# Performance Attribution for Equity Portfolios

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## Introduction

Almost all portfolio managers measure performance with reference to a benchmark. The difference in return between a portfolio and its benchmark is the active return of the portfolio. Portfolio managers and their clients want to know what caused this active return. Performance attribution decomposes the active return. The two most common approaches are the Brinson-Hood-Beebower (hereafter referred to as the Brinson model) and a regression-based analysis.[1]

The **pa** package provides tools for conducting both methods for equity portfolios. The Brinson model takes an ANOVA-type approach and decomposes the active return of any portfolio into asset allocation, stock selection, and interaction effects. The regression-based analysis utilizes estimated coefficients from a linear model to attribute active return to different factors.

## Data

We demonstrate the use of the **pa** package with a series of examples based on real-world data sets from MSCI Barra's Global Equity Model II (GEM2).[2]

> GEM2 is the latest Barra global multi-factor equity model. It provides a foundation for investment decision support tools via a broad range of insightful analytics for developed and emerging market portfolios. The latest model version provides:
>
> - Improved accuracy of risk forecasts and increased explanatory power.
> - An intuitive structure that accommodates different investment processes in developed vs. emerging markets.
> - Greater responsiveness to market dynamics.
> - Comprehensive market coverage.

The original data set contains selected attributes such as industry, size, country, and various style factors for a universe of approximately 48,000 securities on a monthly basis.

For illustrative purposes, this article uses three modified versions of the original data set (`year`, `quarter`, and `jan`), each containing 3000 securities. The data frame, `quarter`, is a subset of `year`, containing the data of the first quarter. The data frame, `jan`, is a subset of `quarter` with the data from January, 2010.

```
> data(year)
> names(year)

 [1] "barrid"    "name"      "return"
 [4] "date"      "sector"    "momentum"
 [7] "value"     "size"      "growth"
[10] "cap.usd"   "yield"     "country"
[13] "currency"  "portfolio" "benchmark"
```

- barrid: Barra security identifier.
- name: company name.
- return: monthly total return in trading currency.
- date: the starting date of the month to which the data belong.
- sector: consolidated sector categories based on the GICS.[3]
- momentum: a measure of sustained relative price performance.
- value: the extent to which a stock is priced inexpensively in the market.
- size: normalized market capitalization.
- growth: capture stock's growth prospects.
- cap.usd: market capitalization in USD.
- yield: dividend yield of a security.
- country: the country in which the company is traded.
- currency: currency in which the security is priced.
- portfolio: top 200 securities based on `value` scores in January are selected as portfolio holdings and are held through December 2010. They are equal-weighted each month.
- benchmark: top 1000 securities based on size each month. The benchmark is cap-weighted.

Here is a sample of rows and columns from the data frame `year`:

[1] See Brinson et al. (1986) and Grinold (2006) for more information.
[2] See www.msci.com and Menchero et al. (2008) for more information.
[3] Global Industry Classification Standard

```
                                        name
44557  BLUE STAR OPPORTUNITIES CORP
25345  SEADRILL
264017 BUXLY PAINTS (PKR10)
380927 CDN IMPERIAL BK OF COMMERCE
388340 CDN IMPERIAL BK OF COMMERCE
         return       date     sector  size
44557   0.00000 2010-01-01     Energy  0.00
25345  -0.07905 2010-01-01     Energy -0.26
264017 -0.01754 2010-05-01  Materials  0.00
380927  0.02613 2010-08-01 Financials  0.52
388340 -0.00079 2010-11-01 Financials  0.55
       country portfolio benchmark
44557      USA     0.000  0.000000
25345      NOR     0.000  0.000427
264017     PAK     0.005  0.000000
380927     CAN     0.005  0.000012
388340     CAN     0.005  0.000012
```

The portfolio has 200 equal-weighted holdings. The row for Canadian Imperial Bank of Commerce indicates that it is one of the 200 portfolio holdings with a weight of 0.5% in 2010. Its return was 2.61% in August, and almost flat in November.

