

# Analysing equity portfolios in R

## Using the portfolio package

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## Introduction<sup>1</sup>

R is used by major financial institutions around the world to manage billions of dollars in equity (stock) portfolios. Unfortunately, there is no open source R package for facilitating this task. The **portfolio** package is meant to fill that gap. Using **portfolio**, an analyst can create an object of class `portfolioBasic` (weights only) or `portfolio` (weights and shares), examine its *exposures* to various factors, calculate its *performance* over time, and determine the *contributions* to performance from various categories of stocks. Exposures, performance and contributions are the basic building blocks of portfolio analysis.

## One Period, Long-Only

Consider a simple long-only portfolio formed from the universe of 30 stocks in the Dow Jones Industrial Average (DJIA) in January, 2005. Start by loading and examining the input data.

```
> library(portfolio)
> data(dow.jan.2005)
> summary(dow.jan.2005)
```

symbol	name
Length:30	Length:30
Class :character	Class :character
Mode :character	Mode :character

price	sector
Min. : 21.0	Industrials :6
1st Qu.: 32.1	Staples :6
Median : 42.2	Cyclicals :4
Mean : 48.6	Financials :4
3rd Qu.: 56.0	Technology :4
Max. :103.3	Communications:3
	(Other) :3

cap.bil	month.ret
Min. : 22.6	Min. : -0.12726
1st Qu.: 53.9	1st Qu.: -0.05868
Median : 97.3	Median : -0.02758
Mean :126.0	Mean : -0.02914
3rd Qu.:169.3	3rd Qu.: 0.00874
Max. :385.9	Max. : 0.04468

```
> head(dow.jan.2005)
```

	symbol	name	price
140	AA	ALCOA INC	31.42
214	MO	ALTRIA GROUP INC	61.10
270	AXP	AMERICAN EXPRESS CO	56.37
294	AIG	AMERICAN INTERNATIONAL GROUP	65.67
946	BA	BOEING CO	51.77
1119	CAT	CATERPILLAR INC	97.51

	sector	cap.bil	month.ret
140	Materials	27.35	-0.060789
214	Staples	125.41	0.044681
270	Financials	70.75	-0.051488
294	Financials	171.04	0.009441
946	Industrials	43.47	-0.022600
1119	Industrials	33.27	-0.082199

The DJIA consists of exactly 30 large US stocks. We provide a minimal set of information for constructing a long-only portfolio. Note that `cap.bil` is market capitalization in billions of dollars, `price` is the per share closing price on December 31, 2004, and `month.ret` is the one month return from December 31, 2004 through January 31, 2005.

In order to create an object of class `portfolioBasic`, we can use this data and form a portfolio on the basis of a “nonsense” variable like `price`.

```
> p <- new("portfolioBasic", instant = as.Date("2004-12-31"),
+ id.var = "symbol", in.var = "price",
+ sides = "long", ret.var = "month.ret",
+ data = dow.jan.2005)
> summary(p)
```

Portfolio: Unnamed portfolio

	count	weight
Long:	6	1

Top/bottom positions by weight:

	id	pct
1	AIG	16.7
2	CAT	16.7
3	IBM	16.7
4	JNJ	16.7
5	MMM	16.7
6	UTX	16.7

In other words, we have formed a portfolio of the highest priced 6 stocks out of the 30 stocks in the DJIA. The `id.var` argument causes the portfolio to use `symbol` as the key for identifying securities throughout the analysis. `in.var` selects the variable by which stocks are ranked in terms of desirability. `sides` set to `long` specifies that we want a long-only portfolio. `ret.var` selects the return variable for measuring performance. In this case, we are interested in how the portfolio does for the month of January 2005.

<sup>1</sup>The original version of this article, which included historical analyses no longer included in **portfolio**, was published in volume 6/2 of R News and is available at <http://CRAN.R-project.org/doc/Rnews>.

