Easy Event Studies
A Python Package for Conducting Event Studies

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Abstract

Event studies are a fundamental tool in finance and economics for evaluating the impact of significant events on asset prices. This paper introduces `EasyEventStudies`, a Python package which makes conducting event studies as easy as possible.

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1 Introduction

Event studies are one of the primary tools economists use to understand the economic consequences of events. The idea is simple yet powerful: the price of an asset reflects investors' expectations about future earnings. If the price falls after an event—like the Paris Climate Agreement—this price drop reflects investors' expectations of a decrease in future earnings. Thus, event studies allow us to obtain quantitative estimates of economic effects.

This paper describes the Python package `EasyEventStudies`, which allows users to conduct event studies with ease.

2 Quick Start Guide

To demonstrate how the package works, we study how the blowout of the drilling platform *Deepwater Hoeizon* influenced the stock price of the major oil and gas company BP who owned the platform. We first specify two time windows: the estimation window and the event window. During the estimation window (we choose the previous 100 days), we estimate the average daily return of BP's stock. This is simply the average over all daily returns in that period. Our event window starts on April 20, 2010, which was the day the platform exploded. The estimated effect of the explosion of the platform on BP's stock price is given by the difference between the actual return and the average return over the previous 100 days, i.e.

$$\text{Abnormal Return}_{i,t} = \text{Actual Return}_{i,t} - \overline{\text{Return}}_{100}. \tag{1}$$

Using the package, we simply run this code:

Listing 1: Python code for running an event study

```
event_study_results = run_event_study(
    ticker='BP',
    event_date='2015-11-30',
```

```
    estimation_window=[-100, -1],
    event_window=[0, 20],
    model_type="constant_model"
)

plot_CAR_over_time(event_study_results)
```

Here is the plot generated:

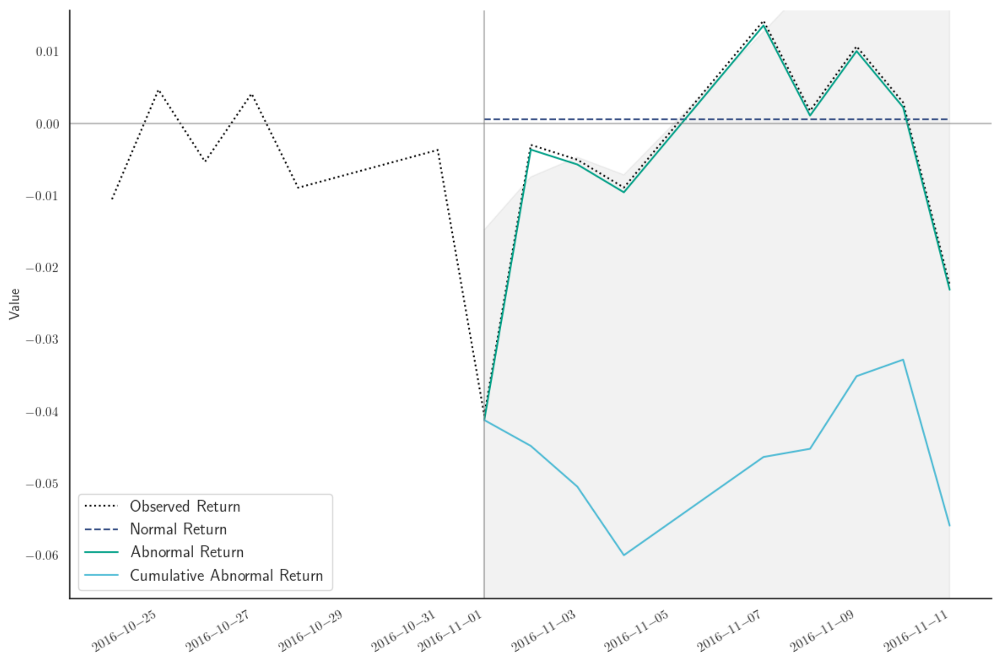

Figure 1: Cumulative Abnormal Returns (CAR) for BP around the Event Date.

