Factor Investing Project

Idiosyncratic Momentum Factors

Author

Nick Kirchner

Yale School of Management

July 30, 2021

Case Report

The content of this write-up will be focused on the creation of an Idiosyncratic Momentum factor for the S&P 500 from December 1997 to December 2019. First, I will describe my data sources, data manipulation, and factor constructions. Afterward, I will present results to choose from the constructed factors and see how they fit into the universe of established factors with an emphasis on classical Momentum factors.

Data and factor construction

I used the WRDS Python library to pull CRSP data and obtain a list of all constituents of the S&P 500 between 1997 and 2020 to use their Cusips to download monthly return and market capitalization data for said companies between 1990 and 2020 as well as returns of the S&P 500 index itself. Unfortunately, Compustat has deleted its S&P500 constituents list on WRDS and the Python library is the only way I am aware of to obtain the said list. Furthermore, I downloaded the monthly 5 Factor returns with the risk-free rate as well as the Momentum factor (UMD) from the Kenneth French database [1]. All stock and index excess returns are calculated by subtracting the appropriate risk-free rate (US - from French's database) from the returns.

For the creation of the Idiosyncratic Momentum factors, idiosyncratic returns of a stock from an asset pricing model (the residuals) are used instead of excess returns as in classical Momentum strategies (such as UMD). In this write-up, two different methods to obtain idiosyncratic returns are employed. The first is the Capital Asset Pricing Model (CAPM) (Sharpe 1964). The other one is the 3 Factor Model from Fama and French (Fama and French, 1993). Both methods use regressions of each stock's excess returns on the index (S&P 500) and other two other risk factors (Size and Value) in the latter to explain a stock's return. The residuals of this regression are treated as a stock's idiosyncratic return (ϵ_{it}) over time and used for later classifications. The regressions are done on rolling 36-month windows and stocks with not enough observations are dropped (see Blitz et. al. 2018).

$$\epsilon_{i,t}^{CAPM} = (r_{i,t} - r_{f,t}) - \beta_1 \times (r_{sp500,t} - r_{f,t}) \tag{1}$$

$$\epsilon_{i,t}^{3F} = (r_{i,t} - r_{f,t}) - \beta_1 \times (r_{sp500,t} - r_{f,t}) - \beta_2 \times HML_t - \beta_3 \times SMB_t \tag{2}$$

Next, the idiosyncratic and excess returns of each stock i at time t are used to sort all stocks at each time into quintiles. To sort them, different methods ($IdioMom_j$ - formula (3)) are employed. The most common classifier is the cumulative return of a stock between the last 2 and 12 months ($IdioMom_1$). The logic is that well-performing stocks of the past will perform better in the future (Momentum) while there is a short term reversal for which the last month is not used. Another popular approach is to construct

[1] `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

a performance measure between the last 7 and 12 months ($IdioMom_1$) claiming that the reversal and underreaction phase of recent months is longer. I employ both to contrast the approaches and see if they cause major differences. Stocks that do not have 12-month idiosyncratic returns are dropped and only idiosyncratic return data from December 1997 onward is used. This results in roughly 480 firms (and never less than 470 firms) per year of the $\tilde{5}00$ of the index represented in the study. Each quintile's monthly return is calculated as an equal or value-weighted (using market capitalization) average of each stock's return after being sorted based on their past performance categorization. The value-weighted approach is more realistic as its weights fluctuate with the implicit return of a stock and thus rebalances naturally while equal weights would require monthly rebalancing. The downturn of value-weighting is that the portfolios might be too concentrated on big companies and thus not reflect the market appropriately.

$$IdioMom_1 = \prod_{t-12}^{t-2}(1+\epsilon_{i,t}^{(j)});\ IdioMom_2 = \prod_{t-12}^{t-7}(1+\epsilon_{i,t}^{(j)}) \tag{3}$$

Results

Table 1.1 shows performance measures for a portfolio that goes long the highest quintile (most Momentum) while shorting the lowest quintile (thus, dollar-neutral) for each mentioned approach. The portfolio measures are done for the classical excess and both idiosyncratic return-based performance measures. Generally, the approach yields positive risk-adjusted returns for each measure and approach, while returns are insignificantly different from zero, however. Each strategy's alpha when regressed upon the market index (S&P 500) and the 5 Factor Model indicates that they do not add significant alpha. It can be seen, however, that performance and alphas increase when idiosyncratic instead of excess returns are used.

