

```

1 !pip install linearmodels
2 import pandas as pd
3 import statsmodels.api as sm
4 import statsmodels.formula.api as smf
5 from linearmodels.panel import PanelOLS
6 from linearmodels.panel import compare

```

Collecting linearmodels

Downloading linearmodels-6.1-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (7.9 kB)

Requirement already satisfied: numpy<3,>=1.22.3 in /usr/local/lib/python3.10/dist-packages (from linearmodels) (1.26.4)

Requirement already satisfied: pandas>=1.4.0 in /usr/local/lib/python3.10/dist-packages (from linearmodels) (2.2.2)

Requirement already satisfied: scipy>=1.8.0 in /usr/local/lib/python3.10/dist-packages (from linearmodels) (1.13.1)

Requirement already satisfied: statsmodels>=0.13.0 in /usr/local/lib/python3.10/dist-packages (from linearmodels) (0.14.4)

Collecting mypy_extensions>=0.4 (from linearmodels)

Downloading mypy_extensions-1.0.0-py3-none-any.whl.metadata (1.1 kB)

Requirement already satisfied: cython>=3.0.10 in /usr/local/lib/python3.10/dist-packages (from linearmodels) (3.0.11)

Collecting pyhdfe>=0.1 (from linearmodels)

Downloading pyhdfe-0.2.0-py3-none-any.whl.metadata (4.0 kB)

Collecting formulaic>=1.0.0 (from linearmodels)

Downloading formulaic-1.0.2-py3-none-any.whl.metadata (6.8 kB)

Collecting setuptools_scm<9.0.0,>=8.0.0 (from setuptools_scm[toml]<9.0.0,>=8.0.0->linearmodels)

Downloading setuptools_scm-8.1.0-py3-none-any.whl.metadata (6.6 kB)

Collecting interface-meta>=1.2.0 (from formulaic>=1.0.0->linearmodels)

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Requirement already satisfied: typing_extensions>=4.2.0 in /usr/local/lib/python3.10/dist-packages (from formulaic>=1.0.0->linearmodels)

Requirement already satisfied: wrapt>=1.0 in /usr/local/lib/python3.10/dist-packages (from formulaic>=1.0.0->linearmodels) (1.16.0)

Requirement already satisfied: python_dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.4.0->linearmodels) (2.8.2)

Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.4.0->linearmodels) (2024.2)

Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.4.0->linearmodels) (2024.2)

Requirement already satisfied: packaging>=20 in /usr/local/lib/python3.10/dist-packages (from setuptools_scm<9.0.0,>=8.0.0->setuptools_scm)

Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages (from setuptools_scm<9.0.0,>=8.0.0->setuptools_scm)

Requirement already satisfied: tomli>=1 in /usr/local/lib/python3.10/dist-packages (from setuptools_scm<9.0.0,>=8.0.0->setuptools_scm)

Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.10/dist-packages (from statsmodels>=0.13.0->linearmodels) (1.0.1)

Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python_dateutil>=2.8.2->pandas>=1.4.0->linearmodels)

Downloading linearmodels-6.1-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (1.7 MB)

1.7/1.7 MB 17.1 MB/s eta 0:00:00

Downloading formulaic-1.0.2-py3-none-any.whl (94 kB)

94.5/94.5 kB 6.2 MB/s eta 0:00:00

Downloading mypy_extensions-1.0.0-py3-none-any.whl (4.7 kB)

Downloading pyhdfe-0.2.0-py3-none-any.whl (19 kB)

Downloading setuptools_scm-8.1.0-py3-none-any.whl (43 kB)

43.7/43.7 kB 2.6 MB/s eta 0:00:00

Downloading interface_meta-1.3.0-py3-none-any.whl (14 kB)

Installing collected packages: setuptools_scm, mypy_extensions, interface-meta, pyhdfe, formulaic, linearmodels

Successfully installed formulaic-1.0.2 interface-meta-1.3.0 linearmodels-6.1 mypy_extensions-1.0.0 pyhdfe-0.2.0 setuptools_scm-8.1.0

```

1 url = 'https://www.qogdata.pol.gu.se/data/qog_bas_ts_jan24.xlsx'
2 data = pd.read_excel(url)
3 data.head()