# The Brinson Model

## Single-Period Brinson Model

Consider an equity portfolio manager who uses the S&P 500 as the benchmark. In a given month, she outperformed the S&P by 3%. Part of that performance was due to the fact that she allocated more weight of the portfolio to certain sectors that performed well. Call this the *allocation effect*. Part of her outperformance was due to the fact that some of the stocks she selected did better than their sector as a whole. Call this the *selection effect*. The residual can then be attributed to an interaction between allocation and selection – the *interaction effect*. The Brinson model provides mathematical definitions for these terms and methods for calculating them.

The example above uses sector as the classification scheme when calculating the allocation effect. But the same approach can work with any other variable which places each security into one, and only one, discrete category: country, industry, and so on. In fact, a similar approach can work with continuous variables that are split into discrete ranges: the highest quintile of market cap, the second highest quintile and so forth. For generality, we will use the term "category" to describe any classification scheme which places each security in one, and only one, category.

Notations:

- $w_i^B$ is the weight of security $i$ in the benchmark.
- $w_i^P$ is the weight of security $i$ in the portfolio.
- $W_j^B$ is the weight of category $j$ in the benchmark. $W_j^B = \sum w_i^B, i \in j$.
- $W_j^P$ is the weight of a category $j$ in the portfolio. $W_j^P = \sum w_i^P, i \in j$.
- The sum of the weight $w_i^B$, $w_i^P$, $W_j^B$, and $W_j^P$ is 1, respectively.
- $r_i$ is the return of security $i$.
- $R_j^B$ is the return of a category $j$ in the benchmark. $R_j^B = \sum w_i^B r_i, i \in j$.
- $R_j^P$ is the return of a category $j$ in the portfolio. $R_j^P = \sum w_i^P r_i, i \in j$.

The return of a portfolio, $R_P$, can be calculated in two ways:

- On an individual security level by summing over $n$ stocks: $R_P = \sum_{i=1}^{n} w_i^P r_i$.
- On a category level by summing over $N$ categories: $R_P = \sum_{j=1}^{N} W_j^P R_j^P$.

Similar definitions apply to the return of the benchmark, $R_B$,

- $R_B = \sum_{i=1}^{n} w_i^B r_i$.
- $R_B = \sum_{j=1}^{N} W_j^B R_j^B$.

Active return of a portfolio, $R_{active}$, is a performance measure of a portfolio relative to its benchmark. The two conventional measures of active return are arithmetic and geometric. The **pa** package implements the arithmetic measure of the active return for a single-period Brinson model because an arithmetic difference is more intuitive than a ratio over a single period.

The arithmetic active return of a portfolio, $R_{active}$, is the portfolio return $R_P$ less the benchmark return $R_B$:

$$R_{active} = R_P - R_B.$$

Since the category allocation of the portfolio is generally different from that of the benchmark, allocation plays a role in the active return, $R_{active}$. The same applies to stock selection where assuming that the portfolio has the exact same categorical exposures as the benchmark does, equities within each category are different. This contributes to $R_{active}$ as well. Allocation effect $R_{allocation}$ and selection effect $R_{selection}$ over $N$ categories are defined as:

$$R_{allocation} = \sum_{j=1}^{N} W_j^P R_j^B - \sum_{j=1}^{N} W_j^B R_j^B,$$

$$R_{selection} = \sum_{j=1}^{N} W_j^B R_j^P - \sum_{j=1}^{N} W_j^B R_j^B.$$

The intuition behind the allocation effect is that a portfolio would produce different returns with different allocation schemes ($W_j^P$ vs. $W_j^B$) while having the same stock selection and thus the same return ($R_j^B$) for each category. The difference between the two returns, caused by the allocation scheme, is called the allocation effect ($R_{allocation}$). Similarly, two different returns can be produced when two portfolios have the same allocation ($W_j^B$) yet dissimilar returns due to differences in stock selection within each category ($R_j^p$ vs. $R_j^B$). This difference is the selection effect ($R_{selection}$).

