CFM 301 Winter 2024 – Financial Data Analytics
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Assignment 4
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Report/Summary of Conclusions from the Code

Included files in submission:
- [Data Codes] *Assignment 4 – Code.ipynb*
- [raw/intermediate data] *datasets-A4.xlsx*

<u>Question 1 – Portfolio Sorting, Hedged Portfolios and Statistics</u>

a)

The code uses the [m, n, l] month rule to construct quintile portfolios for each of the six winsorized factors from Assignment 3 for the period Jan 2000 – Nov 2021. The code actually calculates returns starting Jan **1997** because it helps determine the FF4 and CAPM alphas in part b.

The way our code handles the data avoids look-ahead bias for return prediction because we sort using the factor results from time t and only report the t+1 returns (from ret_t1). This is equivalent to us forming an equally-weighted index at time t using the factor data we have access to, then holding for a month until time t+1 and noting down returns during the period. This way, we don't make any decisions using future data, so there is no look-ahead bias.

This is shown in the screenshot from the code below, where **data_date** is the timestamp of the returns used to calculate the weights that lead to the returns from **return date**.

```
[6]: quantile_sort("lnSize_winsorized")
```

[6]:

data_date	return date	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
1997-01-31	1997-02-28	0.001083	-0.046318	-0.017539	-0.014411	-0.037853
1997-02-28	1997-03-31	-0.063589	-0.113885	-0.034161	0.017856	-0.043479
1997-03-31	1997-04-30	0.016221	0.025494	0.027538	0.010283	0.113056
1997-04-30	1997-05-30	0.206196	0.189984	0.119348	0.079507	0.082713
1997-05-30	1997-06-30	0.0074	0.002987	0.014039	0.017325	-0.003483
...	...	...	...	...	...	...
2021-07-30	2021-08-31	0.027984	0.046413	0.031173	0.006084	0.044354
2021-08-31	2021-09-30	-0.041886	-0.024441	-0.069276	-0.052418	-0.050429
2021-09-30	2021-10-29	0.091362	0.043535	0.083113	0.029173	0.0564
2021-10-29	2021-11-30	-0.063331	0.009399	-0.05942	0.026617	0.013328
2021-11-30	2021-12-31	0.008863	0.053519	0.020908	0.044843	0.010756

299 rows × 6 columns

The monthly returns from Jan 2000 – Nov 2021 for each of our quintile portfolios for each factor are included in the dataset file. Average returns for each quintile (Exhibit 1) are in the Appendix.

b)
The hedge portfolios using quintiles 1 and 5 of each respective factor portfolio, with the goal of generating profit are constructed with the following quintiles long and short:

Note that our quintiles are shorted from smallest to highest (factor value)

lnSize_winsorized

- We know from class that small stocks tend to outperform.
- *So we long quintile 1 and short quintile 5.*

bk2mkt_winsorized

- We know from class that value firms (high book to market) tend to outperform grown firms (low book to market).
- *So we long quintile 5 and short quintile 1.*

ep1_winsorized

- Note ep1 is IBQ (Income before extraordinary items) / Market equity (from Assignment 2)
- ep1 is a measure of the company's income (earnings) per dollar valuation (market cap)
- In theory, a company with a higher earnings to valuation ratio should perform better (is undervalued) compared to a company with a low ratio (overvalued)
- *So we long quintile 5 and short quintile 1*

beta_winsorized

- Frazzini and Pedersen argue that high-beta stocks are overbought due to the inherent leverage they offer
- Therefore high beta stocks generate proportionally lower non-leveraged returns
- So we Long low beta and short high beta
- *This means we long quintile 1 and short quintile 5*

ivol_winsorized

- Idiosyncratic risk is risk that is associated with the stock itself, not to the market
- Ang. et al. found that high idiosyncratic volatility have lower returns
- Hou and Loh argue that investors' lottery preferences, market frictions, etc add excess demand for high ivol stocks, bidding up prices and reducing average returns
- Therefore we want to short high ivol and long low ivol
- *So we long portfolio 1 short portfolio 5*

mom_winsorized

- We learned in class that stocks high momentum stocks tend to perform well, and due to the short 1 month timeframe it can be realized
- *We long portfolio 5 (high momentum) and short portfolio 1 (low momentum)*

The statistics for each hedged portfolio (Exhibit 2), and the statistics for each of the quantile portfolios (Exhibit 3) are included in the appendix.