```

| | ccode | cname | year | ccode_qog | cname_qog | ccodealp | ccodecow | version | cname_year | ccodealp_year | ... | wdi_trade | wdi_unem |
|---|-------|-------------|------|-----------|-------------|----------|----------|---------------|---------------------|---------------|-----|-----------|----------|
| 0 | 4 | Afghanistan | 1946 | 4 | Afghanistan | AFG | 700.0 | QoGBasTSjan24 | Afghanistan 1946 | AFG46 | ... | NaN | |
| 1 | 4 | Afghanistan | 1947 | 4 | Afghanistan | AFG | 700.0 | QoGBasTSjan24 | Afghanistan 1947 | AFG47 | ... | NaN | |
| 2 | 4 | Afghanistan | 1948 | 4 | Afghanistan | AFG | 700.0 | QoGBasTSjan24 | Afghanistan 1948 | AFG48 | ... | NaN | |
| 3 | 4 | Afghanistan | 1949 | 4 | Afghanistan | AFG | 700.0 | QoGBasTSjan24 | Afghanistan 1949 | AFG49 | ... | NaN | |
| 4 | 4 | Afghanistan | 1950 | 4 | Afghanistan | AFG | 700.0 | QoGBasTSjan24 | Afghanistan 1950 | AFG50 | ... | NaN | |

5 rows × 251 columns

```

1 #Prepare the data by dropping rows with missing values in relevant columns
2 regression_data = data[['wdi_birth', 'wdi_unempyfilo', 'year']].dropna()

```

- Due to the complexity of variables such as birth rate and female unemployment, there is a high chance that we will end up not finding anything significant or that there are significant confounding factors that we cannot see due to the simplicity of the OLS model.

```

1 #Run a naive OLS regression on your time series data. Tell me how you expect your Xs to affect your Y and why. Interpret your results.
2 #naive OLS regression with year fixed effects
3 ols_model = smf.ols(formula='wdi_unempyfilo ~ wdi_birth + C(year)', data=regression_data).fit()
4 ols_model.summary()

```



OLS Regression Results

| | | | |
|--------------------------|------------------|----------------------------|-----------|
| Dep. Variable: | wdi_unempyfilo | R-squared: | 0.050 |
| Model: | OLS | Adj. R-squared: | 0.044 |
| Method: | Least Squares | F-statistic: | 9.095 |
| Date: | Mon, 18 Nov 2024 | Prob (F-statistic): | 5.08e-41 |
| Time: | 22:30:17 | Log-Likelihood: | -21920. |
| No. Observations: | 5430 | AIC: | 4.390e+04 |
| Df Residuals: | 5398 | BIC: | 4.411e+04 |
| Df Model: | 31 | | |

Covariance Type: nonrobust

| | coef | std err | t | P> t | [0.025 | 0.975] |
|-----------------------|----------|--------------------------|----------|-------|--------|--------|
| Intercept | 23.7271 | 1.217 | 19.495 | 0.000 | 21.341 | 26.113 |
| C(year)[T.1992] | -0.6397 | 1.532 | -0.418 | 0.676 | -3.643 | 2.364 |
| C(year)[T.1993] | 0.2892 | 1.524 | 0.190 | 0.849 | -2.698 | 3.277 |
| C(year)[T.1994] | 0.6213 | 1.524 | 0.408 | 0.684 | -2.367 | 3.609 |
| C(year)[T.1995] | 0.8799 | 1.525 | 0.577 | 0.564 | -2.109 | 3.869 |
| C(year)[T.1996] | 1.2269 | 1.525 | 0.805 | 0.421 | -1.762 | 4.216 |
| C(year)[T.1997] | 1.0214 | 1.525 | 0.670 | 0.503 | -1.969 | 4.011 |
| C(year)[T.1998] | 0.7866 | 1.526 | 0.516 | 0.606 | -2.204 | 3.777 |
| C(year)[T.1999] | 0.9716 | 1.526 | 0.637 | 0.524 | -2.020 | 3.963 |
| C(year)[T.2000] | 0.7015 | 1.526 | 0.460 | 0.646 | -2.290 | 3.693 |
| C(year)[T.2001] | 0.7971 | 1.527 | 0.522 | 0.602 | -2.196 | 3.790 |
| C(year)[T.2002] | 0.9987 | 1.525 | 0.655 | 0.512 | -1.990 | 3.988 |
| C(year)[T.2003] | 1.4179 | 1.525 | 0.930 | 0.353 | -1.572 | 4.407 |
| C(year)[T.2004] | 1.2677 | 1.525 | 0.831 | 0.406 | -1.722 | 4.258 |
| C(year)[T.2005] | 0.8276 | 1.525 | 0.543 | 0.587 | -2.163 | 3.818 |
| C(year)[T.2006] | 0.5769 | 1.522 | 0.379 | 0.705 | -2.406 | 3.560 |
| C(year)[T.2007] | -0.2288 | 1.522 | -0.150 | 0.881 | -3.212 | 2.755 |
| C(year)[T.2008] | -0.3235 | 1.522 | -0.213 | 0.832 | -3.307 | 2.660 |
| C(year)[T.2009] | 1.0962 | 1.522 | 0.720 | 0.471 | -1.888 | 4.080 |
| C(year)[T.2010] | 1.5755 | 1.522 | 1.035 | 0.301 | -1.409 | 4.560 |
| C(year)[T.2011] | 1.7286 | 1.521 | 1.137 | 0.256 | -1.252 | 4.709 |
| C(year)[T.2012] | 1.9738 | 1.521 | 1.298 | 0.194 | -1.008 | 4.955 |
| C(year)[T.2013] | 2.1458 | 1.521 | 1.410 | 0.158 | -0.837 | 5.128 |
| C(year)[T.2014] | 1.9029 | 1.522 | 1.251 | 0.211 | -1.080 | 4.886 |
| C(year)[T.2015] | 1.5734 | 1.522 | 1.034 | 0.301 | -1.411 | 4.558 |
| C(year)[T.2016] | 1.2746 | 1.523 | 0.837 | 0.403 | -1.711 | 4.260 |
| C(year)[T.2017] | 0.7870 | 1.524 | 0.517 | 0.605 | -2.200 | 3.774 |
| C(year)[T.2018] | 0.1637 | 1.524 | 0.107 | 0.914 | -2.824 | 3.152 |
| C(year)[T.2019] | -0.2728 | 1.525 | -0.179 | 0.858 | -3.262 | 2.716 |
| C(year)[T.2020] | 2.5970 | 1.526 | 1.702 | 0.089 | -0.394 | 5.588 |
| C(year)[T.2021] | 1.5426 | 1.530 | 1.008 | 0.313 | -1.457 | 4.542 |
| wdi_birth | -0.2528 | 0.016 | -15.502 | 0.000 | -0.285 | -0.221 |
| Omnibus: | 1021.562 | Durbin-Watson: | 0.093 | | | |
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | 1742.050 | | | |
| Skew: | 1.237 | Prob(JB): | 0.00 | | | |
| Kurtosis: | 4.257 | Cond. No. | 899. | | | |


