ATHENS UNIVERSITY OF ECONOMICS AND BUSINESS

Department of Statistics

Econometric Modeling of GDP

A Time Series and Panel Data Approach

Author: Chalikias Konstantinos

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1 Introduction

This project analyzes the Gross Domestic Product (GDP) dynamics of six major economies: France, Germany, Italy, Japan, the United Kingdom, and the United States.

The dataset contains quarterly observations from 1979 to 2019, and the dependent variable in this study is the first difference of the natural logarithm of real GDP — a common transformation to approximate quarterly GDP growth rates. The explanatory variables include both domestic and international factors, all transformed to ensure stationarity and interpretability in percentage change terms.

Domestic Variables (Country-Specific)

- **GDP growth** (dependent variable): First differences of the natural logarithm of real GDP.
- **Inflation rate**: First differences of the natural logarithm of the consumer price index (CPI).
- **Real equity returns**: First differences of the natural logarithm of the nominal equity price index, deflated by CPI.
- **Real exchange rate changes**: First differences of the natural logarithm of the exchange rate (expressed in USD), deflated by the country's CPI.
- **Short-term interest rate**: First differences of the quarterly nominal short-term interest rate, calculated as $0.25 \cdot \ln(1 + i/100)$.
- **Long-term interest rate**: Same transformation applied to the long-term nominal interest rate.

Global Variables

- **Oil prices**: First differences of the natural logarithm of nominal oil prices in USD.
- **Agricultural raw materials**: First differences of the natural logarithm of nominal prices in USD.
- **Metal prices**: First differences of the natural logarithm of nominal prices in USD.

Rationale for Transformations

Natural logarithms are applied to convert level variables into proportional terms and to stabilize variance across time. Differencing is then used to address potential non-stationarity and to model changes (growth rates) rather than absolute values. These transformations are standard in time series econometrics.

2 Individual Country Analysis

To identify which variables significantly affect GDP, we begin by analyzing one country in isolation. For this purpose, we selected **France** as the representative case study.

Exploratory Data Analysis

To gain an initial understanding of the data, we examine the time series of France's real GDP. Specifically, we analyze the first differences of the natural logarithm of real GDP, which approximates the quarterly growth rate.

Figure 4 presents the transformed GDP series over time.

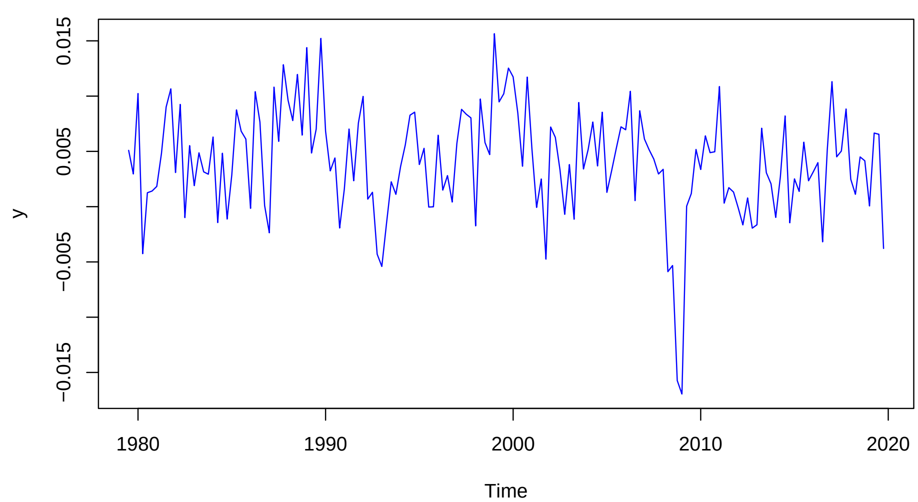

Figure 1: First differences of the natural logarithm of real GDP for France (quarterly)

Stationarity and Normality Tests

The Augmented Dickey-Fuller (ADF) test confirmed that the GDP growth series for France is stationary (ADF statistic = -4.80, p-value < 0.01). The Shapiro-Wilk test indicated that the series is not normally distributed (W = 0.963, p-value < 0.001).

These results suggest that the series is suitable for time series modeling, although it deviates from normality.

