Technological employment and gender inequalities: the contrasting effects of progress on female unemployment in France, Spain, Italy, Netherland and Belgium

Spatial Econometrics - Master EADE - EUR ELMI

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1 Introduction

Female employment remains a major issue in the European labor market, raising many questions about gender equality. Despite progress in education and women's professional integration, disparities persist, particularly in technological sectors. Automation, digitalization, and innovation are reshaping employment structures, creating new opportunities while reinforcing certain inequalities (Autor, Dorn & Hanson, 2015). Access to technology sectors offers job prospects, yet women remain underrepresented (Blau & Kahn, 2017). The rise of science and technology skills does not always benefit female employment due to structural barriers and male dominance in high-value-added positions (Bertrand, 2018).

This study aims to analyze these dynamics through a spatial econometric approach, identifying the direct and indirect effects of technological variables on female unemployment. The analysis focuses on Western Europe, specifically five countries: France, Spain, Italy, the Netherlands, and Belgium. This selection allows for a comparison of economies with different industrial structures and employment policies while sharing a common economic and social context.

Requirements

For this study, several R libraries are required to process spatial data, estimate models, and present results.

```r
library(sf)
library(plm)
library(splm)
library(sp)
library(spdep)
library(dplyr)
library(ggplot2)
library(lmtest)
library(modelsummary)
library(plm)
library(stargazer)
library(tidyr)
```

2 Data

2.1 Variable selection

The female unemployment rate reflects women's employment levels in Western Europe. Its evolution depends on various economic and social factors. First, the rise of technological sectors creates opportunities for women due to more flexible conditions and an increased demand for digital skills (Goldin, 2014). However, these jobs remain male-dominated, limiting their impact (Bertrand, 2018).

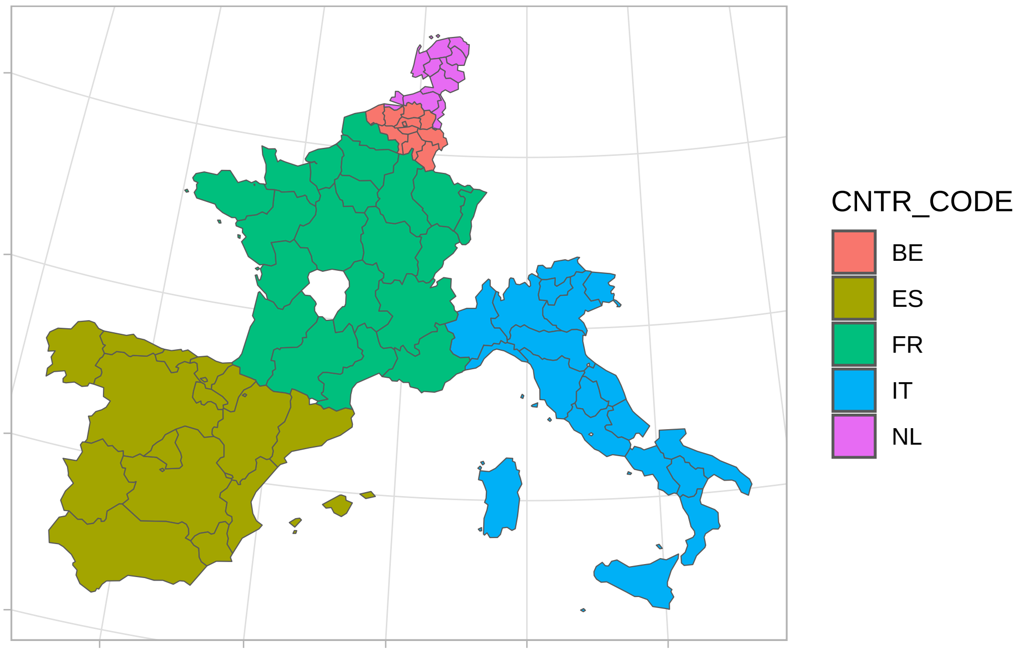
Second, worker qualifications play a crucial role. An increase in human resources in science and technology (HRST) intensifies competition and complicates women's access to skilled jobs, especially if they are underrepresented (Blau & Kahn, 2017). Moreover, GDP growth can reduce female unemployment by creating jobs (González et al., 2019). However, its effect remains limited if opportunities are concentrated in sectors with low female participation. Additionally, higher education levels promote female employment by facilitating access to well-paid positions, particularly in high-value-added sectors (Psacharopoulos & Patrinos, 2018).

Finally, population density influences employment. Urbanization multiplies opportunities but also increases competition, creating an uncertain impact on female unemployment (Glaeser, 2011).