Out of the hedged portfolios, **size** and **idiosyncratic volatility** have significant returns, excess returns, CAPM alpha and FF4 alphas at a 95% confidence level ($p < 0.05$), while **earnings ratio** and **beta** have less significant results and **book-to-market** and **momentum** have insignificant performance. However, only the **size** factor has significant *positive* returns. The reason why some factors do not have positive or significant returns is due to our stock set being only Nasdaq-100 stocks, which are all large-cap and have relatively homogenous factor characteristics.

Question 2 – AQR's Betting-Against-Beta Strategy

We use the following BAB calculation, as from the slides.

$$BAB_{t+1} = \frac{r_{L,t+1} - r_f}{\beta_{L,t}} - \frac{r_{H,t+1} - r_f}{\beta H, t}$$

Here, beta_H refers to our high beta (quintile 5) portfolio and beta_L refers to out low beta (quintile 1) portfolio. In our code, since the quintile portfolios are equally-weighted, I can just take the average beta for all stocks in each respective portfolio to get out two beta measures.

The monthly returns for our BAB portfolio are included in the attached datasets, but a summary of the portfolio's performance, compared to our simple hedged beta portfolio is shown below:

portfolio	bab	beta
index		
Overall Return (%)	2.40	-0.70
ret |t|	3.55	1.35
ret p-value	0.00	0.18
Excess Return (%)	1.79	-1.31
xret |t|	3.05	1.85
xret p-value	0.00	0.07
CAPM Alpha (%)	0.86	-0.63
CAPM |t|	2.13	7.22
CAPM p-value	0.03	0.00
FF4 Alpha (%)	0.68	-0.66
FF4 |t|	1.32	7.62
FF4 p-value	0.19	0.00
Sharpe	0.21	-0.10
sharpe |t|	3.36	1.60
sharpe p-value	0.00	0.11

Despite both being zero-cost portfolios, the betting-against-beta portfolio outperforms at a significant level ($p < 0.05$) compared to our simple beta hedge portfolio and has a better Sharpe ratio. Although both portfolios appear to leverage the same underlying belief that high beta stocks are generally going to perform worse compared to low beta stocks in the long run and in aggregate, their different return characteristics suggests that there is something that the BAB factor does differently, and better compared to the simple beta strategy. A potential reason for this could be due to the BAB factor's construction as a **weighted** portfolio of shorting low beta and high beta stocks, which will yield better returns in market conditions where the highest beta is not as high or vice versa.

Question 3 – Factor Mimicking ETFs

a)

The long leg of the idiosyncratic volatility-hedged (low volatility) portfolio yields an average monthly return of 1.41%. Compared to the market return, it significantly returns an average excess return of 0.87% per month ($p < 0.05$) at a 95% significance level. Therefore, this portfolio has delivered value to investors over this period, as this portfolio consistently beat the market.

portfolio	low_ivol
Overall Return (%)	1.41
ret |t|	5.20
ret p-value	0.00
Excess Return (%)	0.80
xret |t|	5.39
xret p-value	0.00
CAPM Alpha (%)	0.87
CAPM |t|	35.33
CAPM p-value	0.00
FF4 Alpha (%)	0.76
FF4 |t|	30.79
FF4 p-value	0.00
Sharpe	0.29
sharpe |t|	4.73
sharpe p-value	0.00

However, it is important to note that this may not hold in the future, and when considering operating expenses included in management fees and transaction fees related to monthly rebalancing, which could possibly surpass a cost of 1% per month, this portfolio may not benefit investors in the real world.

b)

The annualized turnover rate of our portfolio is 610.31%, meaning on average, the number of times that new stocks have participated in this portfolio is over 6 times the size of the portfolio. If the bid-ask spread of stocks in the portfolio exceed even a few cents, this constant rebalancing could eat at the excess returns of the portfolio to the point where it does not even make money, without considering management fees.