Interaction effect, $R_{interaction}$, is the result of subtracting return due to allocation $R_{allocation}$ and return due to selection $R_{selection}$ from the active return $R_{active}$:

$$R_{interaction} = R_{active} - R_{allocation} - R_{selection}.$$

The Brinson model allows portfolio managers to analyze the relative return of a portfolio using any attribute of a security, such as country or sector. Unfortunately, it is very hard to expand the analysis beyond two categories.[4] As the number of categories increases, this procedure is subject to the curse of dimensionality. To some extent, the regression-based model detailed later ameliorates this problem.

## Single-Period Brinson Tools

Brinson analysis is run by calling the function `brinson` to produce an object of class `brinson`. Below we show the tools provided in the **pa** package to analyze a single period portfolio based on the Brinson model.

```
> data(jan)
> br.single <- brinson(x = jan, date.var = "date",
+                      cat.var = "sector",
+                      bench.weight = "benchmark",
+                      portfolio.weight = "portfolio",
+                      ret.var = "return")
>
```

The data frame, `jan`, contains all the information necessary to conduct a single-period Brinson analysis. `date.var`, `cat.var`, and `return` identify the columns containing the date, the factor to be analyzed, and the return variable, respectively. `bench.weight` and `portfolio.weight` specify the name of the benchmark weight column and that of the portfolio weight column in the data frame.

Calling `summary` on the resulting object `br.single` of class `brinson` reports essential information about the input portfolio (including the number of securities in the portfolio and the benchmark as well as sector exposures) and the results of the Brinson analysis.

```
> summary(br.single)

Period:                          2010-01-01
Methodology:                     Brinson
Securities in the portfolio:     200
Securities in the benchmark:     1000

Exposures
            Portfolio Benchmark
Energy          0.085    0.2782
Materials       0.070    0.0277
Industrials     0.045    0.0330
ConDiscre       0.050    0.0188
ConStaples      0.030    0.0148
HealthCare      0.015    0.0608
Financials      0.370    0.2979
InfoTech        0.005    0.0129
TeleSvcs        0.300    0.1921
Utilities       0.030    0.0640

Returns
                   2010-01-01
Allocation Effect    -0.00140
Selection Effect      0.01418
Interaction Effect    0.00191
Active Return         0.01469
```

The `br.single` summary shows that the active return of the portfolio, in January, 2010 was 1.47%. This return can be decomposed into allocation effect (-0.14%), selection effect (1.42%), and interaction effect (0.19%).

```
> plot(br.single, var = "sector", type = "return")
```

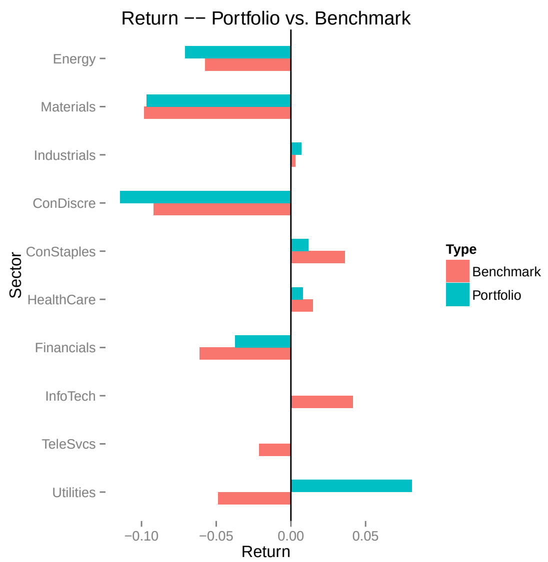


Figure 1: Sector Return.

Figure 1 is a visual representation of the return of both the portfolio and the benchmark sector by sector in January, 2010. This plot shows that in absolute terms, Utilities performed the best with a gain of more than 5% and Consumer Discretionary, the

[4] Brinson et al. (1991) proposed a framework to include two variables in the Brinson analysis.

worst performing sector, lost more than 10%. Utilities was also the sector with the highest active return in the portfolio.