As expected, none of the years show a significant relationship between birth rate and female unemployment at the 5% level. The R-squared is also quite small which further highlights the model's inadequacies as well as the lack of a clear relationship.

```

1 # Create first differences for the dependent and independent variables
2 regression_data['diff_wdi_unempyfilo'] = regression_data['wdi_unempyfilo'].diff()
3 regression_data['diff_wdi_birth'] = regression_data['wdi_birth'].diff()
4
5 # Drop the first observation of each group (since diff creates NaN for the first row)
6 regression_data_diff = regression_data.dropna()
7
8 # Run the first difference model (no need for year dummies; they are differenced out)
9 fd_model = smf.ols(formula='diff_wdi_unempyfilo ~ diff_wdi_birth', data=regression_data_diff).fit()
10
11 # Display the summary

```

```
12 fd_model.summary()  
13
```



| OLS Regression Results | | | | | |
|-----------------------------------|---------------------|----------------------------|------------|-----------------|----------------------|
| Dep. Variable: | diff_wdi_unempyfilo | R-squared: | 0.078 | | |
| Model: | OLS | Adj. R-squared: | 0.078 | | |
| Method: | Least Squares | F-statistic: | 457.4 | | |
| Date: | Mon, 18 Nov 2024 | Prob (F-statistic): | 1.68e-97 | | |
| Time: | 22:42:54 | Log-Likelihood: | -15554. | | |
| No. Observations: | 5429 | AIC: | 3.111e+04 | | |
| Df Residuals: | 5427 | BIC: | 3.113e+04 | | |
| Df Model: | 1 | | | | |
| Covariance Type: nonrobust | | | | | |
| | coef | std err | t | P> t | [0.025 0.975] |
| Intercept | -0.0022 | 0.058 | -0.039 | 0.969 | -0.115 0.111 |
| diff_wdi_birth | -0.3494 | 0.016 | -21.387 | 0.000 | -0.381 -0.317 |
| Omnibus: | 1907.823 | Durbin-Watson: | 2.019 | | |
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | 510075.723 | | |
| Skew: | -0.368 | Prob(JB): | 0.00 | | |
| Kurtosis: | 50.480 | Cond. No. | 3.53 | | |

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

After using first-differencing for the model, we see that the relationship between the two is now significant in contrast to the previous naive OLS model. This is to a degree an expected outcome because first-differencing may account for serial autocorrelation or seasonality that may present itself in the data. The coefficient has also increased by a small amount, indicating that as birth rate increases, female unemployment rate decreases by around -0.35. This isn't a substantial amount but it is interesting because I would have expected an increase in birth rate to be associated with less women entering the workforce or at least being delayed in their entry.