2.2 Data preparaion

The dataset used in this study originates from Eurostat and was compiled into a single dataset (`data.csv`) using Python. The data preparation process begins with cleaning the main dataset, removing missing values, and ensuring that numerical variables are in the correct format. Only regions from France, Spain, Belgium, Italy, and the Netherlands are retained, covering the period 2012-2021.

Geographical data is then integrated from a shapefile containing the contours of European regions (NUTS 2). The map is adjusted to focus on Western Europe, and economic and spatial information is merged for analysis. Finally, a map of the studied regions is generated to visualize the sample.



2.3 Description of the data

2.3.1 Dataset Overview

The dataset contains 770 observations across 12 variables, covering multiple European regions. Each observation represents a region-year pair, capturing socio-economic and demographic trends from 2012 to 2020. It includes five countries: Belgium (BE), Spain (ES), France (FR), Italy (IT), and the Netherlands (NL).

Regional and Temporal Identification:

- `id`: Unique identifier for each region
- `year`: Year of the observation.
- `country`: Country of the region.
- `geo`: Full regional name (e.g., "Région de Bruxelles-Capitale/Brussels Hoofdstedelijk").

Economic and Employment Indicators:

- `female_unemp`: Female unemployment rate.
- `tech_employment`: Share of workers in technology-related sectors.
- `HRST`: Percentage of the workforce in science and technology.

- `regional_GDP`: Regional GDP in thousands of euros.
- `higher_edu`: Share of the population with higher education.

Demographic and Population Density Indicators:

- `log_pop_density`: Log-transformed population density for statistical normalization.

2.3.2 Descriptive Statistics

The average female unemployment rate is 11.6%, with a standard deviation of 6.87%. This indicates differences in employment conditions across regions. The average tech employment rate is 3.32%, suggesting a small share of the workforce in high-tech sectors. Regional GDP averages 77.6 K€, but the high standard deviation (95 K€) reveals significant economic disparities.

```
Rows: 770
Columns: 12
$ id              <chr> "BE10", "BE10", "BE10", "BE10", "BE10", "BE10", "BE10~
$ year            <int> 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020,~
$ country         <chr> "BE", "BE", "BE", "BE", "BE", "BE", "BE", "BE", "BE",~
$ geo             <chr> "Région de Bruxelles-Capitale/Brussels Hoofdstedelijk~
$ employment_15_64 <dbl> 54.0, 52.5, 54.3, 54.2, 55.3, 56.2, 56.8, 56.9, 56.5,~
$ female_unemp    <dbl> 16.7, 17.0, 16.1, 15.8, 16.0, 14.7, 11.8, 12.5, 12.8,~
$ tech_employment <dbl> 7.0, 5.6, 6.3, 6.2, 5.8, 6.1, 7.4, 6.6, 6.6, 7.6, 5.7~
$ HRST            <dbl> 52.7, 51.7, 53.6, 53.1, 54.1, 57.3, 58.9, 58.1, 60.7,~
$ regional_GDP    <dbl> 73.30012, 74.15148, 76.04918, 78.88248, 80.09173, 82.~
$ higher_edu      <dbl> 42.7, 41.5, 43.5, 43.4, 44.1, 46.6, 47.5, 47.1, 49.3,~
$ pop_density     <dbl> 7194.2, 7260.7, 7319.4, 7408.0, 7454.6, 7421.6, 7471.~
$ log_pop_density <dbl> 8.881030, 8.890232, 8.898284, 8.910316, 8.916587, 8.9~
```

```
Descriptive stats
===========================================================
Statistic              N   Mean   St. Dev.  Min      Max
-----------------------------------------------------------
pdata.female_unemp    770 11.622   6.868    2.500   38.000
pdata.tech_employment 770  3.323   1.638    0.800    9.900
pdata.HRST            770 43.288   8.503    25.700  70.500
pdata.regional_GDP    770 77.590   94.848   6.156   758.004
pdata.higher_edu      770 30.845   9.761    12.400  59.700
pdata.pop_density     770 320.866 839.470   25.500 7,560.800
-----------------------------------------------------------
```

