

Analyzing Mutual Fund Performance

Mutual Funds

One of the main uses of asset pricing models is to analyze the performance of mutual funds. A mutual fund is a type of investment vehicle that pools money from many individual investors to purchase a diversified portfolio of stocks, bonds, or other securities. The fund is managed by a professional portfolio manager who invests the money in accordance with the fund's investment objectives and strategy.

There are many different types of mutual funds, including equity funds, bond funds, balanced funds, index funds, and specialty funds. Each type of fund has its own investment strategy and risk profile, and investors should carefully consider their investment objectives and risk tolerance before choosing a mutual fund to invest in.

In this notebook I analyze the *Fidelity Value Fund* (Ticker: FDVLX). According to the fund description, the fund invests in securities of companies that possess valuable fixed assets or that the fund manager believes are undervalued in the marketplace in relation to factors such as assets, earnings, or growth potential (stocks of these companies are often called “value” stocks). Normally investing primarily in common stocks.

```
start_date = "1994-12-01"  
end_date = "2026-01-01"  
ticker = "FDVLX"
```

The Augmented Five-Factor Model

We will estimate the Fama-French five-factor model augmented by the momentum factor,

$$R_i = a_i + b_i R_m + s_i SMB + h_i HML + r_i RMW + c_i CMA + m_i MOM + e_i$$

where $R_i = r_i - r_f$ represents the monthly excess returns for security i over the risk-free rate, and $R_m = r_m - r_f$ represents the monthly excess returns of the market.

The estimation of α_i , which is commonly called the alpha, now controls for many important sources of variation in the investment opportunity set. If the model is correct then the alpha should be close to zero.

The different loadings on the factors also have a clear interpretation. For a mutual fund we have that:

- $b_i < 1$ implies that the fund has less systematic risk than the market whereas a $b_i > 1$ implies that the fund takes more systematic risk than the market.
- $s_i > 0$ implies that the fund loads mostly on small stocks whereas $s_i < 0$ implies that the fund loads on large stocks.
- $h_i > 0$ implies that the fund loads on value stocks whereas $h_i < 0$ implies that the fund loads on growth stocks.
- $r_i > 0$ implies that the fund loads on stocks with robust operating profitability whereas $r_i < 0$ implies that the fund loads on stocks with weak operating profitability.
- $c_i > 0$ implies that the fund loads on stocks with low investment whereas $c_i < 0$ implies that the fund loads on stocks with high investments.
- $m_i > 0$ implies that the fund loads on winners whereas a negative $m_i < 0$ implies that the fund loads on losers, i.e. follows a contrarian strategy.

The *Capital Asset Pricing Model* (CAPM) is obtained by restricting $s_i = 0$, $h_i = 0$, $r_i = 0$, $c_i = 0$, and $m_i = 0$. Other nested models such as the Fama-French three-factor model can be obtained in a similar way.

Python Packages

```
import pandas as pd
import getfactormodels as gfm
import yfinance as yf
import statsmodels.formula.api as smf
import matplotlib.pyplot as plt

import warnings
warnings.simplefilter(action="ignore", category=FutureWarning)
```

Getting the Factors

The following code downloads the factors from the Fama-French five-factor model augmented by the momentum factor. I used to download this data using `pandasdatareader`, but the library is no longer maintained and does not work with Python 3.14. Thus, I switched to `getfactormodels`, which works very well.

```
ff5 = gfm.FamaFrenchFactors(model="5", frequency="m").to_pandas()
carhart = gfm.CarhartFactors(frequency="m").to_pandas()

ff_mom = pd.merge(ff5, carhart[['MOM']], left_index=True, right_index=True)
ff_mom = ff_mom.rename(columns={"Mkt-RF": "RMRF"})

ff_mom.index = pd.to_datetime(ff_mom.index)

display(ff_mom)
```

