) (modeled ILO estimate) [SL.EMP.VULN.FE.ZS]	209 non-null float64
65 Vulnerable employment, male (% of male employment) (modeled ILO estimate) [SL.EMP.VULN.MA.ZS]	209 non-null float64
66 Vulnerable employment, total (% of total employment) (modeled ILO estimate) [SL.EMP.VULN.ZS]	209 non-null float64
67 Wage and salaried workers, female (% of female employment) (modeled ILO estimate) [SLEM.WORK.FE.ZS]	209 non-null float64
68 Wage and salaried workers, male (% of male employment) (modeled ILO estimate) [SLEM.WORK.MA.ZS]	209 non-null float64
69 Wage and salaried workers, total (% of total employment) (modeled ILO estimate) [SLEM.WORK.ZS]	209 non-null float64

Education

The order of the columns corresponding to employment, health, and medical care were mixed.

Medical care & development investment

Employment

```
new_order = (
    list(range(0, 3)) + #교육
    list(range(3, 7)) +
    list(range(9, 33)) +
    list(range(69, 72)) +
    list(range(63, 66)) +
    list(range(7, 9)) + #건강
    list(range(51, 55)) + [58] +
    list(range(33, 51)) + #고용
    list(range(55, 58)) +
    list(range(66, 69)) +
    list(range(74, 94)) +
    list(range(59, 63)) + #기타
    [72, 73]
)
```



New order :

Education

Medical care &
development
investment

Employment

3. Summarize column names

```
# 열 이름 바꾸기 코드
```

```
# 열 이름에서 괄호 속 코드만 추출 후 열 이름을 코드로 바꾸기  
df_org.columns = [  
    col.split('[')[-1].replace(']', '') if '[' in col else col  
    for col in df_org.columns  
]
```

```
df_org = df_org.rename(columns={
```

```
'Time': 'Year',  
'Country Code': 'cty_code',
```

```
'SE.XPD.CPRM.ZS': 'primary_public_edu_exp',  
'SE.XPD.CSEC.ZS': 'secondary_public_edu_exp',  
'SE.XPD.CTER.ZS': 'tertiary_public_edu_exp',  
'SE.XPD.CTOT.ZS': 'T_public_edu_exp',
```

```
'SH.XPD.CHEX.GD.ZS': 'health_exp',  
'SH.XPD.GHED.GD.ZS': 'gov_health_exp',
```

```
'SE.TER.CUAT.BA.FE.ZS': 'F_bachelor_25p',  
'SE.TER.CUAT.BA.MA.ZS': 'M_bachelor_25p',  
'SE.TER.CUAT.BA.ZS': 'T_bachelor_25p',  
'SE.TER.CUAT.MS.FE.ZS': 'F_master_25p',  
'SE.TER.CUAT.MS.MA.ZS': 'M_master_25p',  
'SE.TER.CUAT.MS.ZS': 'T_master_25p',  
'SE.TER.CUAT.DO.FE.ZS': 'F_doctoral_25p',  
'SE.TER.CUAT.DO.MA.ZS': 'M_doctoral_25p',  
'SE.TER.CUAT.DO.ZS': 'T_doctoral_25p',
```

```
'SL.EMP.MPYR.FE.ZS': 'F_employers',  
'SL.EMP.MPYR.MA.ZS': 'M_employers',  
'SL.EMP.MPYR.ZS': 'T_employers',
```

```
'SL.AGR.EMPL.ZS': 'T_agriculture_emp',  
'SL.AGR.EMPL.FE.ZS': 'F_agriculture_emp',  
'SL.AGR.EMPL.MA.ZS': 'M_agriculture_emp',
```

```
'SL.IND.EMPL.ZS': 'T_industry_emp',  
'SL.IND.EMPL.FE.ZS': 'F_industry_emp',  
'SL.IND.EMPL.MA.ZS': 'M_industry_emp',
```

```
'SL.SRV.EMPL.ZS': 'T_service_emp',  
'SL.SRV.EMPL.FE.ZS': 'F_service_emp',  
'SL.SRV.EMPL.MA.ZS': 'M_service_emp',
```

```
'SL.EMP.TOTL.SP.FE.ZS': 'F_emp_ratio_15P',  
'SL.EMP.TOTL.SP.MA.ZS': 'M_emp_ratio_15P',  
'SL.EMP.TOTL.SP.ZS': 'T_emp_ratio_15P',  
'SL.EMP.1524.SP.FE.ZS': 'F_emp_ratio_15_24',  
'SL.EMP.1524.SP.MA.ZS': 'M_emp_ratio_15_24',  
'SL.EMP.1524.SP.ZS': 'T_emp_ratio_15_24',
```

```
'SH.MED.BEDS.ZS': 'hospital_beds',
```

```
'SH.MED.NUMW.P3': 'nurse_midwife_per_1K',
```

```
'SL.TLF.PART.FE.ZS': 'F_PT_emp',  
'SL.TLF.PART.MA.ZS': 'M_PT_emp',  
'SL.TLF.PART.ZS': 'T_PT_emp',
```

```
'SH.MED.PHYS.ZS': 'physicians_per_1K',
```

```
'SP.POP.GROW': 'annual_population_growth',  
'SP.POP.TOTL.FE.IN': 'F_population',  
'SP.POP.TOTL.MA.IN': 'M_population',  
'SP.POP.TOTL': 'T_population',
```

```
'GB.XPD.RSDV.GD.ZS': 'RD_expenditure',  
'SP.POP.SCIE.RD.P6': 'RD_researchers_per_1M',  
'IP.JRN.ARTC.SC': 'sci_tech_journals',
```

```
'SL.EMP.SELF.FE.ZS': 'F_self_employed',  
'SL.EMP.SELF.MA.ZS': 'M_self_employed',  
'SL.EMP.SELF.ZS': 'T_self_employed',
```

```
'SL.UEM.NEET.FE.ME.ZS': 'F_youth_NEET',  
'SL.UEM.NEET.MA.ME.ZS': 'M_youth_NEET',  
'SL.UEM.NEET.ME.ZS': 'T_youth_NEET',
```

```
'SP.DYN.T065.FE.ZS': 'F_survival_to_65',  
'SP.DYN.T065.MA.ZS': 'M_survival_to_65',
```

```
'SL.UEM.ADVN.FE.ZS': 'F_adv_edu_unemp',  
'SL.UEM.ADVN.MA.ZS': 'M_adv_edu_unemp',
```

```
'SL.UEM.BASC.ZS': 'T_basic_edu_unemp',  
'SL.UEM.BASC.FE.ZS': 'F_basic_edu_unemp',  
'SL.UEM.BASC.MA.ZS': 'M_basic_edu_unemp',
```

```
'SL.UEM.INTM.ZS': 'T_int_edu_unemp',  
'SL.UEM.INTM.FE.ZS': 'F_int_edu_unemp',  
'SL.UEM.INTM.MA.ZS': 'M_int_edu_unemp',
```

```
'SL.UEM.TOTL.FE.ZS': 'F_unemp',  
'SL.UEM.TOTL.MA.ZS': 'M_unemp',  
'SL.UEM.TOTL.ZS': 'T_unemp',
```

```
'SL.UEM.1524.FE.ZS': 'F_youth_Unemp',  
'SL.UEM.1524.MA.ZS': 'M_youth_Unemp',  
'SL.UEM.1524.ZS': 'T_youth_Unemp',
```

```
'SL.EMP.VULN.FE.ZS': 'F_vuln_emp',  
'SL.EMP.VULN.MA.ZS': 'M_vuln_emp',  
'SL.EMP.VULN.ZS': 'T_vuln_emp',
```

```
'SL.EMP.WORK.FE.ZS': 'F_paid_workers',  
'SL.EMP.WORK.MA.ZS': 'M_paid_workers',  
'SL.EMP.WORK.ZS': 'T_paid_workers'
```

```
})  
df_org.info()
```