Q4 – Multi-Factor ETF (with short selling)

a) An equal-weighted portfolio comprising of the minimum volatility factor and the betting-against-beta factor has the following return characteristics:

portfolio	bab_ivol
Overall Return (%)	0.43
ret |t|	1.05
ret p-value	0.30
Excess Return (%)	-0.17
xret |t|	0.38
xret p-value	0.71
CAPM Alpha (%)	-0.53
CAPM |t|	2.32
CAPM p-value	0.02
FF4 Alpha (%)	-0.60
FF4 |t|	2.09
FF4 p-value	0.04
Sharpe	0.05
sharpe |t|	0.75
sharpe p-value	0.46

On average, this portfolio yields positive returns, but underperforms the market, even before fees. The FF4 alpha is -0.6% ($p < 0.05$), so it significantly underperformance this benchmark, and has a poor Sharpe ratio that is insignificantly above zero.

b) Net of fees, our portfolio has the following return characteristics:

portfolio	USMV_BABF
Overall Return (%)	0.38
ret |t|	0.93
ret p-value	0.36
Excess Return (%)	-0.22
xret |t|	0.48
xret p-value	0.63
CAPM Alpha (%)	-0.58
CAPM |t|	2.54
CAPM p-value	0.01
FF4 Alpha (%)	-0.65
FF4 |t|	2.26
FF4 p-value	0.02
Sharpe	0.04
sharpe |t|	0.62
sharpe p-value	0.53

With fees added, this portfolio still yields positive returns on average but underperforms even more, and appears unattractive to investors. This scenario is a good example of the efficient market hypothesis, as this portfolio is theoretically a zero-cost portfolio, requiring no upfront capital to set up due to its construction through balanced long and short legs. The low-volatility long leg from question 3 outperforms this portfolio. If USMV comprised of the long leg from question 3 instead, this portfolio could yield promising returns and be a convincing product.

Question 5 – Fama MacBeth Cross-Sectional Test

For each stock (permno) we will run regressions between the winsorized month t ivol + (CAPM beta, logSize, book-to-market) to month t+1 returns for each month from t_0 = Jan 2000 (or the earliest time after that) for our first stage regression. Note that our code uses the non-winsorized versions of the variables and does the winsorization per month (by clipping the top and bottom 3 standard deviations). Note that in addition to winsorizing the raw factors, we also winsorize the historical returns being analyzed to remove outliers in both variable classes.

Next, the second stage regression will be on the betas to calculate each of our corresponding lambas, or the “price” of each of our factors. We aim to determine whether our not idiosyncratic volatility is priced significantly (lambda significantly different than 0). The results of our t-test are below:

	0
ivol |t|	1.23
ivol_p_value	0.22
capm_beta |t|	2.02
capm_beta_p_value	0.04
lnSize |t|	1.04
lnSize_p_value	0.30
bk2mkt |t|	3.49
bk2mkt_p_value	0.00

We see that idiosyncratic volatility fails to be significant at a 95% significance level (p = 0.22), but some of the other control variables appear to be significant such as CAPM beta and book-to-market (value) factors.

The failure of our idiosyncratic volatility factor to be significantly priced, when modelled in conjunction with the other factors (capm beta, firm size and book-to-market), signify that it is either captured in the other factors, or is not a significant indicator of positive t+1 returns by itself. That is, an investment strategy that goes long on idiosyncratic volatility is not likely to perform well.

This conclusion makes sense from our learnings in the course. We know that low volatility stocks generally outperform high volatility stocks due to lottery preferences driving up the price for high volatility stocks, so an investment strategy focusing on holding high volatility stocks should not perform well.

Question 6 – Q1 but on All NYSE/NASDAQ Common Stocks

Following the stock screening and cleaning procedures from the assignment, we obtain a dataset with the following summary statistics for monthly returns:

```
------------------------------------------
Summary Statistics for [ RET ] variable
------------------------------------------
N: 1244648
mean: 1.1427%
standard deviation: 19.7417%
median: 0.2721%
minimum: -99.3600%
1st Percentile: -42.9907%
99th Percentile: 62.2120%
maximum: 1988.3589%
```