## Multi-Period Brinson Model

To obtain Brinson attribution on a multi-period data set, one calculates allocation, selection and interaction within each period and aggregates them across time. There are three methods for this – arithmetic, geometric, and optimized linking. Arithmetic measure calculates relative performance of a portfolio and its benchmark by a difference; geometric measure does so by a ratio. Arithmetic measure is more intuitive but a well-known challenge in arithmetic attribution is that active returns do not add up over multiple periods due to geometric compounding.[5] Geometric is able to circumvent the adding-up problem. Menchero (2004) discussed various linking algorithms to connect arithmetic return with geometric return and argued that the *optimized linking algorithm* is the best way to link attribution over time.

`Arithmetic Attribution.` The arithmetic attribution model calculates active return and contributions due to allocation, selection, and interaction in each period and sums them over multiple periods. The arithmetic active return over $T$ periods $R_{arithmetic}$ is expressed as:

$$R_{arithmetic} = \sum_{t=1}^{T} R_t^{active},$$

and $R_t^{active}$ is the active return in a single period $t$.

`Geometric Attribution.` The geometric attribution is to compound various returns over $T$ periods where,

$$1 + R_P = \prod_{t=1}^{T} (1 + R_t^P),$$

$$1 + R_B = \prod_{t=1}^{T} (1 + R_t^B),$$

and $R_t^P$ and $R_t^B$ are portfolio and benchmark returns in a single period $t$, respectively. Geometric return $R_{geometric}$ is thus the difference between $R_p$ and $R_B$:

$$R_{geometric} = R_p - R_B.$$

`Optimized Linking Algorithm.` The well-known challenge faced in arithmetic attribution is that the actual active return over time is not equal to the arithmetic summation of single-period active returns,

$$R_{geometric} \neq R_{arithmetic},$$

i.e.,

$$R_P - R_B \neq \sum_{t=1}^{T} R_t^{active}.$$

Menchero (2004) proposed an optimized linking coefficient $b^{opt}$ to link arithmetic returns of individual periods with geometric returns over time,

$$R_p - R_B = \sum_{t=1}^{T} b_t^{opt} R_t^{active},$$

where $b_t^{opt}$ is the optimized linking coefficient in a single period $t$.

The optimized linking coefficient $b_t^{opt}$ is the summation of a *natural scaling* $A$ and an *adjustment* $a_t$ specific to a time period $t$,

$$b_t^{opt} = A + a_t,$$

where $A$ is an coefficient for linking from the single-period to the multi-period return and $a_t$ is an adjustment to eliminate residuals[6].

Since active return over time $R_P - R_B$ is a summation of active return in each period adjusted to the optimized linking algorithm, the following is true:

$$R_P - R_B = \sum_{t=1}^{T} b_t^{opt}(R_t^{allocation} + R_t^{selection} + R_t^{interaction}),$$

where $R_t^{allocation}$, $R_t^{selection}$, and $R_t^{interaction}$ represent allocation, selection and interaction in each period $t$, respectively.

Within each period $t$, the adjusted attribution is thus expressed as

$$\hat{R}_t^{allocation} = b_t^{opt} R_t^{allocation},$$

$$\hat{R}_t^{selection} = b_t^{opt} R_t^{selection},$$

and

$$\hat{R}_t^{interaction} = b_t^{opt} R_t^{interaction}.$$

Therefore, across $T$ periods, active return $R_{active}$, the difference between portfolio return $R_P$ and benchmark return $R_B$, can be written as

$$R_{active} = \sum_{t=1}^{T} (\hat{R}_t^{allocation} + \hat{R}_t^{selection} + \hat{R}_t^{interaction}),$$

where $R_{active} = R_P - R_B$.

[5]See Bacon (2008) for a complete discussion of the complexity involved.

[6]See Menchero (2000) for more information on the optimized linking coefficients.