2.4 Data Visualization

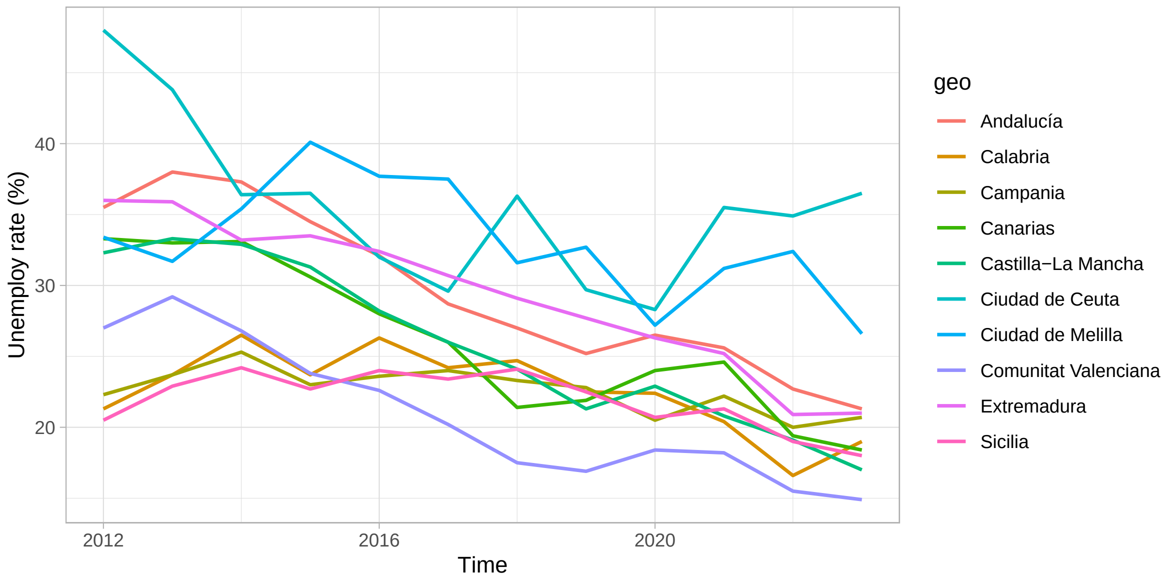
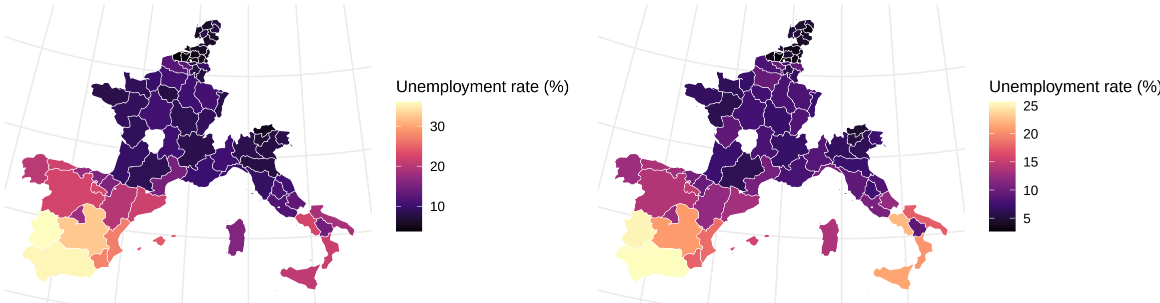


Figure 1: Evolution of Female unemployment in the 10 most affected regions (2021)

Certain regions, particularly Ciudad de Ceuta and Ciudad de Melilla, display significant fluctuations, suggesting structural instability in the female labor market.

Several factors may explain these variations. On one hand, economic transformation and digital advancements have facilitated women's access to specific jobs, especially in sectors less dependent on manual labor. On the other hand, the persistence of high unemployment in some regions may result from sectoral imbalances, where female employment remains concentrated in vulnerable sectors (tourism, services, public administration)

Between 2012 and 2021, female unemployment decreased in Western Europe. The most affected regions in 2012, notably in Spain and Italy, experienced improvements. Despite this decline, inequalities persist, with Southern Europe remaining more exposed to female unemployment. This trend can be attributed to multiple factors. Economic recovery post-2008 led to job creation. Some sectors, such as technology, provided new opportunities. However, regions reliant on tourism or low-skilled jobs (e.g., Andalusia) continue to struggle. Reducing disparities will depend on inclusion policies and local economic dynamics.