The results indicate that the Deepwater Horizon explosion resulted in a loss of approximately 20% of BP's share price in the first 20 days. This loss is statistically significant at the 5% level, as indicated by the gray confidence interval.

3 Discussion and Advice for Running Event Studies

My preferred way of running an event study is using the constant mean model and estimating the mean over a relatively short period of time (e.g., 100 days). This approach assumes that the asset has a roughly constant daily return, which is plausible in the short term. I am not a big fan of the market model or the three-factor model, as they often have a poor fit. However, they are standard in the literature, so you should present them as a robustness check. For these models, you need to estimate parameters for the relationship between the asset's return and the market return, so use a longer estimation window. If your estimation window is too short, you will have a very large variance because the parameters are estimated with high variance.

With respect to choosing the event date, my advice is to think about when information became public knowledge. Sometimes, this is not so clear. For instance with the Paris Climate Agreement, this is not the announcement date of the agreement but the first days of the United Nations Climate Conference when it became very likely that a significant agreement would be signed. The specific choice of the date will always be somewhat arbitrary, so use multiple dates and events that align with your hypothesis.

4 Data Sources

The package automatically downloads financial data from Yahoo Finance. Therefore, search for the ticker symbol on their website (`https://finance.yahoo.com`). The data for the market return, size, and value factors are from the Kenneth R. French Data Library (Fama, 2023).

5 Functions in the Package

The package has two main functions: the `run_event_study` function and the `plot_CAR_over_time` function.

5.1 `run_event_study`

The function has six arguments and returns a pandas DataFrame with detailed results:

Listing 2: Python code for running an event study

```python
def run_event_study(
    ticker: str,
    event_date: str,
    estimation_window: Tuple[int, int] = [-100, -1],
    event_window: Tuple[int, int] = [0, 10],
    historical_days: int = 10,
    model_type: str = "market_model"
):
```

- `ticker`: The ticker symbol of the financial asset on Yahoo Finance, e.g., "BP" for BP or "AAPL" for Apple.
- `event_date`: The date of the event in string format, e.g., "2015-11-30" for November 30th, 2015.
- `estimation_window`: Specifies the time window used for estimating the model for normal returns. It is given as a start and end day relative to the event date. For example, `[-100, -1]` uses the window from 100 days before until 1 day prior to the event date.
- `event_window`: The event window is given in the same format as the estimation window. So if you are interested in the first 10 days after the event, you input `[0, 10]`.

- `historical_days`: The number of historical observed returns prior to the event you want to save in the output DataFrame. The default is 10.

- `model_type`: You can specify `'constant_model'`, `'market_model'`, or `'three_factor_model'`. These are explained in Section 6.

5.2 `plot_CAR_over_time`

This function takes the DataFrame generated by the `run_event_study` function and creates a plot:

Listing 3: Python code for running an event study

```python
def plot_CAR_over_time(event_study_results,
                       days_before_event: int = 10,
                       days_after_event: int = 10):
```

- `event_study_results`: The DataFrame generated by the `run_event_study` function.

- `days_before_event`: The number of days prior to the event you want to display in the plot.

- `days_after_event`: The number of days after the event you want to display in the plot.

6 Implemented Estimators in Detail

We implement the estimators from Campbell et al. (1998). Abnormal returns for asset i at time t are calculated as

$$\text{Abnormal Return}_{i,t} = \text{Actual Return}_{i,t} - \text{Normal Return}_{i,t}. \tag{2}$$

We discuss different models for normal returns in Subsection 6.1. We then turn to cumulative abnormal returns in Subsection 6.2 and the variance estimators in Subsection 6.3.

6.1 Models for Normal Returns

In the current version of the package, there are three models for normal returns: (1) the constant mean return model, (2) the market model, and (3) the three-factor model.