## Multi-Period Brinson Tools

In practice, analyzing a single-period portfolio is meaningless as portfolio managers and their clients are more interested in the performance of a portfolio over multiple periods. To apply the Brinson model over time, we can use the function `brinson` and input a multi-period data set (for instance, `quarter`) as shown below.

```
> data(quarter)
> br.multi <- brinson(quarter, date.var = "date",
+                cat.var = "sector",
+                bench.weight = "benchmark",
+                portfolio.weight = "portfolio",
+                ret.var = "return")
```

The object `br.multi` of class `brinsonMulti` is an example of a multi-period Brinson analysis.

```
> exposure(br.multi, var = "size")

$Portfolio
     2010-01-01 2010-02-01 2010-03-01
Low       0.140      0.140      0.155
2         0.050      0.070      0.045
3         0.175      0.145      0.155
4         0.235      0.245      0.240
High      0.400      0.400      0.405

$Benchmark
     2010-01-01 2010-02-01 2010-03-01
Low      0.0681     0.0568     0.0628
2        0.0122     0.0225     0.0170
3        0.1260     0.1375     0.1140
4        0.2520     0.2457     0.2506
High     0.5417     0.5374     0.5557
```

The `exposure` method on the class `br.multi` object shows the exposure of the portfolio and the benchmark based on a user-defined category. Here, it shows the exposure on `size`. We can see that the portfolio overweights the benchmark in the lowest quintile in `size` and underweights in the highest quintile.

```
> returns(br.multi, type = "linking")

$Raw
              2010-01-01 2010-02-01 2010-03-01
Allocation       -0.0014     0.0064     0.0046
Selection         0.0146     0.0178    -0.0152
Interaction       0.0020    -0.0074    -0.0087
Active Return     0.0151     0.0168    -0.0193

$Aggregate
              2010-01-01, 2010-03-01
Allocation                    0.0095
Selection                     0.0173
Interaction                  -0.0142
Active Return                 0.0127
```

The `returns` method shows the results of the Brinson analysis applied to the data from January, 2010 through March, 2010. The optimized linking algorithm is applied here by setting the type to *linking*. The first portion of the `returns` output shows the Brinson attribution in individual periods. The second portion shows the aggregate attribution results. The portfolio formed by top 200 value securities in January had an active return of 12.7% over the first quarter of 2010. The allocation and the selection effects contributed 0.95% and 1.73% respectively; the interaction effect made a loss of 1.42%.

```
> plot(br.multi, type = "return")
```

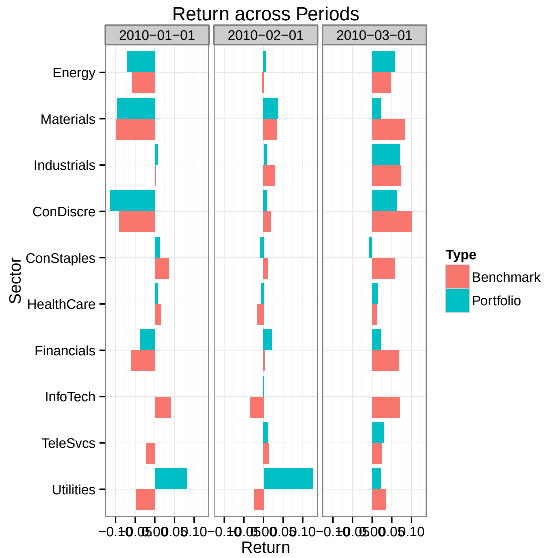


Figure 2: Sector Return Across Time.

Figure 2 depicts the returns of both the portfolio and the benchmark of the allocation effect from January, 2010 through March. 2010. This plot shows that for the portfolio, `Utilities` performed the best with a gain of more than 5% in January and February, 2010 but tanked in March, 2010.

## Regression

### Single-Period Regression Model

One advantage of a regression-based approach is that such analysis allows one to define their own attribution model by easily incorporating multiple variables in the regression formula. These variables can be either discrete or continuous.