(a) 2012 (b) 2021

Figure 2: Female unemployment rate by region

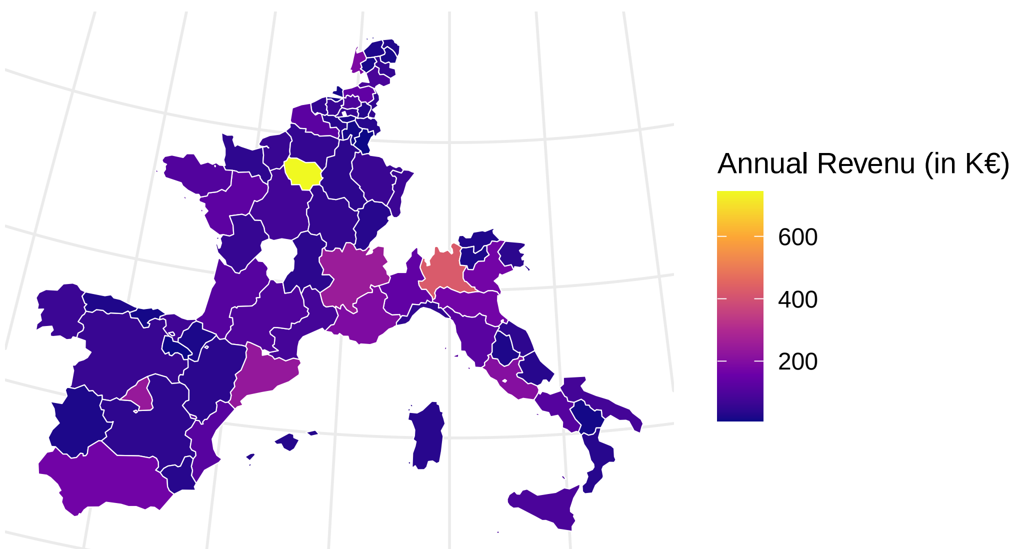


Figure 3: Regional GDP distribution (2021)

This map illustrates that the wealthiest regions are concentrated around major metropolitan areas, particularly Île-de-France and Northern Italy. In Spain and Italy, the south exhibits lower GDP levels, confirming economic disparities. These differences influence female unemployment. Wealthy regions offer more stable and high-quality jobs, whereas low-GDP areas remain dependent on precarious sectors such as tourism and agriculture. This explains why economic growth alone is insufficient to reduce female unemployment.

3 Spatial models estimation

This section defines the econometric method and prepares the dataset for analysis. The model examines the effects of technological employment, science and technology workforce, regional GDP, higher education, and population density on female unemployment. The dataset is structured as a panel to capture variations across regions and over time.

```
formula <- female_unemp ~ tech_employment + HRST + regional_GDP +
                          higher_edu + pop_density
```

```
Balanced Panel: n = 77, T = 10, N = 770
```

3.1 Spatial Weighted matrix (W)

To begin the analysis, we define the spatial weight matrix. This matrix is built using the Queen contiguity method, which considers two regions as neighbors if they share at least one point on their borders.

First, we construct the initial neighbor list and convert it into a spatial weight matrix (`W`) using row-standardization. Regions without neighbors are identified and removed to ensure proper connectivity. A new weight matrix is then created for the filtered dataset.

The final matrix includes 73 regions and 308 nonzero links, with an average of 4.22 neighbors per region. The weights are row-standardized, meaning each row sums to one. This ensures comparability across regions while maintaining the relative importance of spatial interactions.

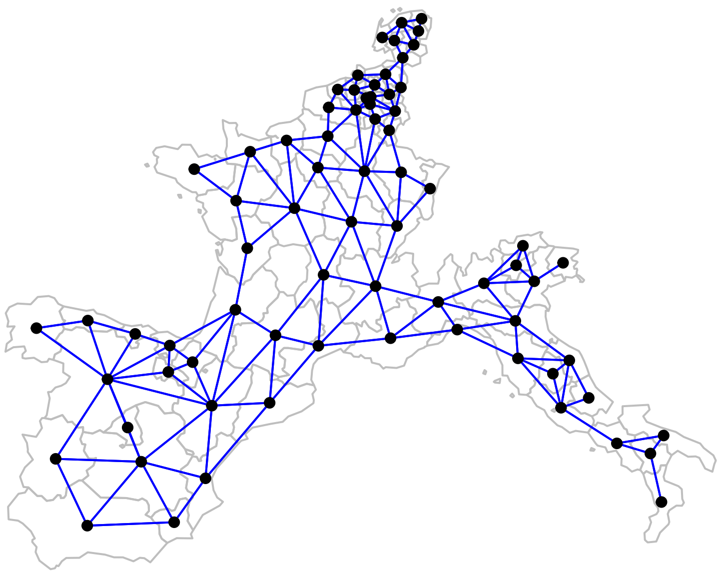


Figure 4: Spatial neighboring wtructure with Queen contiguity matrix

3.2 Non-spatial models

3.2.1 Panel data Tests

```
====== BP Test : OLS vs FE/RE ======


    Lagrange Multiplier Test - (Breusch-Pagan)

data:  formula
chisq = 1504, df = 1, p-value < 2.2e-16
alternative hypothesis: significant effects
```