Model Selection

To identify the most appropriate model for France's GDP growth, we begin with a linear regression model of the form $y = \alpha x + \epsilon$, where all available independent variables are initially included.

An examination of the independent variables shows no significant multicollinearity, making them suitable for inclusion in the model.

To refine the model, we apply a stepwise selection algorithm based on the Akaike Information Criterion (AIC). This removes or adds variables one at a time, aiming to minimize the AIC and improve the model's overall fit without overfitting.

The final model is :

$$\text{GDP} = \text{Short-term interest rate} + \text{Agricultural raw materials} + \text{Metal prices} + \epsilon_t$$

Only these 3 variables seem to be important for explaining GDP. The Shapiro-Wilk test indicated that the model's residuals follow the normal distribution.

However, autocorrelation testing using the Durbin–Watson statistic (DW = 1.55, p-value=0.001), together with the ACF and PACF plots, suggests the presence of serial correlation that must be addressed. To correct for this issue, an ARIMA model should be applied. The revised specification will include the growth rate of GDP with one lag, as well as the lagged error term.

The issue of autocorrelation now appears to be resolved. Testing for heteroscedasticity using the Breusch–Pagan test indicated no evidence of heteroscedasticity. The final model specification is validated

$$\text{GDP} = \text{Short-term interest rate} + \text{Agricultural raw materials} + \text{Metal prices}$$

$$+\text{GDP}_{t-1} + \theta_1 \epsilon_{t-1} + \epsilon_t$$

Figure 2 presents ACF and PACF plots for model residuals.

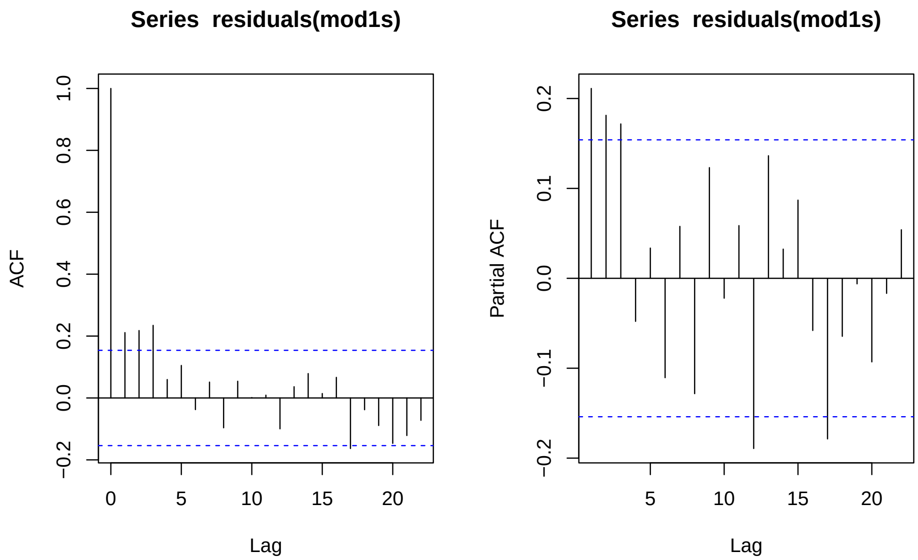

Figure 2: ACF and PACF plots for model

3 Structural Break Analysis

Now that the final model for France is selected, Structural Break Analysis will be performed, to try and find break points in the series. Break points occur when there is a change in the data, often due to shifts in economic conditions or changes in how variables are defined and measured.

As a first step, the France GDP series was examined in isolation. The results suggest the presence of one structural break, occurring in the third quarter of 2007, which coincides with the start of the global financial crisis in 2008.

When testing for breakpoints in the full model specification, including short-term interest rates, agricultural raw materials, and metal prices, the results point to a different breakpoint. In this case, the break is identified in the third quarter of 1993. This shift likely is because of the additional variables, which capture the variability of the 2007–2008 period, shifting the breakpoint earlier.

To account for this structural change, a dummy variable was introduced. The dummy takes the value of 1 before the third quarter of 1993 and 2 afterward. With this adjustment, along with the AR and MA terms of the ARIMA model, the fit improves substantially.