3. Summarize column names

#	Column	Non-Null Count	Dtype	38	gov_health_exp	209	non-null	float64	81	T_youth_Unemp	209	non-null	float64	
0	Time Code	209	non-null	int64	39	hospital_beds	192	non-null	float64	82	F_vuln_emp	209	non-null	float64
1	Country Name	209	non-null	object	40	SM.POP.TOTL.ZS	19	non-null	float64	83	M_vuln_emp	209	non-null	float64
2	cty_code	209	non-null	object	41	SM.POP.NETM	209	non-null	int64	84	T_vuln_emp	209	non-null	float64
3	primary_public_edu_exp	160	non-null	float64	42	nurse_midwife_per_1K	200	non-null	float64	85	F_paid_workers	209	non-null	float64
4	secondary_public_edu_exp	155	non-null	float64	43	physicians_per_1K	193	non-null	float64	86	M_paid_workers	209	non-null	float64
5	tertiary_public_edu_exp	155	non-null	float64	44	F_employers	209	non-null	float64	87	T_paid_workers	209	non-null	float64
6	T_public_edu_exp	164	non-null	float64	45	M_employers	209	non-null	float64	88	annual_population_growth	209	non-null	float64
7	F_bachelor_25p	181	non-null	float64	46	T_employers	209	non-null	float64	89	F_population	209	non-null	int64
8	M_bachelor_25p	181	non-null	float64	47	Agriculture_emp	209	non-null	float64	90	M_population	209	non-null	int64
9	T_bachelor_25p	182	non-null	float64	48	F_agriculture_emp	209	non-null	float64	91	T_population	209	non-null	int64
10	SE.SEC.CUAT.L0.FE.ZS	192	non-null	float64	49	M_agriculture_emp	209	non-null	float64	92	F_survival_to_65	209	non-null	float64
11	SE.SEC.CUAT.L0.MA.ZS	192	non-null	float64	50	T_industry_emp	209	non-null	float64	93	M_survival_to_65	209	non-null	float64
12	SE.SEC.CUAT.L0.ZS	193	non-null	float64	51	F_industry_emp	209	non-null	float64	dtypes:	float64(87), int64(5), object(2)			
13	SE.SEC.CUAT.PO.FE.ZS	178	non-null	float64	52	M_industry_emp	209	non-null	float64					
14	SE.SEC.CUAT.PO.MA.ZS	178	non-null	float64	53	T_service_emp	209	non-null	float64					
15	SE.SEC.CUAT.PO.ZS	179	non-null	float64	54	F_service_emp	209	non-null	float64					
16	SE.PRM.CUAT.FE.ZS	189	non-null	float64	55	M_service_emp	209	non-null	float64					
17	SE.PRM.CUAT.MA.ZS	189	non-null	float64	56	F_emp_ratio_15P	209	non-null	float64					
18	SE.PRM.CUAT.ZS	190	non-null	float64	57	M_emp_ratio_15P	209	non-null	float64					
19	SE.TER.CUAT.ST.FE.ZS	191	non-null	float64	58	T_emp_ratio_15P	209	non-null	float64					
20	SE.TER.CUAT.ST.MA.ZS	191	non-null	float64	59	F_emp_ratio_15_24	209	non-null	float64					
21	SE.TER.CUAT.ST.ZS	192	non-null	float64	60	M_emp_ratio_15_24	209	non-null	float64					
22	SE.SEC.CUAT.UP.FE.ZS	192	non-null	float64	61	T_emp_ratio_15_24	209	non-null	float64					
23	SE.SEC.CUAT.UP.MA.ZS	192	non-null	float64	62	F_PT_emp	189	non-null	float64					
24	SE.SEC.CUAT.UP.ZS	193	non-null	float64	63	M_PT_emp	189	non-null	float64					
25	F_master_25p	181	non-null	float64	64	T_PT_emp	189	non-null	float64					
26	M_master_25p	181	non-null	float64	65	F_self-employed	209	non-null	float64					
27	T_master_25p	182	non-null	float64	66	M_self-employed	209	non-null	float64					
28	F_doctoral_25p	184	non-null	float64	67	T_self-employed	209	non-null	float64					
29	M_doctoral_25p	184	non-null	float64	68	F_adv_edu_unemp	198	non-null	float64					
30	T_doctoral_25p	185	non-null	float64	69	M_adv_edu_unemp	198	non-null	float64					
31	F_youth_NEET	209	non-null	float64	70	T_basic_edu_unemp	190	non-null	float64					
32	M_youth_NEET	209	non-null	float64	71	F_basic_edu_unemp	190	non-null	float64					
33	T_youth_NEET	209	non-null	float64	72	M_basic_edu_unemp	190	non-null	float64					
34	RD_expenditure	194	non-null	float64	73	T_int_edu_unemp	198	non-null	float64					
35	RD_researchers_per_1M	181	non-null	float64	74	F_int_edu_unemp	198	non-null	float64					
36	sci_tech_journals	209	non-null	float64	75	M_int_edu_unemp	198	non-null	float64					
37	health_exp	209	non-null	float64	76	F_unemp	209	non-null	float64					
				77	M_unemp	209	non-null	float64						
				78	T_unemp	209	non-null	float64						
				79	F_youth_Unemp	209	non-null	float64						
				80	M_youth_Unemp	209	non-null	float64						

The column name was too long
=> extracted the part of the column
name in [] and summarized them

4. Delete columns and rows

```
# 열 삭제 코드  
df_org = df_org[[col for col in df_org.columns if not ('.' in col and col == col.upper())]]  
df_org = df_org.drop(columns=['Country Name'])  
df_org = df_org.drop(columns=['primary_public_edu_exp'])  
df_org = df_org.drop(columns=['secondary_public_edu_exp'])  
df_org = df_org.drop(columns=['tertiary_public_edu_exp'])  
df_org = df_org.drop(columns=['RD_researchers_per_1M'])  
  
df_org.info()
```

```
# 행 삭제 코드  
#delete ARE, JPN  
  
df = df_org[~df_org['cty_code'].isin(['ARE', 'JPN'])]  
  
unique_codes = df['cty_code'].unique()  
print(unique_codes)
```

<Columns>

Country Name was removed because it was judged to overlap with cty_code

Other four columns were dropped because of high proportion of NaN values compared to other variables

<Rows>

For ARE and JPN, rows were excluded due to significant missing values in key variables.