For further examinations, the value-weighted factor based on the 12-2 cumulative return is used as Table 1.1 shows that there are no significant differences in performance or alphas. In the literature the 12-2 categorization is more commonly used and more comparable to the UMD (Up minus Down) factor from French's website [2]. Furthermore, the returns are value weighted as this is in line with the other factors (see Fama and French). The three MOM factors based on excess returns (MOM), CAPM idiosyncratic returns (IMOM-CAPM), and 3 Factor idiosyncratic returns (IMOM-3F) are regressed on the index and 5 Factors (Fama and French 2015 - HML, SMB, RMW, CMA & UMD)[3] to show their loading. The three Momentum factors are scaled by the ex-post volatility (as in Asness et. al. 2011) to obtain constant volatility. The results from Table 1.2 show that none deliver significant alpha and are highly explainable by UMD. This is as expected as UMD is a Momentum factor. It is interesting, however, that the R^2 and UMD's significance decreases while α increases when (more parameterized) idiosyncratic returns are used. This hints at the fact that the IMOM-3F is purer and less correlated with other risk premia and thus might provide better diversification benefits in a multi-factor portfolio than the classical Momentum approach based on excess returns. Another interesting fact is that the IMOM-3F is significantly positively loading on HML (Value). Normally, Momentum is said to be globally negatively correlated with Value (see Asness et. al. 2011). This may be the consequence that idiosyncratic returns are obtained by regressions on HML which includes small stocks as well and may not fully capture the Value factor in S&P 500 stocks.

Additionally, the returns of the S&P 500 are regressed on a 5 Factor Model with UMD and each of the

[2] `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_mom_factor.html`

[3] Value, Size, Quality, Aggressiveness and Momentum

Table 1.1: **Performance of Momentum factors based on different construction.**

This table shows the performance of Momentum factors based on excess returns (MOM) and the idiosyncratic returns of the CAPM and the 3 Factor Model. The factor is constructed by being long the highest quintile and shorting the lowest quintile based on past cumulative (either 12-2 or 12-7 months) performance. Factor returns are obtained by either equal or value-weighting the individual stocks' returns.

				12-2 Equal Weighted				
	Excess Return	t-stat	Volatility	Sharpe Ratio	α-CAPM	t-stat	α-5FM	t-stat
MOM	0.0128	0.2625	0.2284	0.0562	0.0414	0.8992	0.0175	0.3875
IMOM-CAPM	0.0274	0.6960	0.1826	0.1500	0.0537	1.4918	0.0283	0.7836
IMOM-3F	0.0140	0.4469	0.1463	0.0957	0.0344	1.1947	0.0208	0.7241
				12-2 Value Weighted				
MOM	0.0533	1.0878	0.2247	0.2371	0.0776	1.6466	0.0488	1.0602
IMOM-CAPM	0.0469	1.2391	0.1742	0.2693	0.0695	1.9580	0.0463	1.3259
IMOM-3F	0.0300	1.0197	0.1364	0.2200	0.0481	1.7614	0.0365	1.2976
				12-7 Equal Weighted				
MOM	0.0230	0.6523	0.1641	0.1403	0.0335	0.9589	0.0283	0.8494
IMOM-CAPM	0.0179	0.6090	0.1373	0.1307	0.0323	1.1448	0.0222	0.7846
IMOM-3F	0.0249	1.0493	0.1104	0.2258	0.0372	1.6443	0.0318	1.4214
				12-7 Value Weighted				
MOM	0.0399	1.0759	0.1710	0.2331	0.0457	1.2300	0.0477	1.3598
IMOM-CAPM	0.0276	0.9161	0.1400	0.1974	0.0407	1.3922	0.0379	1.2913
IMOM-3F	0.0406	1.5116	0.1240	0.3276	0.0517	1.9762	0.0480	1.7850

three constructed factors as explanatory variables. These regressions from Table 1.3 indicate that the explanatory power of momentum can be captured better by using an Idiosyncratic Momentum factor as they are statistically significant and UMD is not, while this is not the case for the Momentum factor that uses excess returns (MOM). These results have to be taken with a grain of salt however as these regressions suffer from multicollinearity as UMD and the Momentum factors are highly correlated. Regressions of index returns on the constructed factors without UMD (columns 5-8) show an increase in R^2 which also indicates that they are more useful as Momentum factors in explaining S&P 500 returns.

Conclusion

The creation of Idiosyncratic Momentum factors has yielded interesting results. Even though it is not providing statistically significant alpha, regressions show that it is less explained by other factors and can thus contribute to investors by providing diversification benefits (see Asness et. al. 2014). Further, the results are limited as only S&P 500 stocks are considered. This introduces biases as these are the US's 500 biggest companies. Thus, a comparison with factors that are constructed on the whole US stock universe is not ideal. One possible improvement on the IMOM-3F can be realized by obtaining idiosyncratic returns from factors created from large stocks only. The use of Size as a whole on S&P 500 stocks can be questioned altogether. Another interesting angle to explore is how to construct a factor based on risk-adjusted idiosyncratic returns (see Blitz et. al. 2018) and how it would perform for the S&P 500 constituents. Further, the signal could also be cleaned up by using PCA-based industry returns (Blitz et. al. 2011) or calendar effects (Grinblatt and Moskowitz 2004) as Momentum factors tend to be explainable by both. Overall, the results indicate that Idiosyncratic Momentum is superior to Momentum based on excess return as this report broadly confirms the literature but is not holistic enough.