Figure 3 presents the actual growth rate of France's GDP (blue line) against the fitted values from the model (red line)

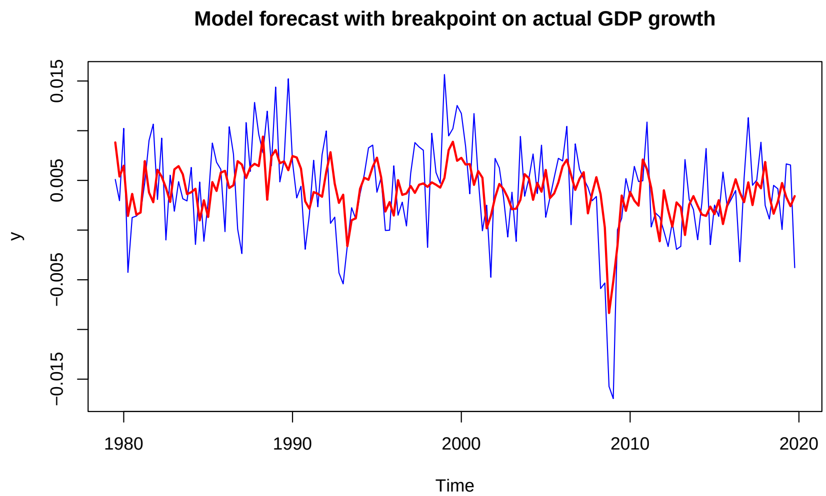

Figure 3: Actual(Blue) Vs Forecasted(Red) GDP growth rate of Frances.

4 Panel Data analysis

The analysis in this section extends to all six countries in the dataset. Since the GDP of one country may influence that of another, constructing a combined model could potentially improve explanatory power and forecasting accuracy. To evaluate this assumption, different models will be estimated and compared.

The six economies considered are France, Germany, Italy, Japan, the United Kingdom, and the United States. Preliminary inspection suggests that their GDP series exhibit a high degree of co-movement, indicating possible interdependencies and shared economic dynamics.

Figure 4 presents the GDP growth over time by country.

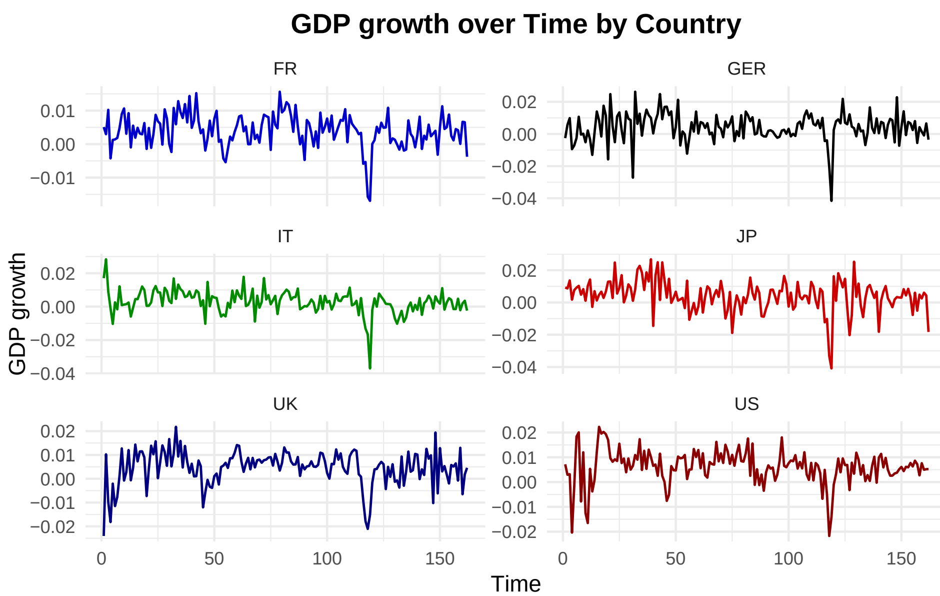

Figure 4: GDP growth over time by country

Panel data methods are great for capturing both the cross-sectional and time-series dimensions of the dataset. By pooling information across countries, these models can account for common shocks while also allowing for country-specific heterogeneity. Two standard specifications are considered: the Fixed Effects model and the Random Effects model.