Suppose a portfolio manager wants to find out how much each of the value, growth, and momentum scores of her holdings contributes to the overall performance of the portfolio. Consider the following linear regression without the intercept term based on a single-period portfolio of $n$ securities with $k$ different variables:

$$\mathbf{r}_n = \mathbf{X}_{n,k}\mathbf{f}_k + \mathbf{u}_n$$

where

- $\mathbf{r}_n$ is a column vector of length $n$. Each element in $\mathbf{r}_n$ represents the return of a security in the portfolio.
- $\mathbf{X}_{n,k}$ is an $n$ by $k$ matrix. Each row represents $k$ attributes of a security. There are $n$ securities in the portfolio.
- $\mathbf{f}_k$ is a column vector of length $k$. The elements are the estimated coefficients from the regression. Each element represents the *factor return* of an attribute.
- $\mathbf{u}_n$ is a column vector of length $n$ with residuals from the regression.

In the case of this portfolio manager, suppose that she only has three holdings in her portfolio. $r_3$ is thus a 3 by 1 matrix with returns of all her three holdings. The matrix $\mathbf{X}_{3,3}$ records the score for each of the three factors (value, growth, and momentum) in each row. $\mathbf{f}_3$ contains the estimated coefficients of a regression $\mathbf{r}_3$ on $\mathbf{X}_{3,3}$.

The active exposure of each of the $k$ variables, $X_i$, $i \in k$, is expressed as

$$X_i = \mathbf{w}_{active}{}'\mathbf{x}_{n,i},$$

where $X_i$ is the value representing the active exposure of the attribute $i$ in the portfolio, $\mathbf{w}_{active}$ is a column vector of length $n$ containing the active weight of every security in the portfolio, and $\mathbf{x}_{n,i}$ is a column vector of length $n$ with attribute $i$ for all securities in the portfolio. Active weight of a security is defined as the difference between the portfolio weight of the security and its benchmark weight.

Using the example mentioned above, the active exposure of the attribute `value`, $X_{value}$ is the product of $\mathbf{w}_{active}{}'$ (containing active weight of each of the three holdings) and $\mathbf{x}_3$ (containing value scores of the three holdings).

The contribution of a variable $i$, $R_i$, is thus the product of the factor returns for the variable $i$, $f_i$ and the active exposure of the variable $i$, $X_i$. That is,

$$R_i = f_i X_i.$$

Continuing the example, the contribution of value is the product of $f_{value}$ (the estimated coefficient for value from the linear regression) and $X_{value}$ (the active exposure of value as shown above).

Therefore, the active return of the portfolio $R_{active}$ is the sum of contributions of all $k$ variables and the residual $u$ (a.k.a. the interaction effect),

$$R_{active} = \sum_{i=1}^{k} R_i + u.$$

For instance, a hypothetical portfolio has three holdings (A, B, and C), each of which has two attributes – size and value.

```
  Return Name Size Value Active_Weight
1    0.3    A  1.2   3.0           0.5
2    0.4    B  2.0   2.0           0.1
3    0.5    C  0.8   1.5          -0.6
```

Following the procedure as mentioned, the factor returns for size and value are -0.0313 and -0.1250. The active exposure of size is 0.32 and that of value is 0.80. The active return of the portfolio is -11% which can be decomposed into the contribution of size and that of value based on the regression model. Size contributes 1% of the negative active return of the portfolio and value causes the portfolio to lose the other 10.0%.

## Single-Period Regression Tools

Another conventional attribution methodolody is the regression-based analysis. As mentioned, the **pa** package provides tools to analyze both single-period and multi-period data frames.

```
> rb.single <- regress(jan, date.var = "date",
+                 ret.var = "return",
+                 reg.var = c("sector", "growth",
+                   "size"),
+                 benchmark.weight = "benchmark",
+                 portfolio.weight = "portfolio")
> exposure(rb.single, var = "growth")

     Portfolio Benchmark
Low      0.305    0.2032
2        0.395    0.4225
3        0.095    0.1297
4        0.075    0.1664
High     0.130    0.0783
```