5. Handling NaN values

If intermediate value is NaN : Linear interpolation

- estimating an unknown value between two known points by assuming the change between them is proportional and lies on the straight line connecting those points.

Country	N	Country	Current ed	Current ed	Current ed
Australia	AUS		82.07	91.2	85.8
Australia	AUS		92.54	93.41	85.8
Australia	AUS		91.62	93.55	nan
Australia	AUS		93.77	94.53	87.02
Australia	AUS		95	95.2	88.57
Australia	AUS		94.65	94.81	88.94
Australia	AUS		92.87	93.03	88.61
Australia	AUS		90.68	91.08	87.65
Australia	AUS		88.07	nan	nan
Australia	AUS		88.07275	89.6356	88.90058
Australia	AUS		88.25725	90.01973	91.07644

Ex : Australia

```
#linear interpolation
interpolation_cols = ['T_public_edu_exp', 'F_bachelor_25p', 'T_bachelor_25p',
                     'M_bachelor_25p', 'F_master_25p', 'M_master_25p', 'T_master_25p', 'F_doctoral_25p', 'M_doctoral_25p', 'T_doctoral_25p',
                     'RD_expenditure', 'hospital_beds', 'F_PT_emp', 'M_PT_emp', 'T_PT_emp']
df_AUS[interpolation_cols] = df_AUS[interpolation_cols].interpolate(method='linear', limit_direction='both')
```

List of columns need to be interpolated

Linear interpolate

```
# df0|| update Update to original df
```

```
mask = df['cty_code'] == 'AUS'
df_subset_sorted = df.loc[mask].sort_values(by='Time Code')
df.loc[df['cty_code'] == 'AUS', interpolation_cols] = df_AUS[interpolation_cols].values
```

5. Handling NaN values

If consecutive values are NaN :

Values that do not exist consecutively

Belgium	BEL			96.95709	96.38167
Belgium	BEL				
Belgium	BEL	91.94972	96.82653	95.64908	94.40839
Belgium	BEL	94.19771	96.02022	95.57105	95.17557
Belgium	BEL	94.31854	96.11328	95.01249	94.96034
Belgium	BEL	93.75147	95.20866	95.0459	94.44009
Belgium	BEL	93.9427	96.27853	95.09343	94.87132
Belgium	BEL	93.32632	96.67049	94.50184	94.55085
Belgium	BEL	94.57438	96.71211	92.54103	94.64889
Belgium	BEL	95.05326	96.2519	93.39079	94.85588
Belgium	BEL	95.60983	96.38616	93.65329	95.2353

First, we fill in the missing values consecutively using ffill (forward fill) and bfill (backward fill). This step is used to first fill in the default values for long missing intervals where linear interpolation is difficult to work with.

After that, use polynomial interpolation with order=2 is used to interpolate the values that are interrupted in the middle, more naturally.

```
df_BEL['interpolation_cols'] = df_BEL['interpolation_cols'].replace(0, np.nan)
df_BEL['interpolation_cols'] = df_BEL['interpolation_cols'].fillna(method='ffill').fillna(method='bfill')
df_BEL['interpolation_cols'] = df_BEL['interpolation_cols'].interpolate(method='polynomial', order=2)
```



Visualization by Key Items

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

# 고용 변수
employment_vars = [
    'F_employers', 'M_employers', 'T_employers',
    'T_agriculture_emp', 'F_agriculture_emp', 'M_agriculture_emp',
    'T_industry_emp', 'F_industry_emp', 'M_industry_emp',
    'T_service_emp', 'F_service_emp', 'M_service_emp',
    'F_emp_ratio_15P', 'M_emp_ratio_15P', 'T_emp_ratio_15P',
    'F_emp_ratio_15_24', 'M_emp_ratio_15_24', 'T_emp_ratio_15_24',
    'F_PT_emp', 'M_PT_emp', 'T_PT_emp',
    'F_self-employed', 'M_self-employed', 'T_self-employed',
    'F_unemp', 'M_unemp', 'T_unemp',
    'F_adv_edu_unemp', 'M_adv_edu_unemp',
    'F_basic_edu_unemp', 'M_basic_edu_unemp', 'T_basic_edu_unemp',
    'T_int_edu_unemp', 'F_int_edu_unemp', 'M_int_edu_unemp',
    'F_unemp', 'M_unemp', 'T_unemp',
    'F_youth_Unemp', 'M_youth_Unemp', 'T_youth_Unemp',
    'F_vuln_emp', 'M_vuln_emp', 'T_vuln_emp',
    'F_paid_workers', 'M_paid_workers', 'T_paid_workers',
    'F_youth_NEET', 'M_youth_NEET', 'T_youth_NEET',
]
```

```
# 교육 변수
education_vars = [
    'T_public_edu_exp', 'F_bachelor_25p', 'M_bachelor_25p', 'T_bachelor_25p',
    'F_master_25p', 'M_master_25p', 'T_master_25p',
    'F_doctoral_25p', 'M_doctoral_25p', 'T_doctoral_25p',
    'RD_expenditure', 'sci_tech_journals'
]

# 건강 변수
health_vars = [
    'health_exp', 'gov_health_exp', 'hospital_beds',
    'physicians_per_1K', 'nurse_midwife_per_1K'
]