Constant Mean Return Model (`"constant_model"`) This model assumes that the expected return is constant over time:

$$R_{it} = \mu_i + \epsilon_{it} \tag{3}$$

where:

- μ_i: Average return of stock i over the estimation window.
- ϵ_{it}: Error term.

This model has 1 degree of freedom.

Market Model (`"market_model"`) The market model assumes a linear relationship between the stock's returns and the market's returns. The data for the market returns are automatically downloaded from the Kenneth R. French Data Library (Fama, 2023).

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it} \tag{4}$$

where:

- R_{it}: Return of stock i at time t.
- R_{mt}: Return of the market index at time t.
- α_i: Intercept term for stock i.
- β_i: Slope coefficient (beta) for stock i.
- ϵ_{it}: Error term.

This model has 2 degrees of freedom.

Fama-French Three-Factor Model ("three_factor_model") The three-factor model includes additional factors for size and value, as originally proposed by Fama and French (1993).

$$R_{it} = \alpha_i + \beta_i R_{mt} + s_i \text{SMB}_t + h_i \text{HML}_t + \epsilon_{it} \tag{5}$$

where:

- R_{it}: Return of stock i at time t.
- R_{mt}: Return of the market portfolio at time t.
- SMB_t: Small Minus Big factor at time t (size effect).
- HML_t: High Minus Low factor at time t (value effect).
- α_i: Intercept term for stock i.
- β_i, s_i, h_i: Factor loadings for stock i.
- ϵ_{it}: Error term.

This model has 4 degrees of freedom.

6.2 Cumulative Abnormal Return (CAR)

For each model, we calculate the abnormal return (AR) for stock i at time t as the difference between the actual and expected returns (which are estimated using the chosen model from the previous section, $\hat{R}_{it}$):

$$AR_{it} = R_{it} - \hat{R}_{it}. \tag{6}$$

The cumulative abnormal return (CAR) over the event window from T_1 to T_2 is the sum of all abnormal returns over the period:

$$CAR_i(T_1, T_2) = \sum_{t=T_1}^{T_2} AR_{it}. \tag{7}$$

6.3 Variance Estimators

The variance of abnormal returns stems from two sources: variance due to model error and variance due to parameter estimation uncertainty.

The variance V_i is obtained by:

$$V_i = \underbrace{\sigma^2_{\epsilon_i}\mathbf{I}}_{\text{Variance from model error}} + \underbrace{\mathbf{X}^*_i(\mathbf{X}'_i\mathbf{X}_i)^{-1}\mathbf{X}^{*\prime}_i\sigma^2_{\epsilon_i}}_{\text{Variance from parameter estimation uncertainty}} \tag{8}$$

where:

- $\sigma^2_{\epsilon_i}$ is the variance of the error term ϵ_{it} in the model (estimated from the estimation window).
- $\mathbf{I}$ is the identity matrix.
- $\mathbf{X}_i$ is the matrix of regressors (such as a constant and market returns for the market model) during the **estimation window**.
- $\mathbf{X}^*_i$ is the matrix of regressors during the **event window**.

The variance of $CAR_i(T_1, T_2)$ is given by:

$$\text{Var}(CAR_i(T_1, T_2)) = \boldsymbol{\gamma}'V_i\boldsymbol{\gamma} = \boldsymbol{\gamma}'\left(\sigma^2_{\epsilon_i}\mathbf{I} + \mathbf{X}^*_i(\mathbf{X}'_i\mathbf{X}_i)^{-1}\mathbf{X}^{*\prime}_i\sigma^2_{\epsilon_i}\right)\boldsymbol{\gamma}, \tag{9}$$

where $\boldsymbol{\gamma}$ is a vector of ones (of length equal to the event window duration).

7 Conclusion

We hope this package aids you in your research endeavors. Please cite this work when using the package, and let us know if you need additional functionality.

References

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