`reg.var` specifies the columns containing variables whose contributions are to be analyzed. Calling `exposure` with a specified `var` yields information on the exposure of both the portfolio and the benchmark by that variable. If `var` is a continuous variable, for instance, `growth`, the exposure will be shown in 5 quantiles. Majority of the high `value` securities in the portfolio in January have relatively low `growth` scores.

```
> summary(rb.single)

Period:                        2010-01-01
Methodology:                   Regression
Securities in the portfolio:   200
Securities in the benchmark:   1000

Returns
                  2010-01-01
Sector              0.003189
Growth              0.000504
Size                0.002905
Residual            0.008092
Portfolio Return   -0.029064
Benchmark Return   -0.043753
Active Return       0.014689
```

The summary method shows the number of securities in the portfolio and the benchmark, and the contribution of each input variable according to the regression-based analysis. In this case, the portfolio made a loss of 2.91% and the benchmark lost 4.38%. Therefore, the portfolio outperformed the benchmark by 1.47%. Sector, growth, and size contributed 0.32%, 0.05%, and 0.29%, respectively.

## Multi-Period Regression Model

The same challenge of linking arithmetic and geometric returns is present in multi-period regression model. We apply the optimized linking algorithm proposed by Menchero (2000) in the regression attribution as well.

Within each period $t$,

$$R_t^{active} = \sum_{i=1}^{k} R_{i,t} + u_t,$$

where $R_{i,t}$ represents the contribution of a variable $i$ of the time period $t$ and $u_t$ is the residual in that period.

Across $T$ periods, the active return can be expressed by a product of the optimized linking coefficient $b_t^{opt}$ and the individual contribution of each of the $k$ attributes. The adjusted contribution of each of the $k$ variables $i$, $\hat{R}_{i,t}$, is expressed by

$$\hat{R}_{i,t} = b_t^{opt} R_{i,t}.$$

Thus, the overall active return $R_{active}$ can be decomposed into

$$R_{active} = \sum_{t=1}^{T} \sum_{i=1}^{k} \hat{R}_{i,t} + U,$$

where $U$ is the residual across $T$ periods.

## Multi-Period Regression Tools

```
> rb.multi <- regress(quarter, date.var = "date",
+                 ret.var = "return",
+                 reg.var = c("sector", "growth",
+                   "size"),
+                 benchmark.weight = "benchmark",
+                 portfolio.weight = "portfolio")
> rb.multi

Period starts:                          2010-01-01
Period ends:                            2010-03-01
Methodology:                            Regression
Securities in the portfolio:            200
Securities in the benchmark:            1000
```

Regression-based analysis can be applied to a multi-period data frame by calling the same method regress. By typing the name of the class object rb.multi directly, a short summary of the analysis is provided, showing the starting and ending period of the analysis, the methodology, and the average number of securities in both the portfolio and the benchmark.

```
> summary(rb.multi)

Period starts:                          2010-01-01
Period ends:                            2010-03-01
Methodology:                            Regression
Avg securities in the portfolio:        200
Avg securities in the benchmark:        1000

Returns
$Raw
                 2010-01-01 2010-02-01 2010-03-01
Sector               0.0032     0.0031     0.0002
Growth               0.0005     0.0009    -0.0001
Size                 0.0029     0.0295     0.0105
Residual             0.0081    -0.0172    -0.0302
Portfolio Return    -0.0291     0.0192     0.0298
Benchmark Return    -0.0438     0.0029     0.0494
Active Return        0.0147     0.0163    -0.0196

$Aggregate
                 2010-01-01, 2010-03-01
Sector                           0.0065
Growth                           0.0013
Size                             0.0433
Residual                        -0.0392
Portfolio Return                 0.0190
Benchmark Return                 0.0064
Active Return                    0.0127
```

The regression-based summary shows that the contribution of each input variable in addition to the basic information on the portfolio. The summary suggests that the active return of the portfolio in year 2010 is 1.27%. The Residual number indicates the contribution of the interaction among various variables including sector, growth, and growth.