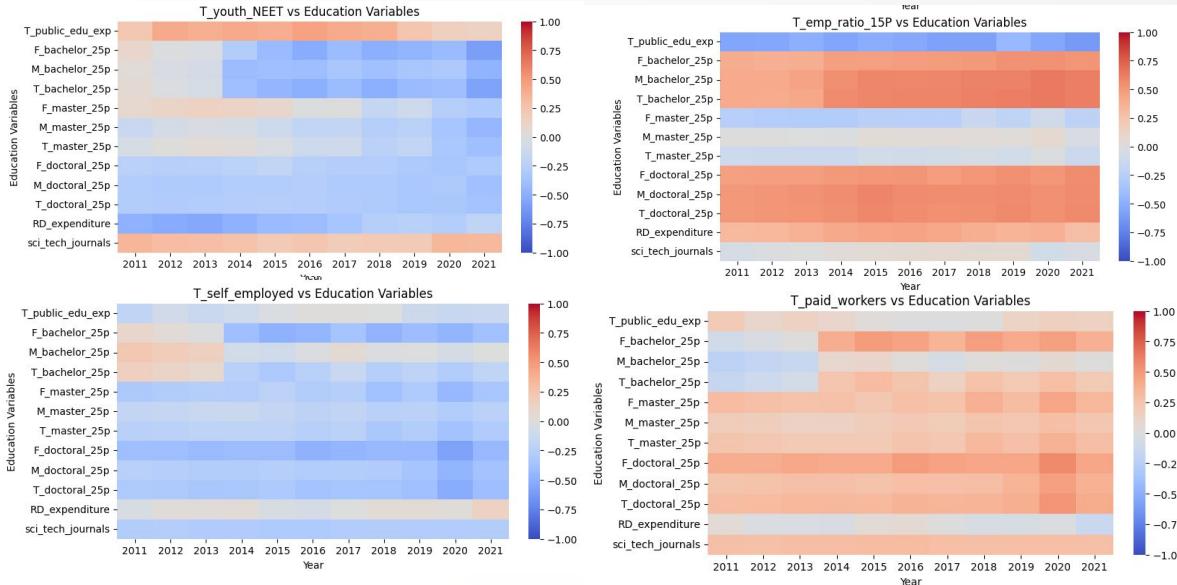
# 인구 변수
ppl_vars = [
    'annual_population_growth', 'F_population', 'M_population', 'T_population',
    'F_survival_to_65', 'M_survival_to_65'
]
```

By categorizing variables, the relationship between employment and key indicators – education, health, and population structure – is visualized in a heat map.

Based on insights from the heat map, we also created bar chart to make clearer comparison of the relationships.



Visualization by Key Items : education and employment

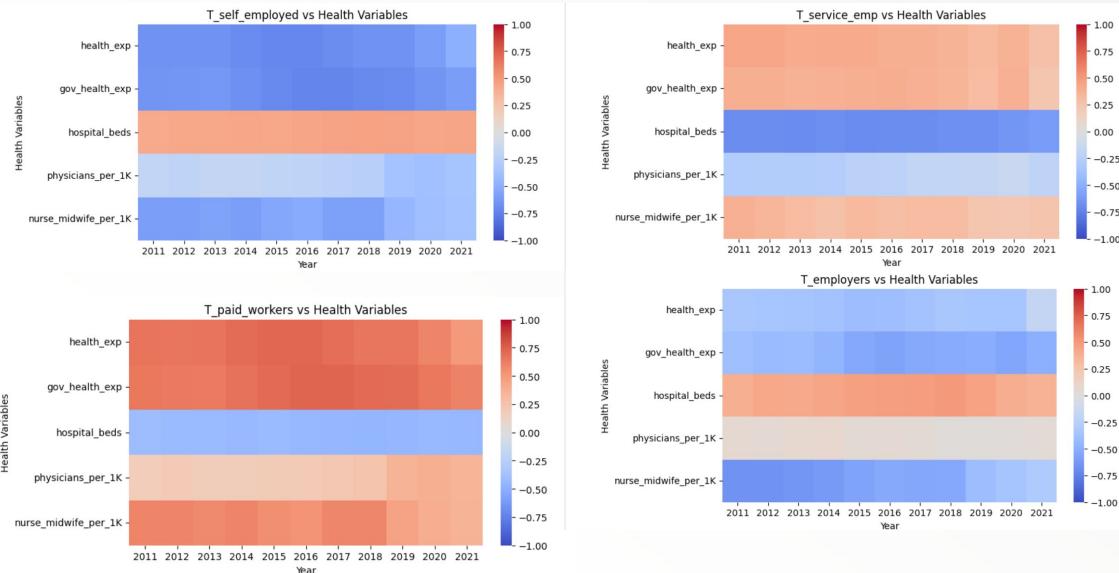


T_bachelor and T_doctoral showed positive correlation with T_emp_ratio_15P and T_paid_workers but negative correlation with T_self-employed and T_youth_NEET.

<Part of Heatmap>



Visualization by Key Items : health and employment

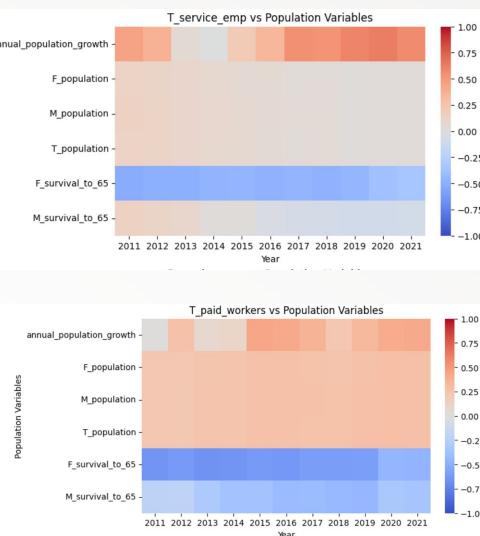
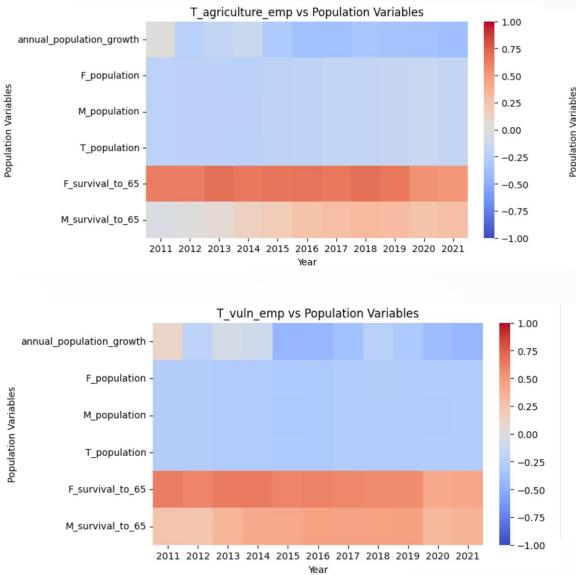


Health_exp, gov_health_exp, nurse_midwife_per_1k showed positive correlation with T_paid_workers and T_service_emp but negative correlation with T_self_employed and T_employers.

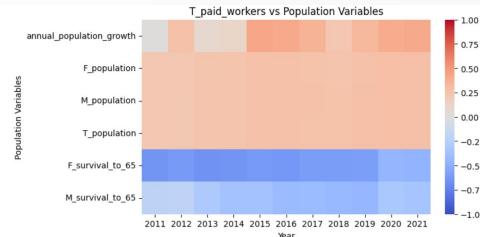
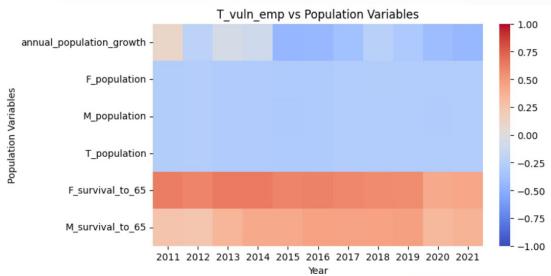
<Part of Heatmap>



Visualization by Key Items : population structure and employment



F_survival_to_65 showed positive correlation with **T_agriculture_emp** and **T_vuln_emp** while negative correlation with **T_service_emp** and **T_paid_workers**.

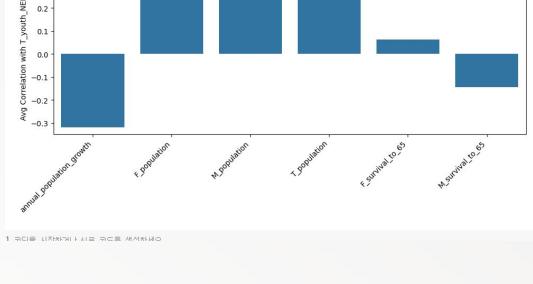
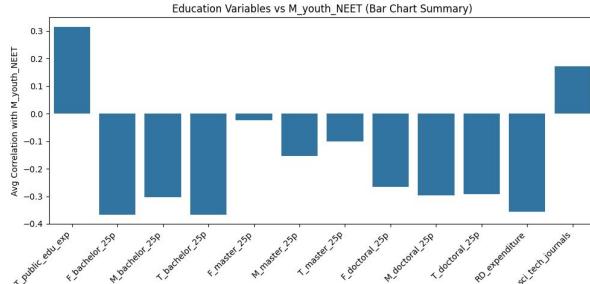
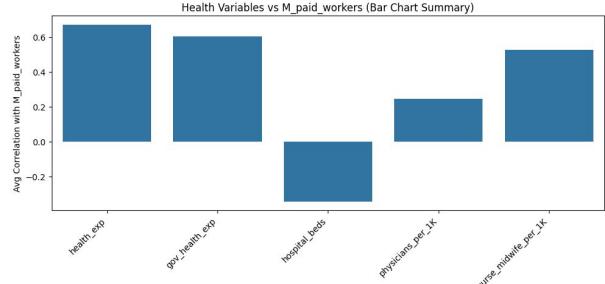
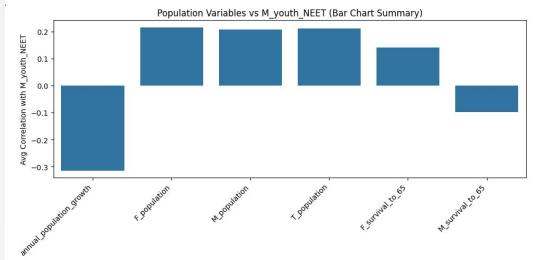
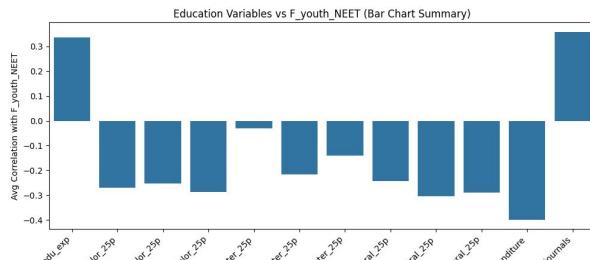
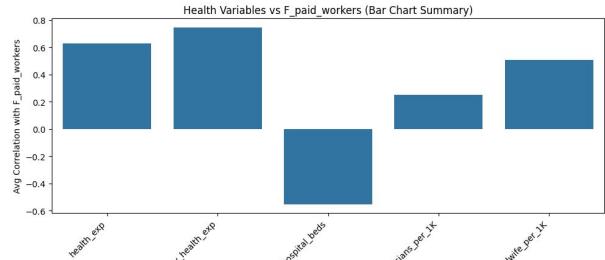


<Part of Heatmap>



Visualization by Key Items

: bar chart



<Par of bar chart>

Based on heatmaps,
we generated a correlation bar chart.

04

Model Training



Input Variables

Output Variable

- T_public_edu_exp	- health_expgov_health_exp	- Employers, total
- F_bachelor_25p	- hospital_beds	
- M_bachelor_25p	- physicians_per_1K	
- T_bachelor_25p	- nurse_midwife_per_1K	
- F_master_25p	- annual_population_growth	
- M_master_25p	- F_population	
- T_master_25p	- M_population	
- F_doctoral_25p	- T_population	
- M_doctoral_25p	- F_survival_to_65	
- T_doctoral_25p	- M_survival_to_65	
- RD_expenditure		
- sci_tech_journals		

Modeling Overview

A regression analysis model was used to predict and analyze the number of employees using multinational data to predict the employment rate.

Modeling Used

-  XGBoost Regressor

Evaluation metrics

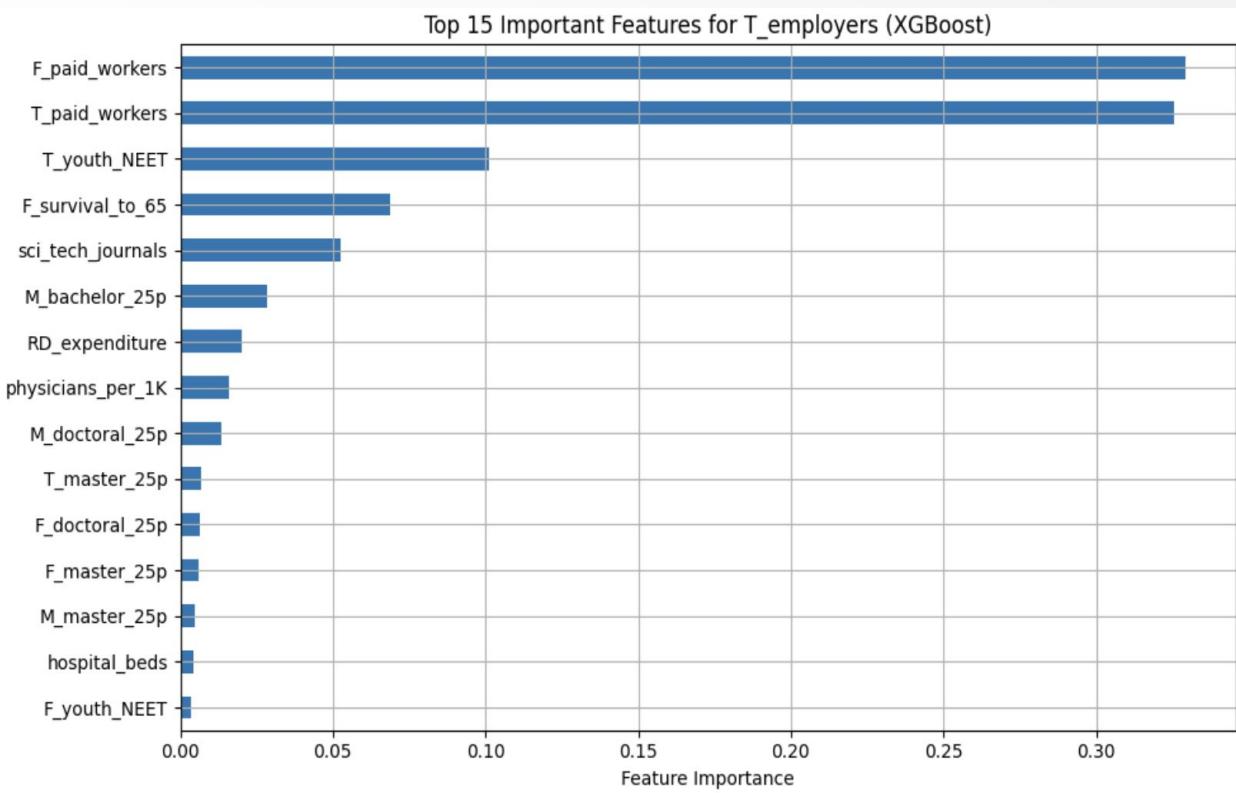
- R2: Coefficient of determination
- MSE: Mean squared error
- RMSE: Root mean squared error

 XGBoost 결과
R² : 0.9274
MSE : 0.1754
RMSE : 0.4188

Result of evaluation

- R2: 0.9274
- MSE: 0.1754
- RMSE: 0.4188

visoration feature importance



Top 3

1. **F_paid_workers**

(the percentage of female paid workers)