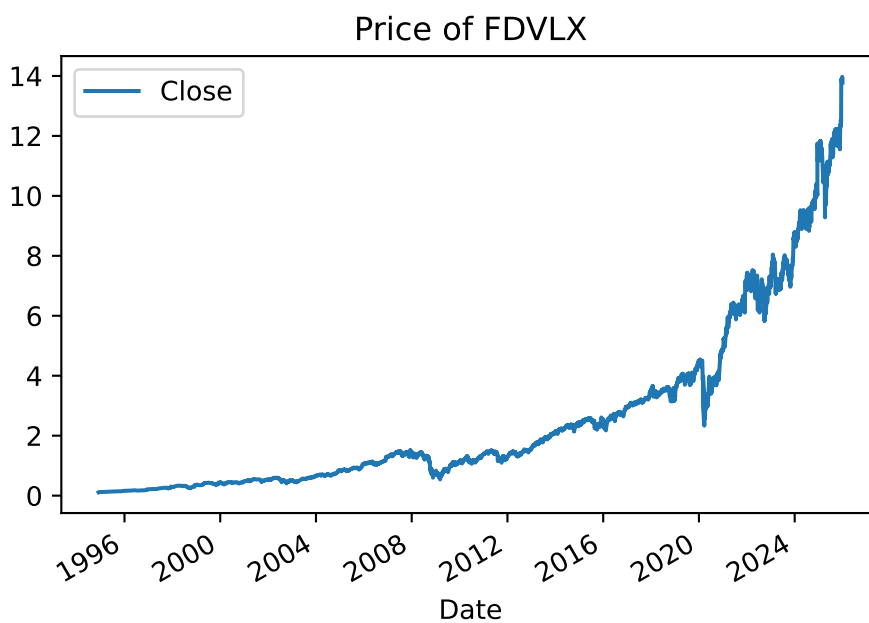
	RMRF	SMB	HML	RMW	CMA	RF	MOM
date							
1963-07-31	-0.0039	-0.0048	-0.0081	0.0064	-0.0115	0.0027	0.0101
1963-08-31	0.0508	-0.0080	0.0170	0.0040	-0.0038	0.0025	0.0100
1963-09-30	-0.0157	-0.0043	0.0000	-0.0078	0.0015	0.0027	0.0012
1963-10-31	0.0254	-0.0134	-0.0004	0.0279	-0.0225	0.0029	0.0313
1963-11-30	-0.0086	-0.0085	0.0173	-0.0043	0.0227	0.0027	-0.0078
...
2025-08-31	0.0185	0.0488	0.0442	-0.0068	0.0208	0.0038	-0.0354
2025-09-30	0.0339	-0.0218	-0.0105	-0.0206	-0.0222	0.0033	0.0463
2025-10-31	0.0196	-0.0131	-0.0309	-0.0521	-0.0403	0.0037	0.0027
2025-11-30	-0.0013	0.0147	0.0376	0.0142	0.0068	0.0030	-0.0180
2025-12-31	-0.0036	-0.0022	0.0242	0.0040	0.0037	0.0034	-0.0241

Getting the Data Ready

Fund Returns

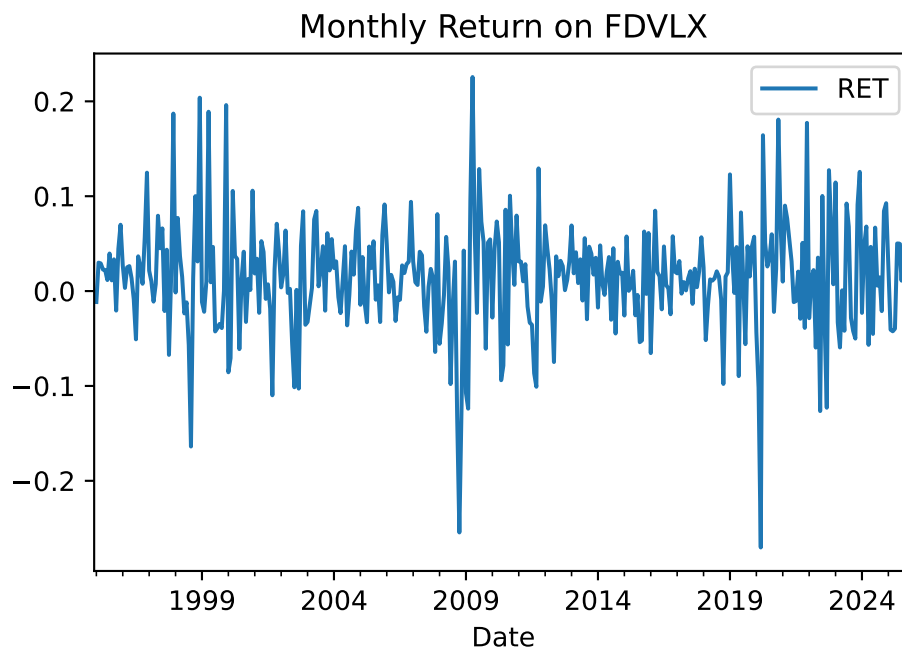
We download the close price series from Yahoo! Finance. For mutual funds the close and adjusted close price is the same since for tax purposes mutual funds reinvest all dividend payments in the fund.

```
stock = yf.download(tickers=ticker, start=start_date, end=end_date, progress=False, multi_level=False)
ax = stock.plot(title="Price of " + ticker)
```



We compute monthly returns and use RET to denote the column containing the returns.

```
ret = stock.resample("ME").last().pct_change()
ret = ret.rename(columns={"Close": "RET"})
ax = ret.plot(title="Monthly Return on " + ticker)
```