The default arguments to `portfolioBasic` form equal-weighted positions; in this case, each of the 6 stocks has 16.67% of the resulting portfolio. The defaults also lead to a portfolio made up of the best 20% (or quintile) of the universe of stocks provided to the data argument. Since 20% of 30 is 6, there are 6 securities in the resulting portfolio.

## Exposures

Once we have a portfolio, the next step is to analyse its exposures. These can be calculated with respect to both numeric or factor variables. The method `exposure` will accept a vector of variable names.

```
> exposure(p, exp.var = c("price", "sector"))
```

```
numeric
  variable exposure
1   price      85.1

sector
  variable exposure
2 Industrials    0.500
1 Financials     0.167
3   Staples     0.167
4  Technology    0.167
```

The weighted average price of the portfolio is 85. In other words, since the portfolio is equal-weighted, the average share price of AIG, CAT, IBM, JNJ, MMM, and UTX is 85. This is a relatively high price, but makes sense since we explicitly formed the portfolio by taking the 6 highest priced stocks out of the DJIA.

Each of the 6 stocks is assigned a sector and 3 of them are Industrials. This compares to the 20% of the entire universe of 30 stocks that are in this sector. In other words, the portfolio has a much higher exposure to Industrials than the universe as a whole. Similarly, the portfolio has no stocks from the Communications, Cyclical or Energy sectors despite the fact that these make up almost 27% of the DJIA universe.

## Performance

Time plays two roles in the portfolio class. First, there is the moment of portfolio formation. This is the instant when all of the data, except for future returns, is correct. After this moment, of course, things change. The price of AIG on December 31, 2004 was \$65.67, but by January 5, 2005 it was \$67.35.

The second role played by time on the portfolio class concerns future returns. `ret.var` specifies a return variable which measures the performance of individual stocks going forward. These returns can be of any duration — an hour, a day, a month, a year — but should generally start from the moment of portfolio formation. In this example, we are using one

month forward returns. Now that we know the portfolio's exposures at the start of the time period, we can examine its performance for the month of January.

```
> performance(p)
```

```
Total return: -1.71 %
```

```
Best/Worst performers:
```

	id	weight	ret	contrib
2	CAT	0.167	-0.08220	-0.01370
3	IBM	0.167	-0.05234	-0.00872
6	UTX	0.167	-0.02583	-0.00431
1	AIG	0.167	0.00944	0.00157
4	JNJ	0.167	0.02018	0.00336
5	MMM	0.167	0.02790	0.00465

The portfolio lost 1.7% of its value in January. The worst performing stock was CAT (Caterpillar), down more than 8%. The best performing stock was MMM (3M), up almost 3%. The `contrib` (contribution) of each stock to the overall performance of the portfolio is simply its weight in the portfolio multiplied by its return. The sum of the 6 individual contributions yields -1.7%.

## Contributions

The contributions of individual stocks are not that interesting in and of themselves. More important is to examine summary statistics of the contributions across different categories of stocks. Consider the use of the `contribution` method:

```
> contribution(p, contrib.var = c("sector"))
```

```
sector
  variable weight contrib roic
5  Communications 0.000 0.00000 0.00000
6  Conglomerates 0.000 0.00000 0.00000
7   Cyclicals    0.000 0.00000 0.00000
8    Energy      0.000 0.00000 0.00000
1   Financials   0.167 0.00157 0.00944
2   Industrials 0.500 -0.01336 -0.02671
9   Materials    0.000 0.00000 0.00000
3   Staples      0.167 0.00336 0.02018
4   Technology   0.167 -0.00872 -0.05234
10  Utilities    0.000 0.00000 0.00000
```

`contribution`, like `exposure`, accepts a vector of variable names. In the case of `sector`, the contribution object displays the 10 possible values, the total weight of the stocks for each level and the sum of the contributions for those stocks. Only 4 of the 10 levels are represented by the stocks in the portfolio. The other 6 levels have zero weight and, therefore, zero contributions.