Across all stocks, our hedged portfolio on size factor (long small and short large cap stocks) has the following return characteristics:

portfolio	q1-q5
Overall Return (%)	0.69
ret |t|	1.90
ret p-value	0.06
Excess Return (%)	0.08
xret |t|	0.19
xret p-value	0.85
CAPM Alpha (%)	0.68
CAPM |t|	9.69
CAPM p-value	0.00
FF4 Alpha (%)	0.72
FF4 |t|	8.68
FF4 p-value	0.00
Sharpe	0.10
sharpe |t|	1.56
sharpe p-value	0.12

We see that overall, we have an overall monthly return of 0.69% that just misses the 95% significance level with (p = 0.06). It appears to match the market returns without having to put down any capital as this is a zero-cost portfolio.

Continued on next page

Now, by cutting out stocks every month that have a size less than the 20th percentile of market capitalizations for stocks in the NYSE, as in Hou et al., we achieve the following:

portfolio	q1-q5
Overall Return (%)	0.17
ret |t|	0.79
ret p-value	0.43
Excess Return (%)	-0.44
xret |t|	1.62
xret p-value	0.11
CAPM Alpha (%)	0.17
CAPM |t|	6.13
CAPM p-value	0.00
FF4 Alpha (%)	0.18
FF4 |t|	5.60
FF4 p-value	0.00
Sharpe	0.01
sharpe |t|	0.20
sharpe p-value	0.84

This portfolio performs poorly, netting returns that barely beat the market at a low significance level and generate negative excess returns to the market.

Compared to the MSCI Minimum Volatility Index (Sept 29, 2023):

Gross Performance as of 09/29/2023 in USD									
Index Name	**1D**	**1W**	**1M**	**3M**	**YTD**	**1Y**	**3Y**	**5Y**	**10Y**
MSCI ACWI Index	**0.0%**	**-0.9%**	**-3.8%**	**-2.3%**	**10.5%**	**21.4%**	**7.4%**	**7.0%**	**8.1%**
MSCI ACWI Minimum Volatility Index	-0.2%	-1.7%	-2.4%	-1.6%	1.7%	10.4%	3.8%	4.3%	7.2%

Our annualized monthly return from the portfolio with microcaps removed falls short from the 10Y returns from the MSCI index at only 12 * 0.16% = 2.04%, while the portfolio holding all stocks slightly outperforms at 0.69% * 12 = 8.28%. This return however, may be difficult to realize as low-cap stocks tend to have lower trading volumes, and must be discounted in accordance to their lower liquidity and potential price fluctuations caused by entering into any significant position in them.

Appendix

Exhibit 1: Average Returns for each Quintile Portfolio (in %, by quintile)

```
Average Quintile Portfolio Returns (%)
-----------------------------
lnSize_winsorized
Quintile 1    3.65
Quintile 2    2.16
Quintile 3    1.49
Quintile 4    1.02
Quintile 5    1.02
dtype: float64
-----------------------------
bk2mkt_winsorized
Quintile 1    2.20
Quintile 2    1.57
Quintile 3    1.82
Quintile 4    1.88
Quintile 5    1.99
dtype: float64
-----------------------------
ep1_winsorized
Quintile 1    2.74
Quintile 2    1.66
Quintile 3    1.42
Quintile 4    1.68
Quintile 5    1.93
dtype: float64
-----------------------------
```

```
Average Quintile Portfolio Returns (%)
-----------------------------
beta_winsorized
Quintile 1    1.64
Quintile 2    1.82
Quintile 3    1.92
Quintile 4    1.75
Quintile 5    2.34
dtype: float64
-----------------------------
ivol_winsorized
Quintile 1    1.41
Quintile 2    1.24
Quintile 3    1.83
Quintile 4    2.09
Quintile 5    2.94
dtype: float64
-----------------------------
mom_winsorized
Quintile 1    2.19
Quintile 2    1.75
Quintile 3    1.53
Quintile 4    1.36
Quintile 5    2.63
dtype: float64
-----------------------------
```