2. **T_paid_workers**

(the total percentage of paid workers)

3. **T_youth_NEET**

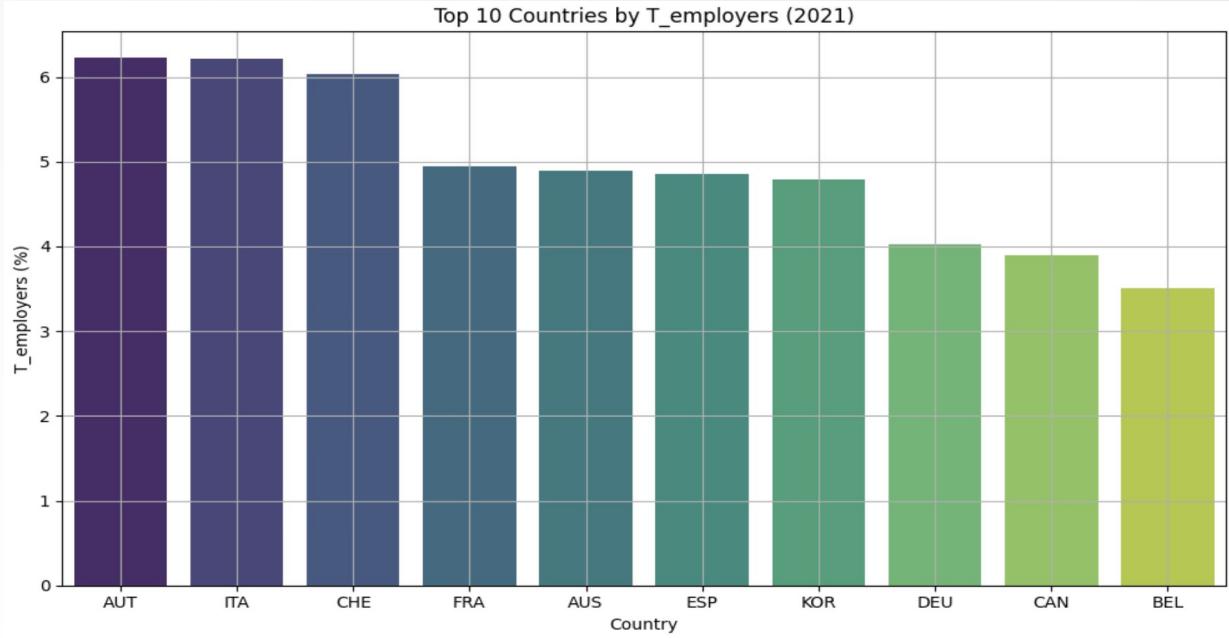
(the proportion of young people not in education, employment, or training)



Top 3 comparison with High Employment Rate Countries

Countries with high employment

cty_code	T_employers
171	AUT 6.223794
178	ITA 6.212315
184	CHE 6.029100
176	FRA 4.941700
170	AUS 4.890054
182	ESP 4.858276
179	KOR 4.792589
177	DEU 4.027615
173	CAN 3.891236
172	BEL 3.501276



Top10

1. Austria
2. Italia
3. Switzerland
4. France
5. Australia
6. Spain
7. Korea
8. Germany
9. Canada
10. Belgium

1. F_paid_workers (the percentage of female paid workers)



💔 The number of female paid workers is the lowest compared to other top countries. This can be seen from statistical data that Korea's female employment rate has been ranked 31st in the OECD for 20 years, that is, in the lower ranks.

💔 **Policy implications:** Policy efforts to address this include minimizing career breaks for women, promoting their return to work after childbirth and childcare, and implementing flexible work systems to create a more stable labor market for women.

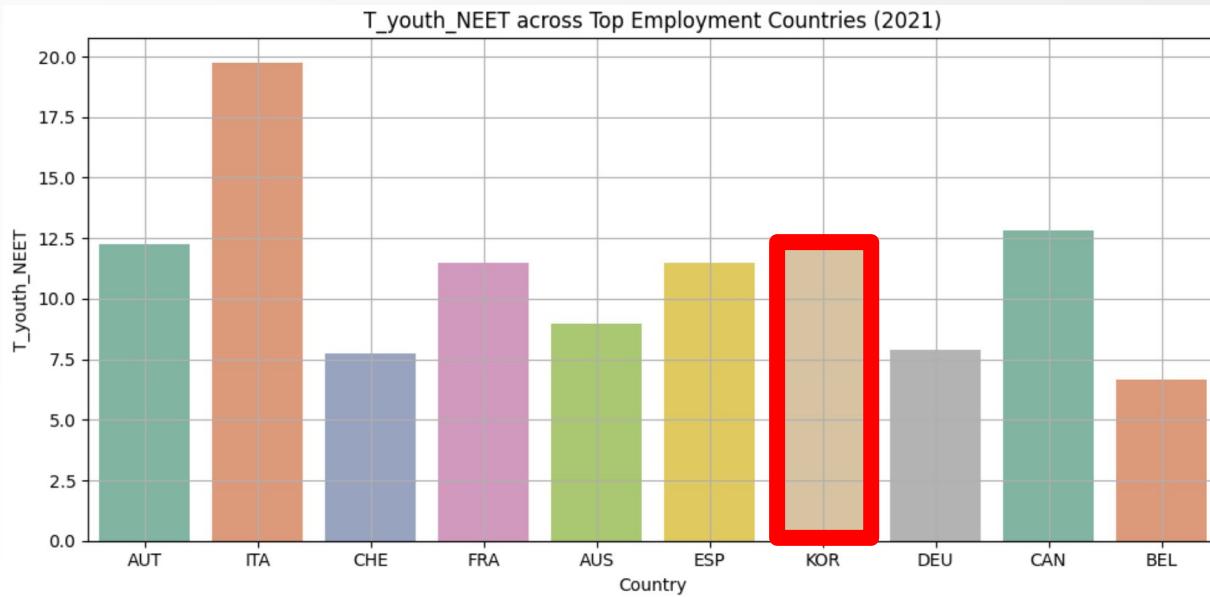
2. T_paid_workers (the total percentage of paid workers)



👉 The lowest compared to other top countries. The low rate can be seen as a large proportion of self-employed and non-wage workers.

👉 **Policy Implications:** To expand the number of paid workers, policies such as increasing regular employment opportunities and offering incentives to companies for hiring should be implemented.

3. T_youth_NEET (the proportion of young people in NEET)



📌 Higher than average. Higher knit rates mean weaker future labor market inflows, which have a long-term negative impact on T_employers.

📌 **Policy Implications:** Need to induce employment of young people and strengthen career education, internships, and vocational training



Final Conclusion

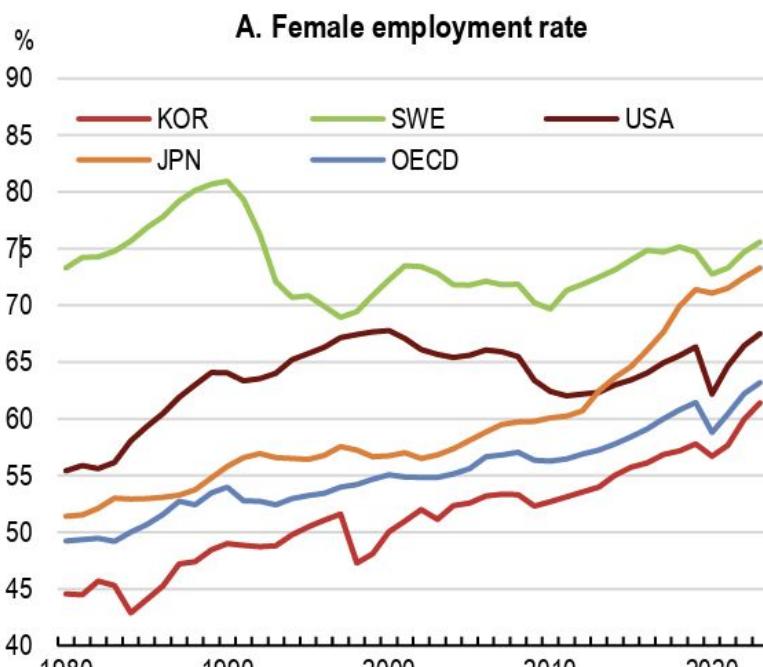
<Policy Recommendations to Improve Korea's Employment Rate>

- Low ratio of paid female workers -> Create policies to support women's postpartum career breaks and guarantee parental leave
 - Low ratio of paid workers -> Promote full-time employment and introduce corporate incentives
 - High youth NEET rate -> Strengthen career education and vocational training programs
- 

05

Insights

F_paid_workers



Female employment has increased over time in South Korea and most OECD countries

However,

According to the OECD, South Korea ranked 31st out of 38 OECD countries in female employment rate in 2023, with a rate of 61.4%, compared to the OECD average of 63.2%.

- Note: Employment rates for 15-64-year-olds. Source: OECD, Labour Force Statistics (database).

F_paid_workers

Marriage and childbirth reduce women's employment



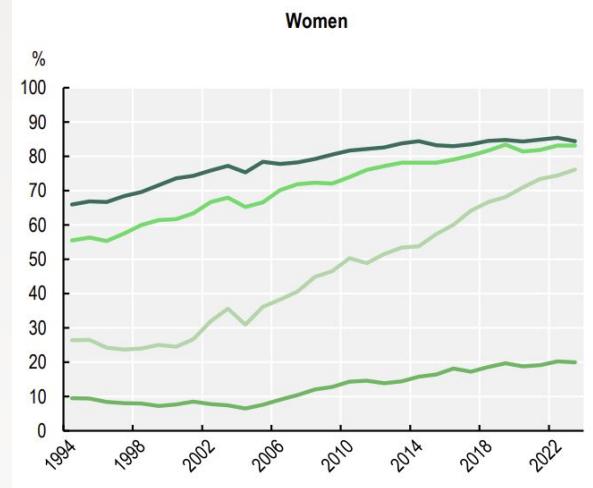