The sector with the biggest weight is Industrials, with half of the portfolio. Those 3 stocks did poorly, on average, in January and are therefore responsible for -1.3% in total losses. There is only a single Technology stock in the portfolio, IBM. Because it was

down 5% for the month, its contribution was -0.87%. Since IBM is the only stock in its sector in the portfolio, the contribution for the sector is the same as the contribution for IBM.

The last column in the display shows the *roic* — the return on invested capital — for each level. This captures the fact that raw contributions are a function of both the total size of positions and their return. For example, the reason that the total contribution for Industrials is so large is mostly because they account for such a large proportion of the portfolio. The individual stocks performed poorly, on average, but not that poorly. Much worse was the performance of the Technology stock. Although the total contribution from Technology was only 60% of that of Industrials, this was on a total position weight only 1/3 as large. In other words, the return on total capital was *much worse* in Technology than in Industrials even though Industrials accounted for a larger share of the total losses.

Think about *roic* as useful in determining contributions on the margin. Imagine that you have the chance to move \$1 out of one sector and into another. Where should that initial dollar come from? Not from the sector with the worst total contribution. Instead, the marginal dollar should come from the sector with the worst *roic* and should be placed into the sector with the best *roic*. In this example, we should move money out of Technology and into Staples.

*contribution* can also work with numeric variables.

```
> contribution(p, contrib.var = c("cap.bil"))
```

```
cap.bil
      rank  variable weight  contrib  roic
1  1 - low (22.6,50.9]  0.167 -0.013700 -0.08220
2      2 (50.9,71.1]  0.333  0.000345  0.00103
4      3 (71.1,131]   0.000  0.000000  0.00000
3      4 (131,191]   0.500 -0.003787 -0.00757
5 5 - high (191,386]  0.000  0.000000  0.00000
```

Analysing contributions only makes sense in the context of categories into which each position can be placed. So, we need to break up a numeric variable like *cap* into discrete, exhaustive categories. The *contribution* function provides various options for doing so, but most users will be satisfied with the default behavior of forming 5 equal sized quintiles based on the distribution of the variable in the entire universe.

In this example, we see that there are no portfolio holdings among the biggest 20% of stocks in the DJIA. Half the portfolio comes from stocks in the second largest quintile. Within each category, the analysis is the same as that above for sectors. The worst performing category in terms of total contribution is the smallest quintile. This category also has the lowest *roic*.

## One Period Long-Short

Having examined a very simple long-only portfolio in order to explain the concepts behind *exposures*, *performance* and *contributions*, it is time to consider a more complex case, a long-short portfolio which uses the same underlying data.

```
> p <- new("portfolioBasic", instant = as.Date("2004-12-31"),
+       id.var = "symbol", in.var = "price",
+       type = "linear", sides = c("long",
+       "short"), ret.var = "month.ret",
+       data = dow.jan.2005)
> summary(p)
```

Portfolio: Unnamed portfolio

	count	weight
Long:	6	1
Short:	6	-1

Top/bottom positions by weight:

	id	pct
12	UTX	28.57
5	IBM	23.81
2	CAT	19.05
8	MMM	14.29
1	AIG	9.52
10	PFE	-9.52
9	MSFT	-14.29
11	SBC	-19.05
6	INTC	-23.81
4	HPQ	-28.57

Besides changing to a long-short portfolio, we have also provided a value of "linear" to the *type* argument. As the summary above shows, this yields a portfolio in which the weights on the individual positions are (linearly) proportional to their share prices. At the end of 2004, the lowest priced stock in the DJIA was HPQ (Hewlett-Packard) at \$20.97. Since we are using price as our measure of desirability, HPQ is the biggest short position. Since we have not changed the default value for *size* from "quintile," there are still 6 positions per side.