Fixed Effect Model

The Fixed Effects model allows each country to have its own intercept, thereby controlling for unobserved country-specific characteristics that may be correlated with the regressors. The focus is on within-country variation over time, which helps avoid bias from unobserved differences between countries.

Random Effect Model

The Random Effects model, by contrast, assumes that the country-specific effects are random draws from a larger population and are uncorrelated with the regressors. This approach exploits both the within-country and between-country variation in the data, potentially leading to more efficient estimates if the assumptions hold.

To determine the appropriate specification, the Hausman test was applied. The results suggest that the Random Effects model is preferred, as the null hypothesis of no correlation between the individual effects and the regressors could not be rejected.

5 Forecast

Using the final Random Effects model with five explanatory variables (inflation rate, real equity returns, short-term interest rate, agricultural raw materials, and metal prices), the dataset is divided into a training set (80% of the total sample) and a test set (the remaining 20%). The model is estimated using the training data, and out-of-sample predictions are then generated for the test dataset.

he overall forecast performance is satisfactory, with a total Root Mean Square Error (RMSE) of 0.00611 and a Mean Absolute Error (MAE) of 0.0046. Table 1 reports the metrics by country.

Country	RMSE	MAE
FR	0.00436	0.00359
GER	0.00700	0.00558
IT	0.00586	0.00485
JP	0.00803	0.00534
UK	0.00663	0.00550
US	0.00366	0.00279

Table 1: Forecast performance metrics (RMSE and MAE) by country

The results indicate that predictive accuracy varies across countries, with the United States and France showing the lowest errors, while Japan and Germany are somewhat harder to predict. Nevertheless, the overall performance suggests that the Random Effects model captures the main dynamics of GDP growth across the six economies.

To further illustrate model performance, Figure 5 presents the actual and predicted GDP growth rates by country during the test period.

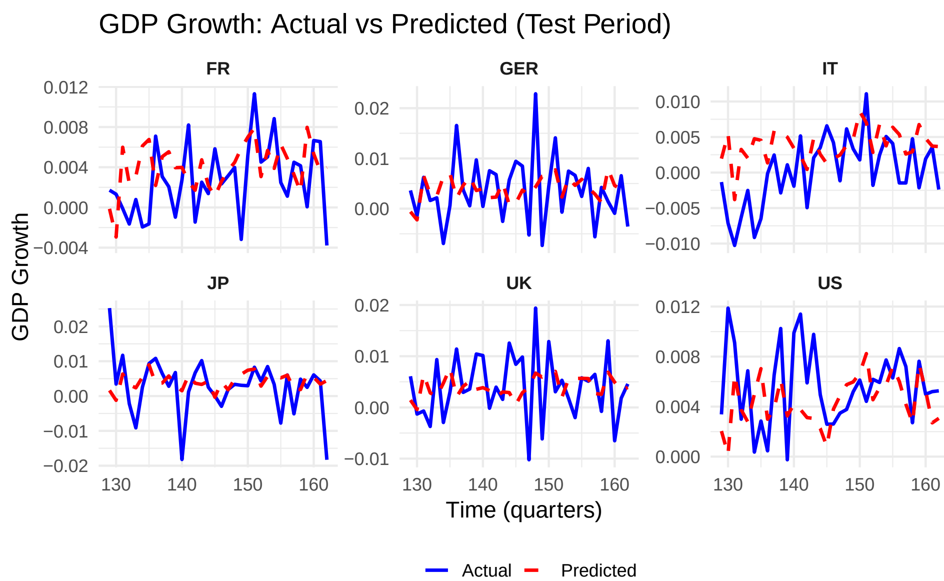

Figure 5: Actual Vs Predicted GDP growth rates by country

6 Conclusion

This study applied time series and panel data econometric methods to model and forecast GDP growth across six major economies. The analysis highlighted the importance of inflation, real equity returns, short-term interest rates, and commodity prices (agricultural raw materials and metals) as significant determinants of GDP dynamics.

The panel Random Effects specification provided a efficient framework by pooling information across economies. Out-of-sample forecasts demonstrated satisfactory predictive accuracy, with overall errors remaining small and the model capturing the main growth dynamics.