	Pooled (OLS)	Individual Fixed effects	Time Fixed effects	Twoway Fixed effects	Ra
(Intercept)	50.735***				
	(1.073)				
tech_employment	0.490***	0.536***	0.439***	0.564***	
	(0.131)	(0.160)	(0.129)	(0.144)	
HRST	−1.877***	−0.657***	−1.850***	−0.573***	
	(0.052)	(0.083)	(0.051)	(0.073)	
regional_GDP	0.010***	−0.029**	0.010***	−0.003	
	(0.002)	(0.010)	(0.002)	(0.009)	
higher_edu	1.279***	0.105	1.282***	0.447***	
	(0.040)	(0.078)	(0.039)	(0.077)	
pop_density	0.001***	0.006	0.001***	0.003	
	(0.000)	(0.005)	(0.000)	(0.004)	
Num.Obs.	730	730	730	730	
R2	0.686	0.428	0.686	0.094	
R2 Adj.	0.684	0.360	0.680	−0.027	
AIC	3987.2	2791.7	3941.8	2569.0	
BIC	4019.3	2819.3	3969.4	2596.6	
RMSE	3.68	1.62	3.57	1.39	

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

```
====== F Test : FE vs OLS ======


    F test for individual effects

data:  formula
F = 37.388, df1 = 72, df2 = 652, p-value < 2.2e-16
alternative hypothesis: significant effects


===== LR Test : Twoway vs Indiv =====

Likelihood ratio test

Model 1: female_unemp ~ tech_employment + HRST + regional_GDP + higher_edu +
    pop_density
Model 2: female_unemp ~ tech_employment + HRST + regional_GDP + higher_edu +
    pop_density
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   6 -1964.9
2   6 -1278.5  0 1372.8  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


====== Hausman Test : FE vs RE ======


    Hausman Test

data:  formula
chisq = 538.44, df = 5, p-value < 2.2e-16
alternative hypothesis: one model is inconsistent
```

Econometric tests show that the OLS model is not suitable due to the presence of specific effects (Breusch-Pagan, $p < 2.2e\text{-}16$). The F-test confirms that individual fixed effects are significant ($p < 2.2e\text{-}16$). An additional F-test supports the use of a two-way fixed effects model ($p < 2.2e\text{-}16$), which accounts for both individual and time-specific effects. Finally, the Hausman test rejects the random effects hypothesis, confirming that the fixed effects model is the best approach.

3.2.2 Spatial Hausman Tests

```
====== Spatial Hausman Test : FE vs RE - SEM ======


    Hausman test for spatial models

data:  x
chisq = 42.732, df = 5, p-value = 4.188e-08
alternative hypothesis: one model is inconsistent


====== Spatial Hausman Test : FE vs RE - SAR ======


    Hausman test for spatial models

data:  x
chisq = 2103.2, df = 5, p-value < 2.2e-16
alternative hypothesis: one model is inconsistent
```

The results of the spatial Hausman tests show that random effects models are not suitable for the data. In both specifications, the hypothesis that random effects produce consistent estimates is rejected. This means that fixed effects are preferable because they better account for unobserved heterogeneity between spatial units. Thus, the two-way fixed effects model is the best choice.

3.2.3 Robust Spatial LM Tests

```
OLS ============================


    Locally robust LM test for spatial lag dependence sub spatial error

data:  formula
LM = 7.069, df = 1, p-value = 0.007843
alternative hypothesis: spatial lag dependence
```

```
	Locally robust LM test for spatial error dependence sub spatial lag

data:  formula
LM = 4.7604, df = 1, p-value = 0.02912
alternative hypothesis: spatial error dependence



Twoway FE ======================


	Locally robust LM test for spatial lag dependence sub spatial error

data:  formula (within transformation)
LM = 16.852, df = 1, p-value = 4.041e-05
alternative hypothesis: spatial lag dependence


	Locally robust LM test for spatial error dependence sub spatial lag

data:  formula (within transformation)
LM = 0.65396, df = 1, p-value = 0.4187
alternative hypothesis: spatial error dependence



Individual FE ==================


	Locally robust LM test for spatial lag dependence sub spatial error

data:  formula (within transformation)
LM = 122.92, df = 1, p-value < 2.2e-16
alternative hypothesis: spatial lag dependence


	Locally robust LM test for spatial error dependence sub spatial lag

data:  formula (within transformation)
LM = 10.32, df = 1, p-value = 0.001316
alternative hypothesis: spatial error dependence
```

```
Time FE ========================


    Locally robust LM test for spatial lag dependence sub spatial error

data:  formula (within transformation)
LM = 2.7948, df = 1, p-value = 0.09457
alternative hypothesis: spatial lag dependence


    Locally robust LM test for spatial error dependence sub spatial lag

data:  formula (within transformation)
LM = 2.3756, df = 1, p-value = 0.1232
alternative hypothesis: spatial error dependence



RE =============================


    Locally robust LM test for spatial lag dependence sub spatial error

data:  formula (random transformation)
LM = 96.129, df = 1, p-value < 2.2e-16
alternative hypothesis: spatial lag dependence


    Locally robust LM test for spatial error dependence sub spatial lag

data:  formula (random transformation)
LM = 1.1247, df = 1, p-value = 0.2889
alternative hypothesis: spatial error dependence
```