Figure 1 shows the result of calling *plot* on this portfolio object. The top plot displays the relationship between position weights and their corresponding *in.var* values, while the bottom plot shows a histogram of position weights.

```
> plot(p)
```

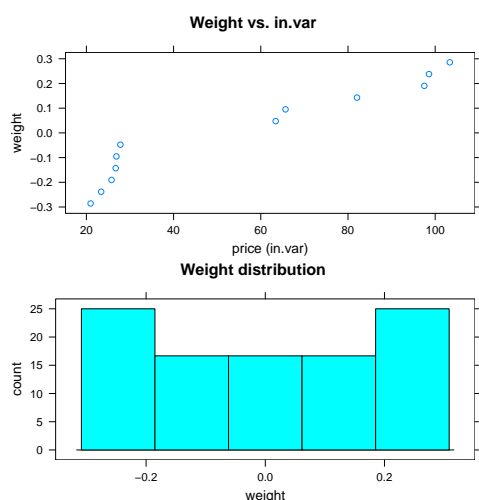


Figure 1: Plot of a portfolioBasic object.

The display for the exposure object is now somewhat different to accommodate the structure of a long-short portfolio.

```
> exposure(p, exp.var = c("price", "sector"))
```

```
numeric
  variable long short exposure
1   price 92.6 -24.2   68.4

sector
  variable  long  short exposure
2  Industrials 0.6190 0.0000  0.6190
1   Financials 0.0952 0.0000  0.0952
3     Staples 0.0476 -0.0952 -0.0476
5 Communications 0.0000 -0.2381 -0.2381
4    Technology 0.2381 -0.6667 -0.4286
```

The long exposure to price is simply the weighted average of price on the long side of the portfolio, where the weighting is done in proportion to the size of the position in each stock. The same is true on the short side. Since a linear weighting used here emphasises the tail of the distribution, the long exposure is greater than the long exposure of the equal weighted portfolio considered above, \$93 versus \$85.

Since the weights on the short side are actually negative — in the sense that we are negatively exposed to positive price changes in these stocks — the weighted average on the short side for a positive variable like price is also negative. Another way to read this is to note that the weighted average price on the short side is about \$24 but that the portfolio has a negative exposure to this number because these positions are all on the short side.

One reason for the convention of using a negative sign for short side exposures is that doing so makes the overall exposure of the portfolio into a simple summation of the long and short exposures. (Note

the assumption that the weights on both sides are equal. In future versions of the **portfolio** package, we hope to weaken these and other requirements.) For this portfolio, the overall exposure is 68. Because the portfolio is long the high priced stocks and short the low priced ones, the portfolio has a positive exposure to the price factor. Colloquially, we are “long price.”

A similar analysis applies to sector exposures. We have 62% of our long holdings in Industrials but zero of our short holdings. We are, therefore, 62% long Industrials. We have 24% of the long holdings in Technology, but 67% of the short holdings; so we are 43% short Technology.

Calling `plot` on the exposure object produces a bar chart for each exposure category, as seen in Figure 2. Since all numeric exposures are grouped together, a plot of numeric exposure may only make sense if all numeric variables are on the same scale. In this example, the only numeric exposure we have calculated is that to price.

```
> plot(exposure(p, exp.var = c("price",
+ "sector")))
```

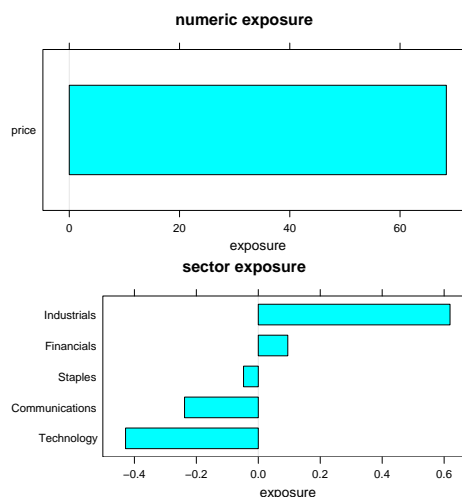


Figure 2: Plot of an exposure object for a single period. Bar charts are sorted by exposure.