Studies analyzing women's employment from a life-course perspective indicate that, unlike the OECD average, South Korea's female employment pattern continues to follow a traditional '**M-shaped**' curve. This pattern is largely attributed to women exiting the workforce due to **marriage and childcare responsibilities**.

"To expand female employment to the levels seen in advanced nations, it is necessary to focus policy efforts on enabling women to better balance work and family life, allowing them to participate more actively in the economy."

F_paid_workers in Austria

Employment rate (%)		2019	2020	2021	2022	2023
Total	Austria	73.6	72.4	72.4	74	74.1
	EU 27	68.4	67.5	68.3	69.8	70.4
Male	Austria	78	76.5	76.7	78	77.9
	EU 27	73.8	72.8	73.3	74.7	75.1
Female	Austria	69.2	68.3	68.1	70	70.3
	EU 27	63.1	62.2	63.3	64.9	65.7

Source: Eurostat (European Union statistics)



Source: OECD, Labour Force Statistics (database).

Female employment rate in Austria for individuals aged 15–64 is 70.3% and approximately 66.6% as of 2023, according to the Eurostat and OECD respectively.

Austria's relatively high female employment is supported by **strong family policies**; parental leave, childcare facilities, and part-time work options, which aim to **support women returning from career breaks**.

Studying how these policies enhance female employment can provide lessons for South Korea.

Austrian Policies Supporting Women Returning from Career Breaks

1. Wiedereingliederungszeit (Phased Reintegration Part-Time Scheme)

- A time-limited part-time work scheme to support gradual return to work after long-term sick leave
- Working hours can be reduced by 25–50%, for up to 9 months
- Particularly useful for women returning after health issues, childbirth, or childcare leave

Korean Relevance:

- Similar policies exist in Korea, such as flexible work hours and part-time job options
- The concept of "phased return" could be integrated with childcare-related return-to-work programs
- Expected impact: reduces re-entry burden, prevents labor market exit, lowers turnover

2. Qualifizierungsförderung für Beschäftigte (Training Support for Employees)

- Subsidy program for companies to cover up to 50% of training and wage costs
- Targets low-skilled workers and women aged 50+
- Helps employed women improve skills and access promotion opportunities

Korean Relevance:

- Korea already runs similar programs via the employment insurance fund, e.g., employer-led training and National Learning Cards (내일배움)
- Could be restructured to specifically support women and mid-career workers
- Expected impact: prevents career break during employment, enables job transition, strengthens women's career development

3. Fachkräftestipendium (Skilled Worker Scholarship)

- Financial support for full-time retraining (up to 4 years) in shortage occupations (e.g., nursing, technical fields)