The tests indicate that OLS and random effects (RE) models are not suitable, as the assumption of spatial independence is rejected in all cases. The individual fixed effects model captures the data structure better because it shows strong spatial dependence in both the dependent variable and the errors. The twoway fixed effects model also shows dependence in the dependent variable but not in the errors, making it more stable.

The twoway fixed effects model is the most appropriate. It reduces bias related to heterogeneity and does not exhibit spatial dependence in the errors. Using a spatial autoregressive (SAR) model could improve the analysis. Additionally, a spatial Durbin model (SDM) might be relevant if there is dependence in the explanatory variables.

3.3 Spatial econometrics models

```r
pool_model <- spml(formula, data = pdata, listw = W, lag = FALSE,
                   model = "pooling")

sem_model <- spml(formula, data = pdata, listw = W, spatial.error = "b",
                  model = "within", effect = "twoway")

sar_model <- spml(formula, data = pdata, listw = W, lag = TRUE, model = "within",
                  effect = "twoway", spatial.error ="none")

sac_model <- spgm(formula, data = pdata, listw = W, listw2 = W, model = "within",
                  lag = TRUE, spatial.error = TRUE, moments = "fullweights")

models <- list(
   "Pooled OLS" = pool_model,
   "SEM FE" = sem_model,
   "SAR FE" = sar_model,
   "SAC FE" = sac_model
)
table <- combine_models(models)
mod_sumsum(table, format = "latex")
```

We focus on the impact of technology, represented by tech_employment and HRST. Several models were tested to find the best way to capture these effects while considering regional interactions.

A fixed-effects model with a spatial component was necessary. The SAC FE model included spatial effects in both the dependent variable and the error. However, the coefficient for spatial autocorrelation in errors (rho) was not significant. This means the error structure adds no useful information. A model with spatial dependence only in the dependent variable is more appropriate. The SAR FE model fits best.

In this model, the lambda spatial lag coefficient is 0.4781 (47.81%). This shows that almost 48% of female unemployment in one region depends on unemployment in neighboring regions. A one percentage point increase in unemployment in nearby regions leads to a 0.478 percentage point rise in local female unemployment. This spatial effect is statistically significant, proving

Term	Pooled OLS	SEM FE	SAR FE	SAC FE
(Intercept)	49.5215 ***	NA	NA	NA
tech_employment	0.5928 ***	0.4244 ***	0.4891 ***	0.3121 ***
HRST	-1.8376 ***	-0.4533 ***	-0.4759 ***	-0.2401 ***
regional_GDP	0.0087 ***	0.0081	0.0027	-0.0047
higher_edu	1.2537 ***	0.3689 ***	0.3942 ***	0.1824 ***
pop_density	8e-04 ***	-0.0025	-0.0012	-0.0028
Log-Likelihood	-1973.4622	-2573.3488	-1200.2887	
AIC	3958.9244	5158.6977	2412.5773	
BIC	3986.4827	5186.2559	2440.1356	
Observations	730	730	730	730
rho	NA	0.4906 ***	NA	NA
lambda	NA	NA	0.4781 ***	0.9613 ***

the advantage of a spatial model over a classical one. The SAR FE model also has a much higher log-likelihood than the others, confirming a better fit.