The performance object is similar for a long-short portfolio.

```
> performance(p)
```

Total return: 2.19 %

Best/Worst performers:

	id	weight	ret	contrib
2	CAT	0.1905	-0.08220	-0.01566
5	IBM	0.2381	-0.05234	-0.01246
12	UTX	0.2857	-0.02583	-0.00738
3	DIS	-0.0476	0.02986	-0.00142
1	AIG	0.0952	0.00944	0.00090
8	MMM	0.1429	0.02790	0.00399
6	INTC	-0.2381	-0.04019	0.00957
10	PFE	-0.0952	-0.10152	0.00967

```
11 SBC -0.1905 -0.06617 0.01260
4 HPQ -0.2857 -0.06581 0.01880
```

The portfolio was up 2.2% in January. By default, the summary of the performance object only provides the 5 worst and best contributions to return. HPQ was the biggest winner because, though it was only down 7% for the month, its large weighting caused it to contribute almost 2% to overall performance. The 19% weight of CAT in the portfolio placed it as only the third largest position on the long side, but its -8% return for the month made it the biggest drag on performance.

The contribution function provides similar output for a long-short portfolio.

```
> contribution(p, contrib.var = c("cap.bil",
+ "sector"))
```

cap.bil					
	rank	variable	weight	contrib	roic
1	1 - low	(22.6,50.9]	0.0952	-0.01566	-0.16440
2	2	(50.9,71.1]	0.3810	0.01399	0.03671
3	3	(71.1,131]	0.0952	0.01260	0.13235
4	4	(131,191]	0.3095	-0.00103	-0.00334
5	5 - high	(191,386]	0.1190	0.01202	0.10098

sector				
	variable	weight	contrib	roic
1	Communications	0.1190	0.0112	0.0939
6	Conglomerates	0.0000	0.0000	0.0000
7	Cyclicals	0.0000	0.0000	0.0000
8	Energy	0.0000	0.0000	0.0000
2	Financials	0.0476	0.0009	0.0189
3	Industrials	0.3095	-0.0191	-0.0616
9	Materials	0.0000	0.0000	0.0000
4	Staples	0.0714	0.0106	0.1488
5	Technology	0.4524	0.0183	0.0404
10	Utilities	0.0000	0.0000	0.0000

As in the last example, the weight column reflects the proportion of the portfolio invested in each category. In this case, we have 45% of the total capital (or weight) of the long and short sides *considered together* invested in the Technology sector. We know from the exposure results above that most of this is invested on the short side, but in the context of contributions, it does not matter on which side the capital is deployed.

Plotting objects of class contribution produces output similar to plotting exposures, as can be seen in Figure 3. This time, however, we see values of roic plotted against the categories that make up each contrib.var. For numeric variables, roic for each interval is shown; numeric intervals will always appear in order.

```
> plot(contribution(p, contrib.var = c("cap.bil",
+ "sector")))
```

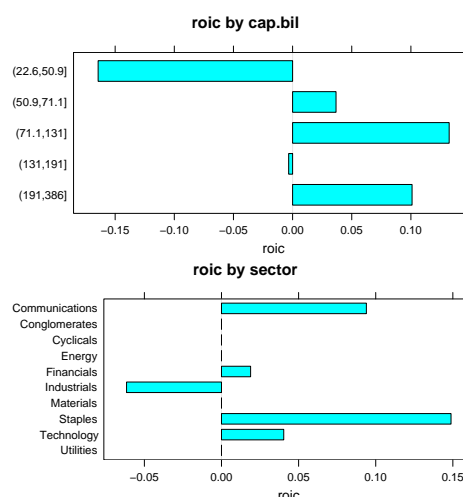


Figure 3: Plot of a contribution object for a single period.

## Conclusion

The current release of the portfolio package is meant to serve as a proof-of-concept. Relatively sophisticated portfolio analytics are possible using an open source package. Although money management is largely a zero-sum game — every dollar that I make is a dollar that someone else has lost — there is no reason why we might not cooperate on the tools that we all use.

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