Exhibit 2: Hedged Portfolio Returns

portfolio	lnSize	bk2mkt	ep1	beta	ivol	mom
Overall Return (%)	2.63	-0.21	-0.80	-0.70	-1.53	0.45
ret |t|	6.30	0.55	1.73	1.35	2.86	0.89
ret p-value	0.00	0.58	0.08	0.18	0.00	0.38
Excess Return (%)	2.02	-0.81	-1.41	-1.31	-2.14	-0.16
xret |t|	4.60	1.59	2.26	1.85	3.06	0.26
xret p-value	0.00	0.11	0.02	0.07	0.00	0.79
CAPM Alpha (%)	2.47	-0.11	-0.71	-0.63	-1.72	0.57
CAPM |t|	30.20	1.69	13.68	7.22	21.99	7.88
CAPM p-value	0.00	0.09	0.00	0.00	0.00	0.00
FF4 Alpha (%)	2.17	-0.26	-0.55	-0.66	-1.59	0.29
FF4 |t|	38.45	5.95	13.59	7.62	22.32	3.66
FF4 p-value	0.00	0.00	0.00	0.00	0.00	0.00
Sharpe	0.37	-0.05	-0.12	-0.10	-0.19	0.04
sharpe |t|	6.02	0.88	2.00	1.60	3.09	0.64
sharpe p-value	0.00	0.38	0.05	0.11	0.00	0.52

Exhibit 3: Quintile Portfolio Returns

lnSize (winsorized)

```
pd.DataFrame.from_dict(quin_portfolios["lnSize_winsorized"]).round(2
```

quintile	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Overall Return (%)	3.65	2.16	1.49	1.02	1.02
ret |t|	6.39	4.90	3.92	2.86	3.15
ret p-value	0.00	0.00	0.00	0.00	0.00
Excess Return (%)	3.04	1.56	0.89	0.42	0.42
xret |t|	7.07	5.80	4.00	2.21	2.79
xret p-value	0.00	0.00	0.00	0.03	0.01
CAPM Alpha (%)	3.08	1.60	1.07	0.56	0.60
CAPM |t|	31.90	21.36	19.26	14.59	18.82
CAPM p-value	0.00	0.00	0.00	0.00	0.00
FF4 Alpha (%)	2.74	1.56	1.04	0.52	0.57
FF4 |t|	36.53	21.73	20.11	13.42	16.62
FF4 p-value	0.00	0.00	0.00	0.00	0.00
Sharpe	0.38	0.28	0.22	0.15	0.17
sharpe |t|	6.18	4.61	3.59	2.50	2.76
sharpe p-value	0.00	0.00	0.00	0.01	0.01

bk2mkt (winsorized)

```
pd.DataFrame.from_dict(quin_portfolios["bk2mkt_winsorized"]).round(2
```

quintile	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Overall Return (%)	2.20	1.57	1.82	1.88	1.99
ret |t|	4.60	3.94	4.45	4.54	5.05
ret p-value	0.00	0.00	0.00	0.00	0.00
Excess Return (%)	1.59	0.96	1.22	1.28	1.39
xret |t|	5.09	3.89	5.54	4.67	5.37
xret p-value	0.00	0.00	0.00	0.00	0.00
CAPM Alpha (%)	1.73	1.03	1.25	1.41	1.61
CAPM |t|	31.58	35.63	20.39	16.13	20.64
CAPM p-value	0.00	0.00	0.00	0.00	0.00
FF4 Alpha (%)	1.68	0.94	1.19	1.31	1.42
FF4 |t|	30.38	31.09	20.28	17.43	21.74
FF4 p-value	0.00	0.00	0.00	0.00	0.00
Sharpe	0.27	0.22	0.25	0.26	0.29
sharpe |t|	4.33	3.61	4.13	4.24	4.73
sharpe p-value	0.00	0.00	0.00	0.00	0.00

ep1 (winsorized)

```
pd.DataFrame.from_dict(quin_portfolios["ep1_winsorized"]).round(2)
```