Visual representation of relative performance of a portfolio against its benchmark is best viewed across a longer time span. Here, we use the data frame year for illustrative purposes.

```
> rb.multi2 <- regress(year, date.var = "date",
+             ret.var = "return",
+             reg.var = c("sector", "growth",
+               "size"),
+             benchmark.weight = "benchmark",
+             portfolio.weight = "portfolio")
> returns(rb.multi2, type = "linking")

$Raw
              2010-01-01 2010-02-01 2010-03-01
Sector            0.0035     0.0034     0.0002
Growth            0.0005     0.0010    -0.0001
Size              0.0031     0.0320     0.0109
Residual          0.0088    -0.0187    -0.0312
Active Return     0.0159     0.0177    -0.0203
              2010-04-01 2010-05-01 2010-06-01
Sector            0.0017     0.0044     0.0077
Growth            0.0001     0.0002     0.0004
Size              0.0145     0.0041     0.0020
Residual         -0.0043     0.0346     0.0201
Active Return     0.0122     0.0433     0.0304
```

```
              2010-07-01 2010-08-01 2010-09-01
Sector            0.0016     0.0051    -0.0023
Growth           -0.0005     0.0005    -0.0006
Size              0.0066     0.0000     0.0100
Residual         -0.0333     0.0189    -0.0229
Active Return    -0.0256     0.0246    -0.0158
              2010-10-01 2010-11-01 2010-12-01
Sector            0.0016    -0.0048    -0.0084
Growth           -0.0011    -0.0004     0.0010
Size              0.0024     0.0143     0.0057
Residual          0.0149     0.0192    -0.0253
Active Return     0.0179     0.0282    -0.0270

$Aggregate
              2010-01-01, 2010-12-01
Sector                        0.0137
Growth                        0.0011
Size                          0.1056
Residual                     -0.0193
Active Return                 0.1014
```

We obtained an object *rb.multi2* of class *regressMulti* based on the data set from January, 2010 through December, 2010. The portfolio beat the benchmark by 10.1% over this period. Based on the regression model, `size` contributed to the lion share of the active return.

```
> plot(rb.multi2, var = "sector", type = "return")
```

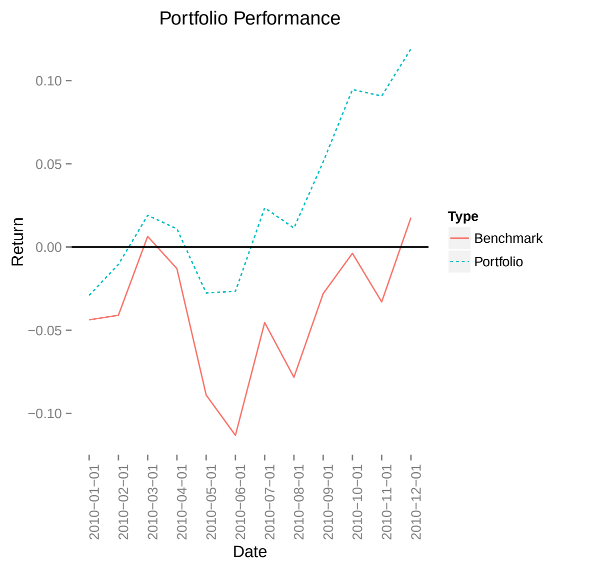


Figure 3: Performance Attribution.

Figure 3 displays both the cumulative portfolio and benchmark returns from January, 2010 through December, 2010. It suggests that the portfolio, consisted of high `value` securities in January, consistently outperformed the benchmark in 2010. Outperformance in May and June helped the overall positive active return in 2010 to a large extent.

# Conclusion

In this paper, we describe two widely-used methods for performance attribution – the Brinson model and the regression-based approach, and provide a simple collection of tools to implement these two methods in `R` with the `pa` package. A comprehensive package, `portfolio` Enos and Kane (2006), provides facilities to calculate exposures and returns for equity portfolios. It is possible to use the `pa` package based on the output from the `portfolio` package. Further, the flexibility of `R` itself allows users to extend and modify these packages to suit their own needs and/or execute their preferred attribution methodology. Before reaching that level of complexity, however, `pa` provides a good starting point for basic performance attribution.

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