- Includes both tuition and living costs
- Especially beneficial for women seeking long-term stable employment and income growth

Korean Relevance:

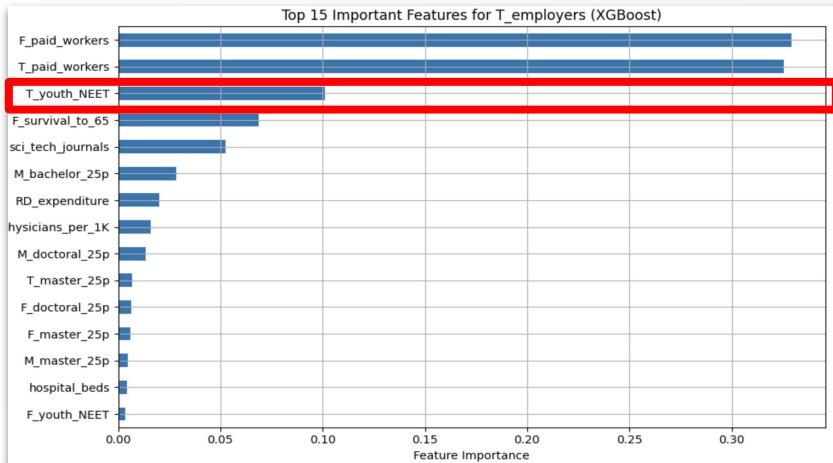
- Similar programs: National Strategic Industry Training, K-Digital Training, nursing assistant programs
- However, living cost support is still limited in Korea
- Could help low-income and career-break women transition into professional roles and address aging workforce needs

Implications for South Korea's Women Returning from Career Breaks Policies

Given that Korea already has partial equivalents, the focus should be on strategic restructuring, not full replication:

1. Institutionalize phased return-to-work schemes, with incentives for companies to participate
2. Restructure training subsidies to be targeted at women and mid-career employees
3. Enhance professional retraining scholarships to include living expense support

T_youth_NEET



According to the Feature Importance Plot, T_youth_NEET (Not in Employment, Education, or Training) which is a Labor Market Efficiency Indicator was the third highest important feature.

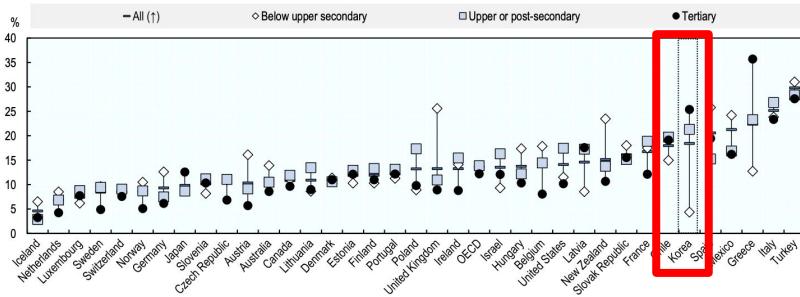
Why does high youth NEET rate matter?

- It signals poor school-to-work transitions and inefficiencies in labor and education systems.
- Long-term NEETs risk falling into poverty, social isolation, and mental health issues.
- It also burdens public welfare and reduces national economic potential.
- Weakens trust in social mobility and delays life transitions (marriage, home, children).

Characteristics of NEET in Korea

Figure 1.5. Korean college or university graduates are more likely to be NEETs than their lower-educated peers

A. Share of youth neither employed nor attending formal education (2017 or latest available), by highest educational attainment



Characteristics:

- NEET rate in Korea: 20% (2019), well above the OECD average (13.4%).
- 45% of NEETs are university graduates where in most countries, it is centered on the low-educated class
- Particularly high among youth aged 25–29 and women.

Key Causes:

- Prolonged job preparation (e.g., public sector exams, extra credentials)
- Mismatch between education and job market needs
- Overconcentration in higher education and large firm preference

Shift in NEET Composition & Policy Implications

Characteristics:

- According to Korea Employment Information Service (KEIS)'s report [계간]2025 봄호 고용이슈, it categorized NEET youth into six types: job seekers, education preparers, caregivers, non-job-seekers, those with physical or mental health issues, and those awaiting military enlistment.
- Of these, only the **“non-job-seeking” group** increased in size, suggesting that many youth are not actively engaged in career planning or training at all.