quintile	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Overall Return (%)	2.74	1.66	1.42	1.68	1.93
ret |t|	4.39	3.64	4.20	5.10	5.63
ret p-value	0.00	0.00	0.00	0.00	0.00
Excess Return (%)	2.13	1.05	0.81	1.08	1.33
xret |t|	4.58	3.65	4.45	6.23	6.48
xret p-value	0.00	0.00	0.00	0.00	0.00
CAPM Alpha (%)	2.16	1.19	0.94	1.26	1.45
CAPM |t|	29.62	25.31	20.90	19.49	23.05
CAPM p-value	0.00	0.00	0.00	0.00	0.00
FF4 Alpha (%)	1.92	1.04	0.93	1.26	1.37
FF4 |t|	31.55	22.39	22.06	20.88	24.15
FF4 p-value	0.00	0.00	0.00	0.00	0.00
Sharpe	0.26	0.21	0.24	0.29	0.32
sharpe |t|	4.19	3.36	3.82	4.72	5.27
sharpe p-value	0.00	0.00	0.00	0.00	0.00

beta (winsorized)

```
pd.DataFrame.from_dict(quin_portfolios["beta_winsorized"]).round(2
```

quintile	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Overall Return (%)	1.64	1.82	1.92	1.75	2.34
ret |t|	6.15	5.83	4.58	3.34	3.79
ret p-value	0.00	0.00	0.00	0.00	0.00
Excess Return (%)	1.03	1.21	1.32	1.14	1.73
xret |t|	5.36	7.19	4.96	3.19	3.95
xret p-value	0.00	0.00	0.00	0.00	0.00
CAPM Alpha (%)	1.19	1.34	1.41	1.28	1.82
CAPM |t|	44.43	44.46	21.18	14.52	19.70
CAPM p-value	0.00	0.00	0.00	0.00	0.00
FF4 Alpha (%)	1.07	1.26	1.27	1.22	1.73
FF4 |t|	39.21	38.62	21.01	15.79	19.56
FF4 p-value	0.00	0.00	0.00	0.00	0.00
Sharpe	0.35	0.33	0.26	0.19	0.22
sharpe |t|	5.68	5.42	4.28	3.10	3.58
sharpe p-value	0.00	0.00	0.00	0.00	0.00

ivol (winsorized)

```
pd.DataFrame.from_dict(quin_portfolios["ivol_winsorized"]).round(2)
```

quintile	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Overall Return (%)	1.41	1.24	1.83	2.09	2.94
ret |t|	5.20	3.82	4.58	4.54	4.53
ret p-value	0.00	0.00	0.00	0.00	0.00
Excess Return (%)	0.80	0.63	1.22	1.49	2.33
xret |t|	5.39	3.96	5.42	5.09	4.71
xret p-value	0.00	0.00	0.00	0.00	0.00
CAPM Alpha (%)	0.87	0.75	1.42	1.45	2.58
CAPM |t|	35.33	17.15	18.12	24.18	29.74
CAPM p-value	0.00	0.00	0.00	0.00	0.00
FF4 Alpha (%)	0.76	0.66	1.36	1.46	2.35
FF4 |t|	30.79	16.57	17.23	28.14	30.37
FF4 p-value	0.00	0.00	0.00	0.00	0.00
Sharpe	0.29	0.21	0.26	0.26	0.27
sharpe |t|	4.73	3.43	4.26	4.26	4.34
sharpe p-value	0.00	0.00	0.00	0.00	0.00

mom (winsorized)

```
pd.DataFrame.from_dict(quin_portfolios["mom_winsorized"]).round(2).
```

quintile	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Overall Return (%)	2.19	1.75	1.53	1.36	2.63
ret |t|	3.85	4.42	3.97	3.97	5.58
ret p-value	0.00	0.00	0.00	0.00	0.00
Excess Return (%)	1.58	1.14	0.92	0.75	2.03
xret |t|	3.87	4.85	3.90	3.78	5.99
xret p-value	0.00	0.00	0.00	0.00	0.00
CAPM Alpha (%)	1.69	1.14	1.02	0.91	2.26
CAPM |t|	20.04	23.98	17.15	16.90	38.64
CAPM p-value	0.00	0.00	0.00	0.00	0.00
FF4 Alpha (%)	1.73	1.06	0.91	0.81	2.02
FF4 |t|	21.73	28.49	17.95	14.60	31.38
FF4 p-value	0.00	0.00	0.00	0.00	0.00
Sharpe	0.22	0.25	0.22	0.22	0.33
sharpe |t|	3.63	4.10	3.64	3.60	5.30
sharpe p-value	0.00	0.00	0.00	0.00	0.00