Table 1.2: **Regression of Momentum Factors on other factors.**

The 12-2 value weighted factors based on excess returns (MOM) and idiosyncratic returns from the CAPM (IMIOM-CAPM) and 3 Factor Model (IMOM-3F) are regressed on the excess return of the S&P 500 and the 4 other Fama and French Factors as well as the Momentum factor UMD. All returns are monthly.

				Dependent variable				
Independent variable	α	S&P 500	SMB	HML	RMA	CMA	UMD	R^2
MOM	-0.0003 -0.43	0.0176 1.03	0.0603** 2.65	-0.0194 -0.67	0.0928*** 3.17	-0.0498 -1.27	0.5117*** 39.96	0.8881
IMOM-CAPM	0.0005 0.49	-0.0749** -2.57	0.1347 3.49	-0.0086 -0.17	0.0359 0.72	0.0528 0.80	0.4126*** 18.96	0.6769
IMOM-3F	0.0010 0.70	-0.1219*** -3.08	-0.0218 -0.42	0.1790** 2.68	0.0279 0.41	0.4147 0.04	0.2972*** 10.09	0.4075

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, t-test statistics in parentheses

Table 1.3: **Regression of S&P 500 excess returns on factor returns.**

The excess returns of the S&P 500 are regressed on the Fama and French Factors as well as the constructed (idiosyncratic) Momentum Factors (MOM, IMOM-CAPM & IMOM-3F). The first three regressions include the UMD factor as well. All returns are monthly.

				Independent variable: S&P 500 excess returns			
Momentum Factor:	MOM	IMOM-CAPM	IMOM-3F	MOM	IMOM-CAPM	IMOM-3F	UMD
α	0.0072*** (3.20)	0.0072*** (3.30)	0.0074*** (3.38)	0.0071*** (3.23)	0.0072*** (3.34)	0.0072*** (3.32)	0.0078*** (3.51)
(I)MOM	-0.3743 (1.48)	-0.4937*** (3.12)	-0.3540** (2.96)	-0.4117*** (5.05)	-0.4624*** (5.81)	-0.4508 (5.60)	
SMB	-0.0425 (0.52)	-0.0092 (0.11)	-0.0557 (0.69)	-0.0433 (0.53)	-0.0099 (0.12)	-0.0679 (0.84)	-0.0391 (0.48)
HML	0.3580*** (3.49)	0.3817*** (3.79)	0.4035*** (3.98)	0.3586*** (3.51)	0.3768*** (3.83)	0.4390*** (4.56)	0.3702*** (3.62)
RMW	-0.5373*** (5.27)	-0.4998*** (4.97)	-0.4843*** (4.73)	-0.5351*** (5.31)	-0.5018*** (5.02)	-0.4770*** (4.67)	-0.5709*** (5.73)
CMA	-0.7251*** (5.42)	-0.6982*** (5.29)	-0.7669*** (5.76)	-0.7275*** (5.48)	-0.6963*** (5.30)	-0.7999*** (6.16)	-0.7141*** (5.33)
UMD	-0.0214 (0.16)	0.0198 (0.23)	-0.0711 (1.09)				-0.2134*** (4.81)
R^2	0.33	0.35	0.36	0.34	0.36	0.35	0.33
n	265	265	265	265	265	265	265

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, t-test statistics in parentheses

Bibliography

[1] Asness, C. S., Moskowitz, T., J. and Pedersen, L., H. (2011): *Value and Momentum everywhere*, The Journal of Finance, vol 68(3), 929-985.

[2] Asness, C. S., Frazzini, A., Israel, R. and Moskowitz, T., J. (2014): *Fact, Fiction and Momentum Investing*, Journal of Portfolio Management .

[3] Blitz, D., Huji, J., and Martes, M. (2011): *Residual Momentum*, Journal of Empirical Finance, vol 52(1), 506-521.

[4] Blitz, D., Hanauer, M., and Vidojevic, M. (2020): *Residual Momentum*, International Review of Economics & Finance, vol 69(1), 932-957.

[5] Chaves, D., B. (2012): *Eureka! A Momentum Strategy that Also Works in Japan*, Working Paper, 1-31.

[6] Fama, E.,F. and French, K., R, (1993): *Common Risk Factors in the Returns on Stocks and Bonds*, Journal of Financial Economics, vol 33, 3-56.

[7] Fama, E.,F. and French, K., R, (2015): *A five-factor asset pricing model*, Journal of Financial Economics, vol 116, 1-22.

[8] Moskowitz, T., J. and Grinblatt, M. (2004): *Do Industries Explain Momentum*, The Journal of Finance, vol 54(4), 1249-1290.

[9] Sharpe, W.,F. (1964): *Capital asset prices: A theory of market equilibrium under conditions of risk*, The Journal of Finance, vol 19(3), 425-442.