4 Results

4.1 SAR Fixed effects

```
Spatial panel fixed effects lag model


Call:
spml(formula = formula, data = pdata, listw = W, model = "within",
    effect = "twoway", lag = TRUE, spatial.error = "none")

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-4.371773 -0.772307 -0.039121  0.660303  5.989786

Spatial autoregressive coefficient:
       Estimate Std. Error t-value  Pr(>|t|)
lambda  0.47805    0.03633  13.159 < 2.2e-16 ***

Coefficients:
                  Estimate Std. Error t-value  Pr(>|t|)
tech_employment  0.4890839  0.1175655  4.1601 3.181e-05 ***
HRST            -0.4759307  0.0594769 -8.0019 1.225e-15 ***
regional_GDP     0.0026982  0.0073301  0.3681    0.7128
higher_edu       0.3942082  0.0632621  6.2314 4.624e-10 ***
pop_density     -0.0011553  0.0033332 -0.3466    0.7289
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The analysis shows that higher unemployment in neighboring regions directly increases local unemployment. This confirms the existence of spatial spillover effects. Regional labor markets are interconnected due to worker mobility, economic exchanges, and the geographic concentration of industries. Since lambda is below 1, spatial transmission alone does not fully explain female unemployment. Local factors still play a key role.

The tech_employment variable has a coefficient of -0.4891. A 1% increase in tech employment reduces female unemployment by 0.489 percentage points. This suggests that tech job growth creates new opportunities for women, offering more flexible working conditions and better inclusion in certain sectors.

However, HRST has a negative coefficient . A 1% rise in the number of skilled workers in science and technology decreases female unemployment by 0.476 percentage points. This result may seem contradictory. It likely reflects stronger competition in the labor market, limiting women's access to highly specialized jobs. In some industries, higher qualification levels do not directly benefit women, especially where entry barriers remain high.

4.2 Direct, indirect, totel effects

```
Impact measures (lag, trace):
                     Direct      Indirect        Total
tech_employment  0.524497048  0.4125420107  0.937039059
HRST            -0.510391485 -0.4014473104 -0.911838795
regional_GDP     0.002893556  0.0022759204  0.005169477
higher_edu       0.422751659  0.3325143963  0.755266055
pop_density     -0.001238984 -0.0009745198 -0.002213503
========================================================
Simulation results ( variance matrix):
Direct:

Iterations = 1:200
Thinning interval = 1
Number of chains = 1
Sample size per chain = 200

1. Empirical mean and standard deviation for each variable,
   plus standard error of the mean:

                      Mean       SD  Naive SE Time-series SE
tech_employment  0.5251234 0.121429 0.0085864      0.0085864
HRST            -0.5018446 0.063647 0.0045005      0.0045005
regional_GDP     0.0030858 0.007394 0.0005228      0.0005981
higher_edu       0.4141295 0.068198 0.0048223      0.0035577
pop_density     -0.0007561 0.003389 0.0002396      0.0002396

2. Quantiles for each variable:

                     2.5%       25%       50%       75%     97.5%
tech_employment  0.312038  0.443990  0.525700  0.610107  0.771130
HRST            -0.623890 -0.544975 -0.502384 -0.459062 -0.379051
regional_GDP    -0.009878 -0.002654  0.003391  0.007979  0.017532
higher_edu       0.291613  0.368803  0.410229  0.460152  0.540632
pop_density     -0.006917 -0.002738 -0.000948  0.001380  0.006428

========================================================
Indirect:
```

```
Iterations = 1:200
Thinning interval = 1
Number of chains = 1
Sample size per chain = 200

1. Empirical mean and standard deviation for each variable,
   plus standard error of the mean:

                     Mean       SD  Naive SE Time-series SE
tech_employment  0.422113 0.117792 0.0083292      0.0083292
HRST            -0.403390 0.081155 0.0057385      0.0057385
regional_GDP     0.002577 0.005980 0.0004229      0.0004692
higher_edu       0.332696 0.075406 0.0053320      0.0053320
pop_density     -0.000630 0.002787 0.0001971      0.0001971

2. Quantiles for each variable:

                     2.5%       25%        50%       75%     97.5%
tech_employment  0.218155  0.333931  0.4140972  0.499071  0.660424
HRST            -0.590592 -0.452247 -0.4065372 -0.350252 -0.251291
regional_GDP    -0.007399 -0.002031  0.0027524  0.006240  0.014377
higher_edu       0.194002  0.285760  0.3311514  0.370697  0.503648
pop_density     -0.005889 -0.002244 -0.0007296  0.001155  0.004933

========================================================
Total:

Iterations = 1:200
Thinning interval = 1
Number of chains = 1
Sample size per chain = 200

1. Empirical mean and standard deviation for each variable,
   plus standard error of the mean:

                     Mean       SD  Naive SE Time-series SE
tech_employment  0.947236 0.232234 0.0164214      0.0164214
HRST            -0.905235 0.136129 0.0096258      0.0096258
regional_GDP     0.005663 0.013336 0.0009430      0.0010648
higher_edu       0.746826 0.136591 0.0096584      0.0074077
pop_density     -0.001386 0.006159 0.0004355      0.0004355
```

```
2. Quantiles for each variable:

                   2.5%       25%       50%       75%    97.5%
tech_employment  0.53355  0.765685  0.948445  1.114202  1.38291
HRST            -1.21217 -0.982659 -0.907470 -0.813471 -0.64681
regional_GDP    -0.01731 -0.004888  0.006209  0.014115  0.03192
higher_edu       0.49668  0.661136  0.735274  0.835268  1.04582
pop_density     -0.01284 -0.005090 -0.001702  0.002567  0.01170
```

In this section, the impact of explanatory variables is broken down into three components: **direct** (the effect of a change in a variable on female unemployment in the same region), **indirect** (the effect on neighboring regions), and **total** (the sum of both) effects.

Tech employment (`tech_employment`) significantly reduces female unemployment. A 1% increase in tech jobs lowers female unemployment by 0.52 percentage points locally and by 0.41 points in neighboring regions. The total effect reaches 0.94 points. This confirms that the tech sector supports female employment both locally and regionally. These findings align with previous studies (Autor, Dorn & Hanson, 2015), which show that tech industry growth creates job opportunities for women, particularly in digital and high-value service sectors. The rise of tech jobs leads to new tasks requiring specialized skills, often accessible to underrepresented groups. Additionally, remote work and flexible jobs in tech improve women's labor market participation (Goldin, 2014).

On the other hand, `HRST` has a negative and significant impact on female unemployment. A 1% increase in highly skilled workers in science and technology raises female unemployment by 0.51 percentage points locally and by 0.4 points in neighboring regions, with a total impact of 0.91 points. This may seem counterintuitive. The rise in skilled workers intensifies competition for high-value jobs. If access inequalities persist, women may struggle to secure new opportunities (Blau & Kahn, 2017). Studies show that STEM (Science, Technology, Engineering and Mathematics) fields remain male-dominated despite diversity efforts (Bertrand, 2018). In some regions, a growing number of skilled workers may even widen inequalities, as demand for specialized skills benefits those already well-integrated into the job market.

Control variables show more moderate effects. Regional GDP (`regional_GDP`) has a minimal impact on female unemployment, with a total effect of just 0.005 percentage points. This suggests that economic growth alone does not significantly reduce female unemployment. Higher education (`higher_edu`) has a stronger effect. A 1 %ge point increase in higher education levels reduces female unemployment by 0.42 percentage points locally and by 0.33 points in neighboring regions, for a total impact of 0.75 points. This confirms that education is key to improving women's employment prospects. Population density (`pop_density`) has a negligible effect, close to zero.

These results highlight several policy challenges for governments and businesses. The growth of tech jobs must be accompanied by initiatives that improve women's access to these sectors. Digital and tech skills training should be strengthened, with a focus on young girls from secondary school onwards. Companies should promote equal opportunities to ensure fair access to skilled positions. Regarding the rise in science and technology skills, policies must prevent stronger competition from further excluding women. Finally, the weak impact of economic growth on female unemployment suggests that targeted policies are needed to address employment inequalities rather than relying solely on overall labor market trends.

5 Conclusion and discution

The study examines the impact of technological progress on female employment in France, Spain, Italy, the Netherlands, and Belgium. It finds that a 1% increase in tech employment reduces female unemployment by 0.52 points locally and 0.41 points in neighboring regions, showing positive spillover effects. However, a 1% rise in highly skilled STEM workers increases female unemployment by 0.51 points locally and 0.4 points in nearby areas, likely due to stronger competition. Economic growth alone has a limited effect, while higher education helps lower female unemployment by 0.42 points. Population density has little impact. The study confirms strong regional interdependencies, emphasizing the need for policies that enhance women's access to STEM education, promote gender diversity in tech sectors, and support female entrepreneurship. While technology creates opportunities, targeted actions are necessary to ensure women fully benefit from labor market transformations.

6 References

- Autor, D., Dorn, D., & Hanson, G. (2015). "*Untangling Trade and Technology: Evidence from Local Labor Markets.*" American Economic Review, 105(5), 214-219.
- Bertrand, M. (2018). "*The Glass Ceiling.*" Economica, 85(338), 15-41.
- Blau, F. D., & Kahn, L. M. (2017). "*The Gender Wage Gap: Extent, Trends, and Explanations.*" Journal of Economic Literature, 55(3), 789-865.
- Glaeser, E. L. (2011). "*Triumph of the City: How Our Greatest Invention Makes Us Richer, Smarter, Greener, Healthier, and Happier.*" Penguin Press.
- Goldin, C. (2014). "*A Grand Gender Convergence: Its Last Chapter.*" American Economic Review, 104(4), 1091-1119.
- González, L., de la Rica, S., & Dolado, J. J. (2019). "*The Impact of Economic Growth on Gender Employment Gaps: A European Perspective.*" European Economic Review, 113, 1-20.
- Psacharopoulos, G., & Patrinos, H. A. (2018). "*Returns to Investment in Education: A Decennial Review of the Global Literature.*" Education Economics, 26(5), 445-458.