Merge with the Factors

Finally, we merge the returns series that we want to analyze with the six factors. Additionally, we compute excess returns for the security.

```
merged = (
    pd.merge(left=ret, right=ff_mom, left_index=True, right_index=True)
    .assign(RETRF=ret["RET"] - ff_mom["RF"])
    .drop(columns=["RET", "RF"])
    .dropna()
)
display(merged)
```

	RMRF	SMB	HML	RMW	CMA	MOM	RETRF
Date							
1995-01-31	0.0180	-0.0307	0.0259	0.0015	-0.0065	-0.0184	-0.015717
1995-02-28	0.0363	-0.0049	0.0099	0.0061	-0.0040	-0.0047	0.025995

	RMRF	SMB	HML	RMW	CMA	MOM	RETRF
Date							
1995-03-31	0.0219	-0.0053	-0.0213	-0.0013	0.0023	0.0045	0.024522
1995-04-30	0.0211	-0.0026	0.0167	0.0043	0.0082	0.0180	0.018285
1995-05-31	0.0290	-0.0217	0.0228	0.0041	0.0001	-0.0055	0.016782
...
2025-08-31	0.0185	0.0488	0.0442	-0.0068	0.0208	-0.0354	0.046998
2025-09-30	0.0339	-0.0218	-0.0105	-0.0206	-0.0222	0.0463	-0.006753
2025-10-31	0.0196	-0.0131	-0.0309	-0.0521	-0.0403	0.0027	-0.012016
2025-11-30	-0.0013	0.0147	0.0376	0.0142	0.0068	-0.0180	0.035435
2025-12-31	-0.0036	-0.0022	0.0242	0.0040	0.0037	-0.0241	0.109415

Estimating the Model

CAPM

We start by estimating a CAPM regression,

$$R_i = a_i + b_i R_m + e_i$$

```
results = smf.ols("RETRF ~ RMRF", data=merged).fit()
print(results.summary(slim=True))
```

```

                                OLS Regression Results
=====
Dep. Variable:                  RETRF    R-squared:                  0.632
Model:                          OLS    Adj. R-squared:              0.631
No. Observations:                372    F-statistic:                  634.4
Covariance Type:                nonrobust  Prob (F-statistic):          3.03e-
82
=====
                                coef    std err          t      P>|t|      [0.025    0.975]
-----

```

Intercept	0.0043	0.002	2.282	0.023	0.001	0.008
RMRF	1.0445	0.041	25.187	0.000	0.963	1.126
=====						

Notes:

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

The results indicate that the CAPM alpha is negative ($\alpha = -0.0050$) and statistically significant at the 5% level ($p\text{-value} = 0.011$). This means that during the period the fund underperformed compared to the market.

The Augmented Five-Factor Model

```
results = smf.ols("RETRF ~ RMRF + SMB + HML + RMW + CMA + MOM", data=merged).fit()
print(results.summary(slim=True))
```

OLS Regression Results						
=====						
Dep. Variable:	RETRF		R-squared:	0.760		
Model:	OLS		Adj. R-squared:	0.756		
No. Observations:	372		F-statistic:	192.4		
Covariance Type:	nonrobust		Prob (F-statistic):	9.24e-		
110						
=====						
	coef	std err	t	P> t	[0.025	0.975]

Intercept	0.0027	0.002	1.680	0.094	-0.000	0.006
RMRF	1.0648	0.039	26.989	0.000	0.987	1.142
SMB	0.3163	0.056	5.654	0.000	0.206	0.426
HML	0.3767	0.066	5.691	0.000	0.247	0.507
RMW	0.2921	0.071	4.106	0.000	0.152	0.432
CMA	0.1150	0.094	1.223	0.222	-0.070	0.300
MOM	-0.1049	0.034	-3.062	0.002	-0.172	-
0.038						

=====

Notes:

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

After controlling for the other factors, the alpha is still negative ($\alpha = -0.0066$) and now statistically significant at the 1% level (p-value = 0.000). In other words, after controlling for our systematic factors this fund underperformed by $-0.66 \times 12 = -7.92\%$ per year compared to the market portfolio.

We learn the following from the coefficient estimates.

Fac- tor	Coefficient	Significance	Interpretation
SMB	0.3787	1%	The fund invested in small stocks
HML	0.3618	1%	The fund invested in value stocks
RMW	0.4136	1%	The fund invested in stocks with strong profitability
CMA	0.1115	Not significant	The fund invested in both high and low investment stocks
MOM	-0.2101	1%	The fund was significantly contrarian by chasing losers

Therefore, the results from the regression somewhat agree with the fund description. The exposure to SMB is positive on size, even though Morningstar categorizes the fund as *Mid-Cap Value*. The fund returns load significantly on HML, which is consistent with the fund being a value fund. The negative exposure to momentum might come from the fact that value firms often have low P/E ratios, which commonly occur after stock price declines.