- The challenge is not only helping NEET youth find jobs, but also **re-engaging those who have stopped looking entirely**
- Government should develop integrated, personalized **policies to build psychological resilience and strengthen career readiness.**



Key Lessons from the UK NEET Re-engagement Pilots

Characteristics:

- The UK Department for Education's report, "*What Works Re-engaging Young People Who Are Not in Education, Employment or Training (NEET)*" (DFE-RR065), provides valuable insights into effective strategies for re-engaging NEET youth

Personalized Support with Dedicated Advisers

- Each participant was assigned a dedicated adviser who provided continuous guidance and support throughout the program.
- This individualized approach helped build trust and address specific barriers faced by each young person

Focus on 'Soft Outcomes'

- Beyond employment or educational placements, the programs aimed to improve participants' confidence, motivation, and social skills.
- These soft outcomes were crucial in preparing youth for sustained engagement in work or education.

Flexibility and Tailored Interventions

- The programs were designed to be flexible, allowing for adjustments based on individual needs and circumstances.
- This adaptability ensured that interventions remained relevant and effective for diverse participants.

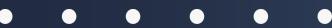


Implications for South Korea's NEET Policies

- While the UK's NEET Re-engagement Pilots focused primarily on youth aged 16–18, applying the same model directly to South Korea may be ineffective, as approximately 45% of NEETs in South Korea are university graduates. Therefore, any intervention must be tailored to address the specific characteristics of the older, more educated NEET population.

Implement Personalized Support Systems

- Assign dedicated advisers or mentors to NEET youth to provide continuous, individualized guidance.
- Develop personalized action plans that address specific barriers and goals for each participant.
- Establish integrated mental health and career support systems such as services centers at universities or community hubs to provide psychological counseling, career coaching, and employment services in a single location



Implications for South Korea's NEET Policies

Emphasize Soft Skill Development

- Incorporate activities that build confidence, communication skills, and resilience.
- Recognize and measure improvements in soft skills as key indicators of program success.

Strengthen Industry-academia partnerships

- Expanding Field Internships to Shorten Job Preparation Time
- Financial incentives and recognition in university evaluations are necessary to encourage company participation.

THANK YOU FOR LISTENING !

Do you have any questions?

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